Exploratory Network Analysis of Clinical Interactions in the ED

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[a] *Repository (https://github.com/tommyflynn/Flynn_N741_Project/tree/master/Flynn_Project)*

Abstract

Patient acuity in the Emergency Department is triaged at the beginning of the care process using the Emergency Severity Index (ESI) metric. The ESI is presumed to predict resource consumption in the ED, and is a validated predictor of hospital admission for the majority of ED patients. It is not sensitive to non-medical patient characteristics, such as patient race, nor is it accountable to changes in patient condition over time. ED administrators and charge nurses are left with an impression of the unit that does not reveal the reality of current paitient conditions or ED resources being utilized. The lack of real-time ED resource and patient condition information creates opportunities for unrecognized patient deterioration, medical errors, increased wait times, and decreased patient satisfaction. An objective measurement of patient resource consumption that passively observes and calulates relative patient need in real-time would allow charge nurses and administrators to make informed decisions for effective, efficient, and safe patient care. This study tests a novel approach to measuring patient acuity (ED resource consumption) using real-time location system (RTLS) contact data and network analysis. This paper presents the approach and analytic results of several ED contact networks in relation to patient acuity (ESI)

Research Question & Specific Aims

- Can network analysis of clinical interactions between patients and staff provide insight into the complex Emergency Department patient care process? (Canto et al. 2000) Aim 1: Graph the network of clinical interactions in the ED between patients and staff to explore potential similarities, future research questions, and more robust applicationg of igraph in R studio.

Background & Objectives

Intelligent clinical monitoring software is not a new idea, but advancements in the field of data science continue to yield powerful new tools that may make such software a reality in the near future.(Yu et al. 2015, Donoho (2017)) Real-time location systems (RTLS) are increasingly common in hospitals across the nation, especially in clinical areas where patient care and flow are both complex and time-sensitive, such as the Emergency Department (ED).(Yao, Chu, and Li 2012) A bird's-eye view of a busy urban ED might resemble a hive of frenzied bees, but as we have learned of beehives, patterns of work and interactions within EDs are necessarily purposed and complexly adaptive to the various needs of the system (or hive) as a whole.(Kridi, Carvalho, and Gomes 2016) By leveraging the technology of RTLS and analytical power of netowrk analysis, future ED monitoring systems will provide ED leadership with real-time resource allocation and patient condition information. The Emergency Severity Index (ESI) is a validated metric used to triage patients in US Emergency Departments.(Tanabe et al. 2004) That triage nurse may decide to involve the charge nurse or a physician given various concerns about the patient. These interactions, observed and measured by the Real Time Location System (RTLS), continue as more patients are triaged, moved into patient rooms, and so on toward a vast and complex network of interactions. This web of care is likely to correlate with the amount and quality of care delivered to individual patients. - **The purpose**

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of this study is to explore the network of clinical interactions that take place in the Emergency Department and present graphical representations of those networks. To meet this purpose, I received permission to analyse existing data that includes the following; the frequency and duration of all face-to-face interactions (patients, providers, nurses, technicians, & administrators) that occured in the ED for 81 12hr shifts, the location of those interactions, and individual patients' medical and demographic characteristics including acuity, chief complaint, gender, age, arrival mode, and disposition. The network structural characteristics will be assessed in relation to the industry standard acuity measure, the Emergency Severity Index (ESI), and potential confounding variables. Using this data will require specific knowledge of the R statistical packages, network analysis, and data science. See Tables 1-4 for my learning goals with respective action items, timeline, and outcomes.

