Hospital Services Demand Forecast Using Graph Neural Networks

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***Abstract*—Good healthcare service relies on resource planning and demand forecast. While in hospital admission, patients are transferred between the different care units of the hospital in order to go through medical examinations and treatments. Thus, there is a great importance to plan resource allocation in the care units according to demand. This study suggests a graph network as an inductive representation of the patients' stays while admitted. A classification model is trained to predict the care units to which a patient may attend. The graph based model shows significant improvement in demand prediction when compared to traditional classification models.**

INTRODUCTION In his famous book "The House of God", Samuel Shem describes the chaotic nature of hospital life and hospitalization experience. Patients are transferred back and forth between care units in a manner he called "Buff and Turf" [1]. The need to pre-plan hospital resources is crucial for better healthcare service [3], and in particular its importance increases dramatically in times of pandemic, as seen during COVID-19 [2]. This study introduces an approach by which hospitalization data is described as a directed bipartite graph, in which patients and care units are nodes, and each transfer of a patient to a care unit is an edge. Each patient node holds basic information on the patient. Then, a Graph Convolution Network (GCN) model is trained to classify edges, in the sense of predicting assignment of patients to care units. Utilizing such a classifier may improve demand forecasting and resource planning in the hospital departments and thus improve the hospital organization throughput. In addition, using the model may improve the service to individual patients as a decision support tool to decide which medical examination and treatments each patient may require.

Background and Related Work

A variety of machine learning models are used to forecast demand of hospital services [14]. Ranging from Support Vector Machines (SVM) and tree ensembles to deep neural networks [16]. Graph Neural Networks (GNN) are an emerging field of study which is based on data representation as a graph of nodes to represent samples and features, and links to represent relationship between them [17]. Graph Neural Networks are proven to deliver high performance predictions on variety of tasks. Beyond analysis of social networks, GNN are used to classify drug-drug interactions and document topic classification from a cite graph [7]. Graph Convolution Networks (GCN) extend the concept of Convolution Neural Networks

(CNN) which is mainly used to classify images to the field of graph networks [5]. GraphSAGE (SAmple and aggreGatE) enables inductive learning for large scale data, which is suitable for tasks in which new nodes and links are added to graph constantly [6]. It does so by leveraging node feature information to efficiently generate node embeddings for previously unseen data. Figure 1 illustrates GNNs. The top figure shows a scheme of a GCN based architecture, where node embedding is based on a computational graph using neighbourhood sampling. The bottom graph illustrates GraphSAGE which adds aggregation of each node's features to the computation graph. As a result, a richer, inductive representation is learned. [1]

Method

Classification Task

In order to be able to efficiently estimate the traffic to care units and medical treatments around the hospital, we decided to rely solely on data that is available upon admission of incoming patients. Therefore, data records include personal and admission information but do not include further medical tests or examinations. The classification task was defined to determine for each admitted patient which medical services they may require (care units).

Graph Structure

The graph nodes are patients and care units. Edges are visits (transfers) of patients to care units. Each patient node holds initial information of the patient and the admission as data features. The edges are directed from patients to care units, forming a bipartite heterogeneous graph.

Classification Model

The classification task is defined as of the link prediction type. Thus, predicting links may serve as demand forecast for each care unit, and an hospitalization service plan for patients. A GCN architecture with two GraphSAGE layers embed the nodes and a fully connected neuron layer is the classification head.

Inference

The model may be used for inference by the following scenarios:

- Given a new graph, predict the patients transfers to care units.
- Given a graph of current hospital data, predict the next transfers to care units.
- For both the above scenarios, prediction may be dedicated to a specific care unit.
- For new incoming patient, predict the care units they may be required to admit.