Methods

RTLS Data

This study applies a secondary data analysis design due to the exploritory nature of the research aims. Data was made available with permissions from the originating research team. The purpose of the original study was to describe contact characteristics between patients and staff in the ED of a busy urban hospital to inform cross-infection control measures. Data were collected using a radio-frequency identification system that triangulated patient and staff (nurses, providers, and ancillary staff) locations within the ED at Emory University Hospital Midtwon. Data for this secondary analysis were collected using a prospective, longitudinal, observational design with a random sampling of one day shift and one night shift per week for one year, July 1, 2009 to June 30, 2010. This strategy was chosen to minimize sampling bias related to seasonal or weekly fluctuations in census, acuity, and ED staffing changes. Although a total of 104 shifts were observed, the original research team retained only 81 shifts for reasons related to issues with the RFID system and study staff sick leave.(Lowery-North et al. 2013)

Analysis Plan

Data Exploration & Cleaning

Code for analyses were maintained in private repositories in the GitHub version control platform. Patient characteristic data was evaluated for missing or implausible data with discriptive analyses, and RFID generated networks will be included for statistical analysis if variables of network density, centrality, and a network diversity scale are distributed normally across networks. The data were inconsitant in the way individual participants were tagged. There were 1102 unique nodes in the vertices data, 1023 unique nodes in the edges dataset, and 1017 unique patients in the patient characteristics dataset. Furthermore, there were a number of extra dates of data collection in the nodes and patients data. After learning several new tricks, the data were finally subsetted into 35 data frames to be graphed with iGraph.(Csardi and Nepusz 2006)

Analysis

The open-source R statistical language and R-Studio user interface from the developers at CRAN were used for all data exploration, wrangling, cleaning, description, and analysis.(R Core Team 2017) Pandoc's Markdown allows for seemless integration of code, results, visualizations, and author interpretation of the research into a single document.(Allaire et al. 2017) Running all code and calculating all results within the menuscript itself, Markdown eliminates risk for errors in transferring statistical software output into foreign documents. The data were explored, cleaned, and assessed for statistical assumptions using the Tidyverse group of R packages.(Wickham 2017, Wickham (2016)) Data were prepared for network visualization and plotted with the network object package iGraph. (Csardi and Nepusz 2006).

Results

Table 1: Overall Participation

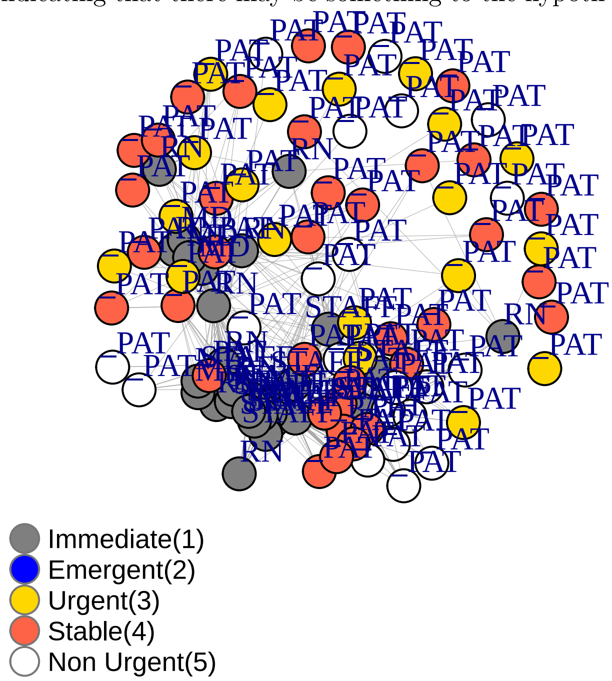
Participants (n)	Shifts	Participants/Shift	Participation Rate (mean%)	Total Ties	Ties/Shift
3635	35	103.8571	63.09335	21600	617.1429

Table 2: Patient Acuity

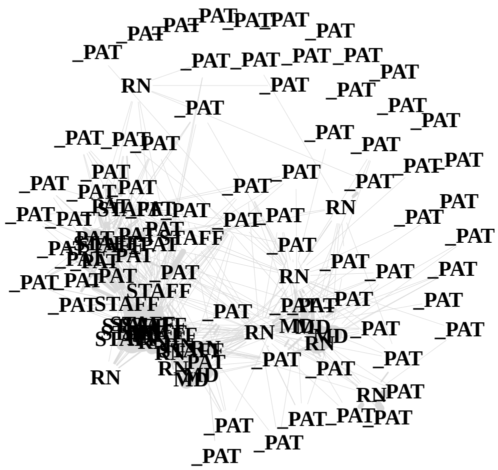
Acuity Level	Count
Immediate (1)	14
Emergent (2)	694
Urgent (3)	1191
Stable (4)	417
Non Urgent (5)	27

The bulk of this project ended up focussing on data exploration and wrangling. Although the data came in tables that had been *cleaned*, there turned out to be a significant amount of wrangling and organizing to re-clean it for the purposes of this study.

We selected 3 representative shifts for visualization and exploration. Although I was not able to analyze these networks to the extent I had hoped, there are a number of visualizations shown below. The first shift represented below shows an interesting cluster of highly acute (gray) patients, indicating that there may be something to the hypothesis that acuity will correlate to network position. 10-1.pdf

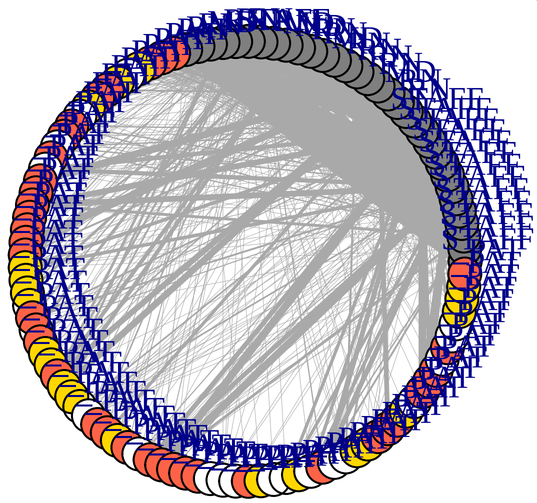


The graph below is does not display the individual patient acuities, but it does give a slightly better overview of the various positions of patients, staff, RNs, & MDs thoughout the network.



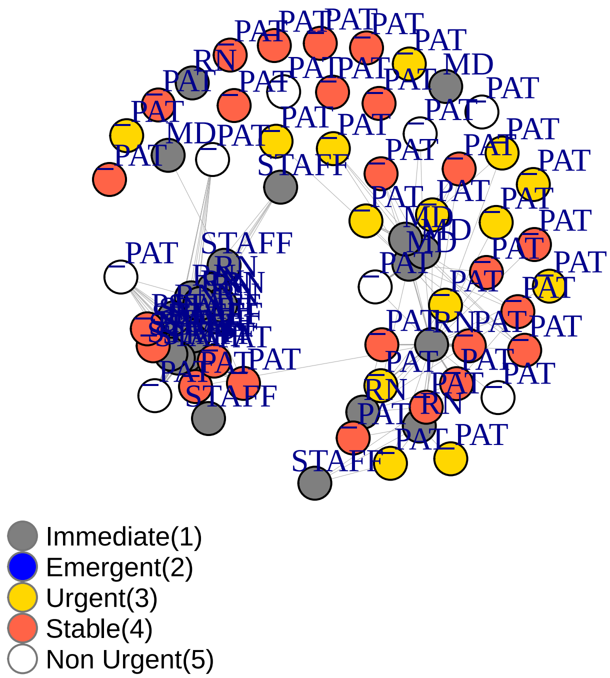
labels-1.pdf

The following network offers a unique perspective of the distribution of ties in the network by essentially *getting the nodes out of the way.* What is particularly interesting is teh way the ties appear to be more dense where patients are scored at an acuity of level 1, or "Immediate". A closer look at the distribution of edges may provide further insights in following analyses.