[1] Source: https://arxiv.org/pdf/1706.02216.pdf

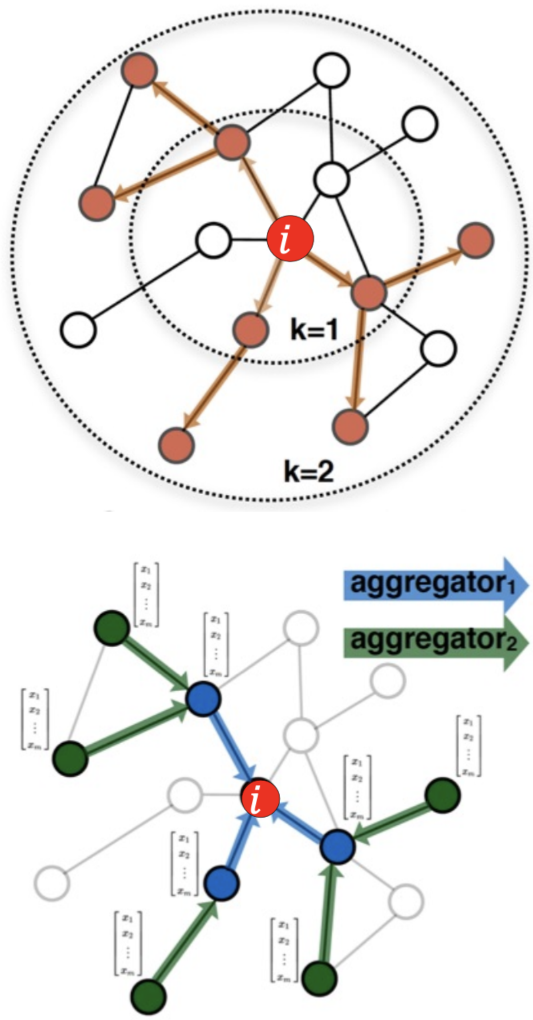

Figure 1. Graph Convolution Networks. (top) General GCN architecture. (bottom) GraphSage architecture.

Experiments and Results

Experiment Setup

Dataset We used data from the MIMIC (Medical Information Mart for Intensive Care) version IV database [8]. This dataset holds records of over 300K patients, 400k hospital admission, 70k emergency department admissions and 2M care unit transfers. We used Postgres database to extract a dataset that holds records that detail the course of the patients while admitted to the hospital. The dataset includes information regarding timestamps of the admission and the transfers, the admission and patient information (admission type, admission location, insurance, language, marital status, race, age and gender). We split the data to 90% train and 10% test by the timestamp of admission, so test data succeeds train data. We used Plotly [10], Networkx [11] and Seaborn [12] to analyze the illustrate the data.

Base Model Architecture To compare the performance of the GCN model, we trained a Multi Output Classifier on the dataset:

1) We converted the dataset to be 1-hot. I.e. for each patient, we created a 1-hot record with a bit indication for every care unit.
2) We split the data by timestamp of admission to 90% train and 10% test.
3) We trained the range of classifiers: Random Forest, Gradient Boosting, AdaBoost and Logistic Regression using AutoML by AutoGluon [15].

GCN Model Architecture We used PyTorch Geometry (PyG) to implement the classification model [9]. We filtered out from the graph 10% of the nodes and edges, by their timestamp to be used as a test set. The model architecture includes two SageConv layers with 64 hidden channels, followed by a classification head. The training data was added negative edges in 2:1 ratio. The model was trained for 5/10/20 epochs. The best test performance were accepted on 10 epochs.

Performance Measures We measured Accuracy, Precision, Recall and ROC-AUC for the two models using the Scikit-Learn library [13].

Exploratory Data Analysis

Transfers by Care Unit Mere count of patients when comparing care unit traffic reveals Emergency Department and Medicine as the most active care units (Figure 2).

Partition by Class (Feature) The more interesting findings are revealed when performing a breakdown by feature partitions of the patients. To visualize patients' in-hospital experience, we analysed for each feature:

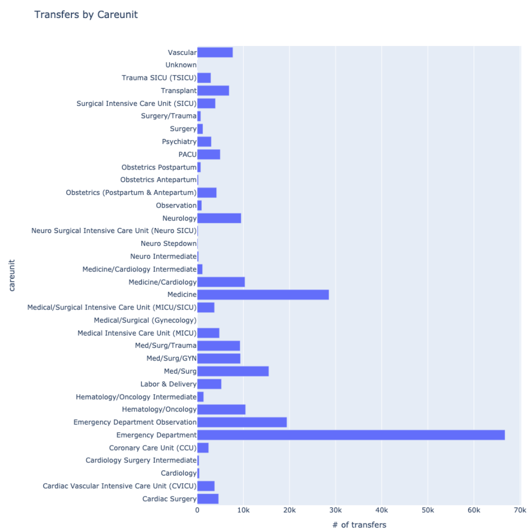

Figure 2. Number of transfers to care units

1) The distribution of the patients between departments. E.g. The fraction male patients admitting to each care unit.
2) The distribution of this feature per department. The fraction of male patients in each care unit.