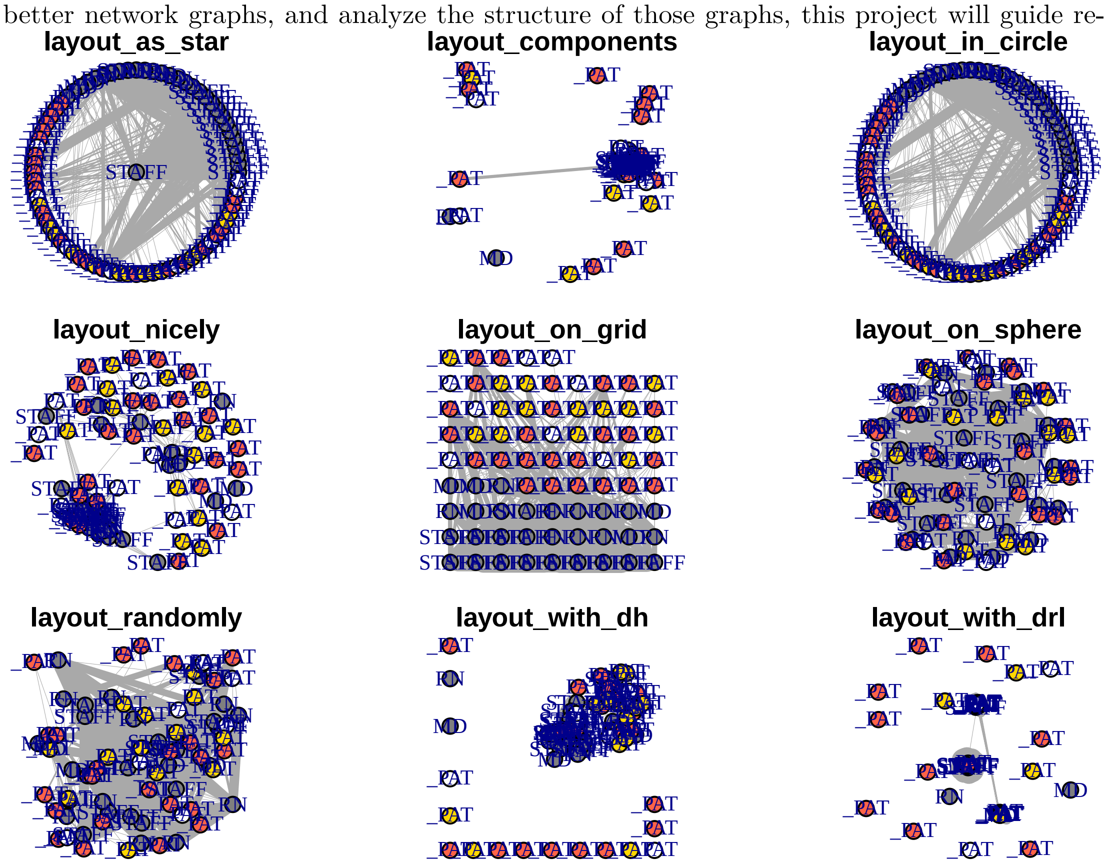


circle-1.pdf

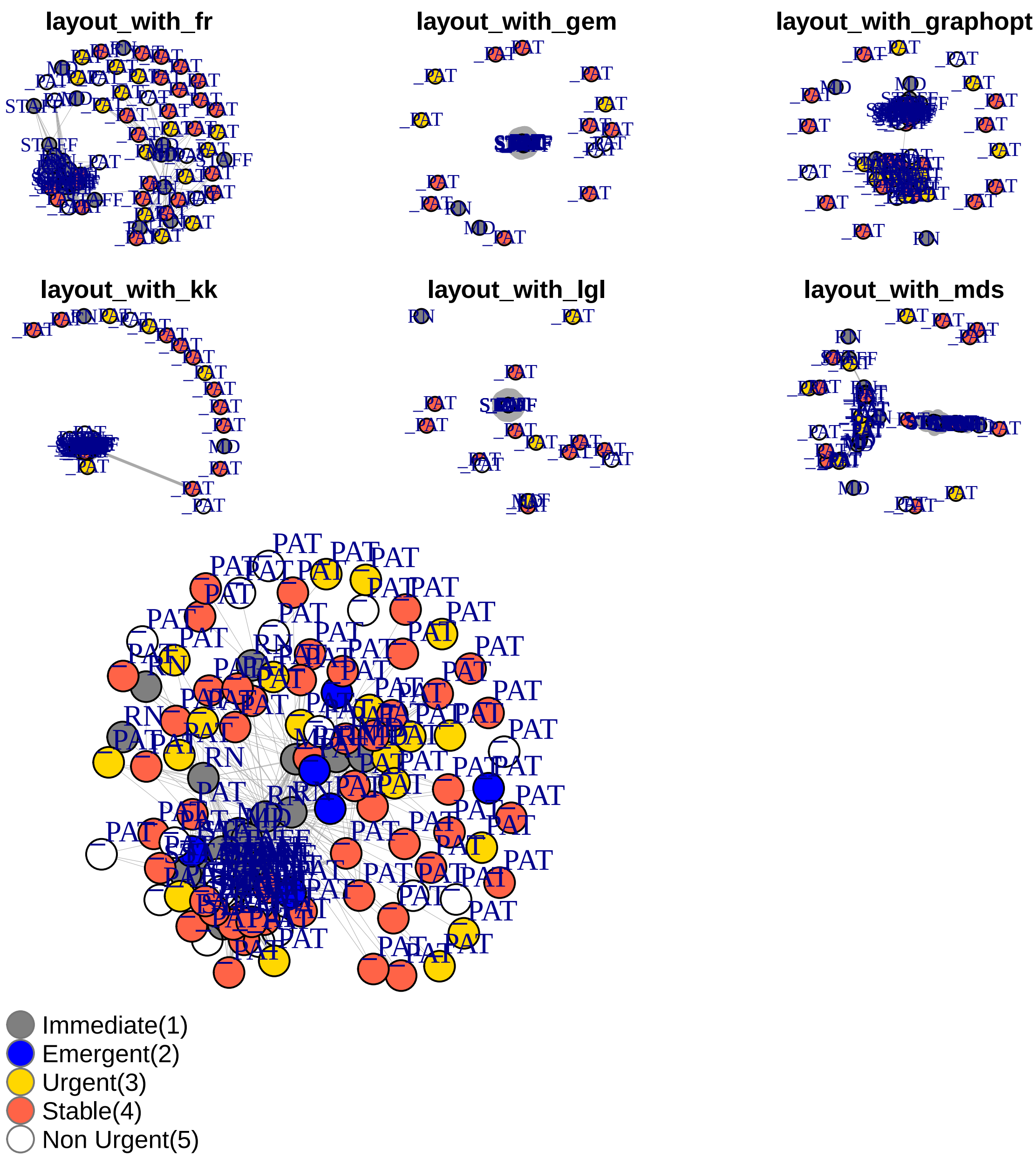
The remaining graphs are generated from two other shifts. Although much of the overall visual characteristics appear similar, there are a number of interesting differences that have given me ideas for further inquiry. 23-1.pdf