We found that the partition does not necessarily correlate to the class ratio. Some interesting examples:

- Breakdown by Gender reveals that 66.45% of the patients admitted to the cardiology department are male. This correlates to common knowledge re men suffering heart diseases more than women. In addition, the fraction of men transferred to the cardiology department is 26.72% while only 0.83% of the women who were hospitalized required the cardiology care unit (Figure 3. Also, naturally only women attend the obstetrics care units.
- When examining admission to the cardiology department by race, 69.09% of the patients in cardiology are "white", while only 1.34% of the "white" admissions require transfer to cardiology, in comparison for example to 26.09% of the "Black / African American" patients (Figure 4. This may suggest difference in the health states for different populations.
- Complete set of graphic illustrations is available in the supplemental material.

Graph Representation We visualized the hospital graph using red color to indicate care units and blue for patients. Figure 5 illustrates the graph. It can be seen

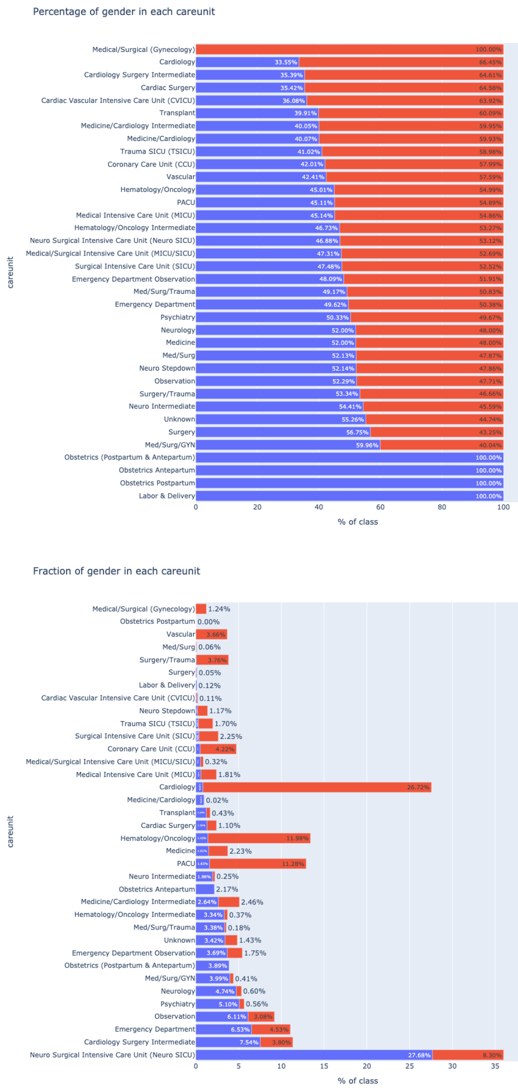

Figure 3. Distribution of patients to care unit breakdown by gender.

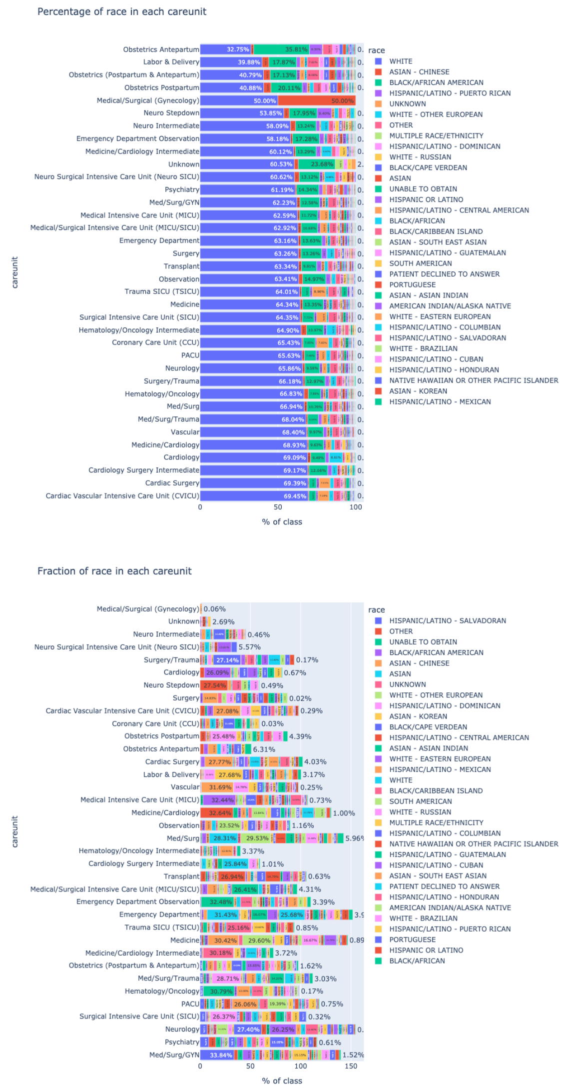

Figure 4. Distribution of patients to care unit breakdown by race.

that the Emergency Department and Medicine care unit are the most active departments.