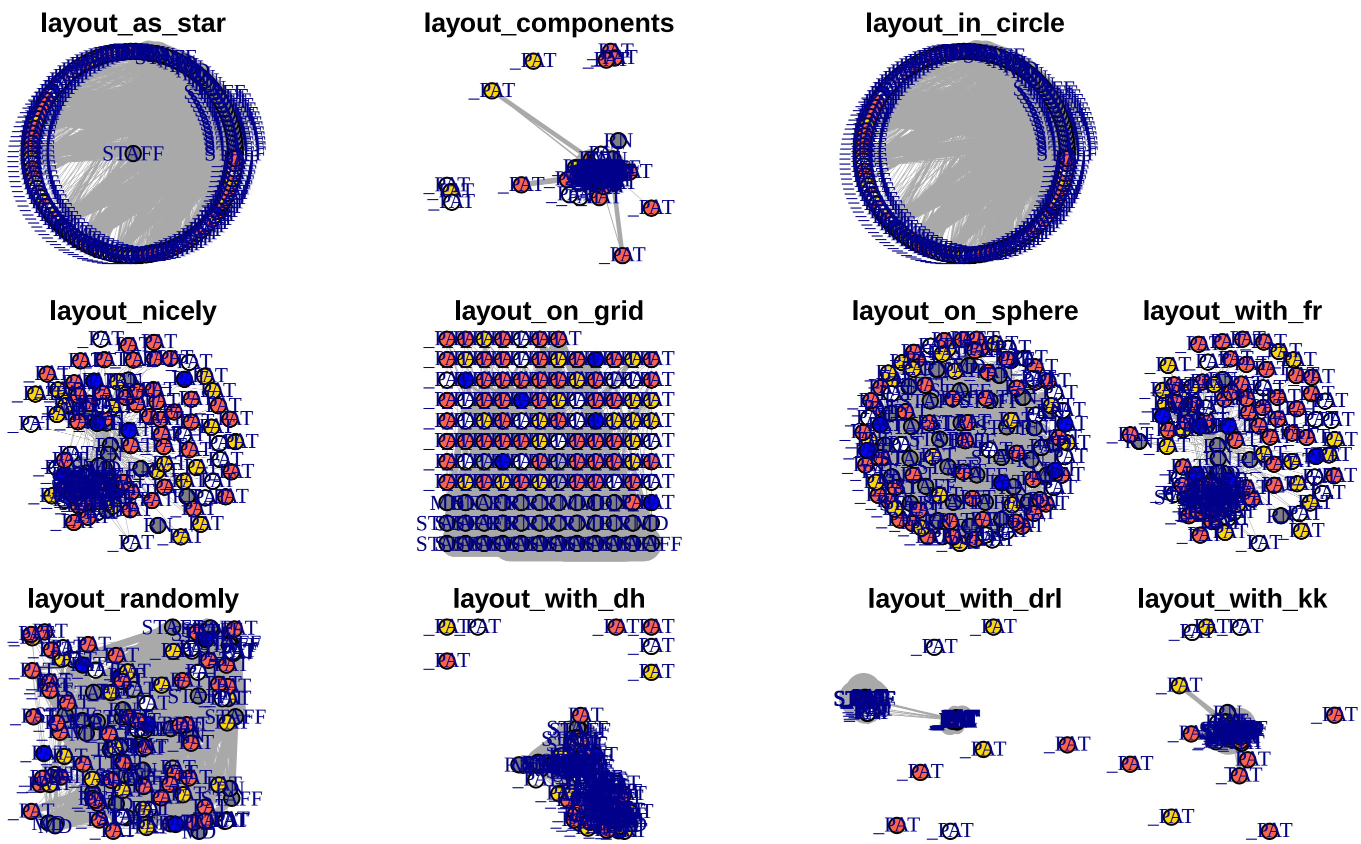


As I am able to code more complex data and create better network graphs, and analyze the structure of those graphs, this project will guide re-



search questions.


layout_with_fr
layout_with_gem
layout_with_graphopt
layout_with_kk
layout_with_lgl
layout_with_mds
Immediate(1)
Emergent(2)
Urgent(3)
Stable(4)
Non Urgent(5)



Discussion

Allocating staff resources in an Emergency Department is an ongoing challenge. It also has important implications for patient safety and health outcomes. The primary limitation to this study was the PI's lack of experience with programming, the R programming language, and statistical analysis. This project has been an important element in the PI's learning process.

Conclusion

I was not able to finish my analysis and had to remove my second aim which would have been interesting. However, as this is going to be the analysis I do for my dissertation, the project is far from over. I look forward to finding meaning in the real clinical interaction networks that is reflected in the patterns and variations that is seen in the graphs presented here.

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