Classification Results

The trained GCN model scored accuracy of 89.16% on the train set, and 85.88% on the test set. In comparison, the best select model by AutoGluon was LightGBM model which scored 92.05% accuracy on the train set and 91.84% on the test set. The significant difference is revealed when comparing the discriminative performance between the models. While GCN was able to predict service demand on new samples, LightGBM failed to do so, falling to near zero discrimination on the test set (Table 1). Figure 6 illustrates the dramatic difference by comparing the ROC-AUC scores on the test set: 85.53% for the GCN model, compared to only 50.13% on the LightGBM one.

Discussion and Future work

This study hypothesized that a GNN based model learns to leverage knowledge aggregated from adjacent nodes to develop ability to classify new nodes. We demonstrated how a GCN and GraphSAGE based classifier outperforms a state of the art classifiers. We experimented a model that predicts visits to care units

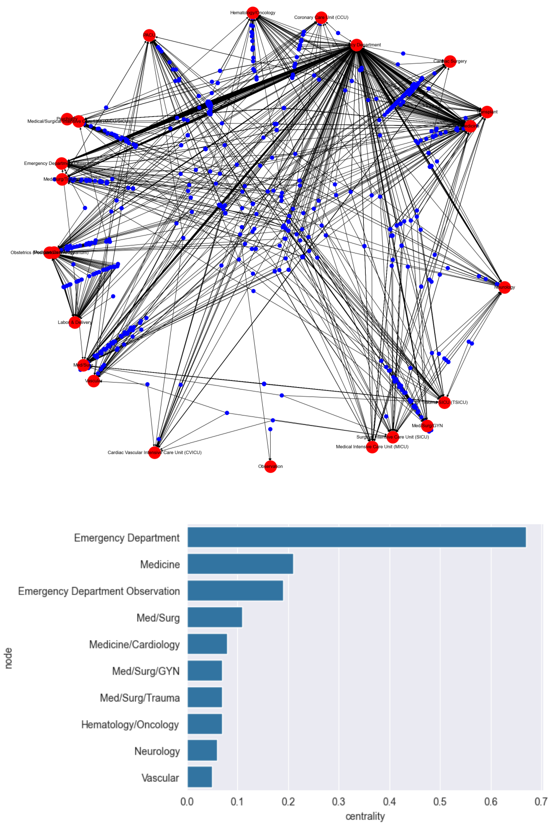

Figure 5. Graph representation of patients and care units. The lower image ranks nodes by centrality measure.

	Accuracy	Precision	Recall	ROC-AUC
Train				
GCN	0.8916	**0.8130**	**0.8766**	**0.9540**
LightGBM	**0.9204**	0.0539	0.0256	0.5013
Test				
GCN	0.8588	**0.2231**	**0.5988**	**0.8553**
LightGBM	**0.9184**	0.0676	0.0246	0.5010

Table 1. Train and Test scores for the GCN and LigtGBM models. The best results for each score and each test are marked in bold.

while hospitalization. As a deliberate consideration, we chose to base the prediction merely on demographic and general information so all necessary data to predict the service path is available upon admission. We showed that while a boosted tree ensemble failed to generalize to a useful predictor, the GCN model achieved acceptable results.

Future Work

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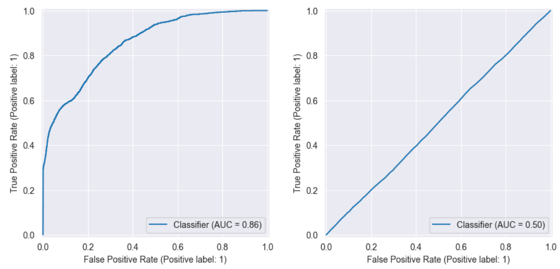

Figure 6. ROC-AUC graphs. Score is 86% for the GCN model (left) and 50% for LightGBM classifier (right).

- Research for graph structure to improve representation and learning.
- Add patient medical data to enhance decision support while hospitalized.
- Develop downstream tasks - re-admission prediction, risk assessment, suggested treatment, etc.

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