Project title: Optimizing Emergency Department Scheduling to Preserve and Protect our Scarce Nursing Resources.

Company description: Medecipher is a Denver-based health IT startup, funded by the National Science Foundation. Medecipher was started due to a lack of data-driven decision support tools for clinical operations leaders to use when designing, implementing, and adapting their care delivery models to ensure optimal outcomes for their patients, staff, and budget. We're passionate about giving operations leaders at health systems the tools they need to make data-driven and supported decisions about their capacity and resources – from predictive staffing levels to recalibration of bed allocation.

Background – staffing for COVID-19 times and beyond: Hospitals are under tremendous pressure to quickly respond and adjust their staffing to changing demand and capacity introduced by the COVID-19 pandemic. Adding to these challenges, the United States currently faces a worsening nurse staffing shortage expected to exceed half a million nurses by 2025, in large part due to retirement of the aging nursing workforce and influx of new patients into our health system. The burden of a growing resource shortage has already impacted nurses working in the profession as they mitigate the additional workload. The additional patient volume and rising shortage creates increases wait time for patients, higher risks of mistakes, and insufficient personal attention to patients in the hospitals. Prior to the pandemic, states such as California mandated patient ratios to protect their staff from burnout and turnover. Nurses were leaving their organizations in record numbers, with turnover rates as high as 40%, citing unsafe nurse staffing practices.

In the short term, we are seeing health systems urgently recruit travel nurses to the areas of greatest COVID-19 outbreak, and high prices going along. Over the past week, weekly pay for short-travel nursing has doubled in hot spots; from an average of $4-6,000/week to over $9,500/week for Washington state hospitals. While hospitals can rely on travel nurses to fill short-term gaps, the human and financial cost is not sustainable. Current strategies and practices for determining nurse staffing levels have proven inadequate to meet demand, and the problem continues to worsen. We are severely stressing out our professional workforce.

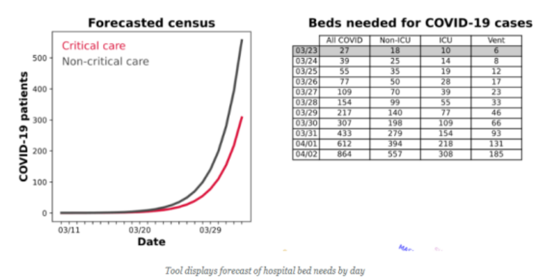
While COVID-19 is the current crisis, the nurse staff shortage is not going away, and may only get worse if it pushes nurses into early retirement. Nurse who were already pushed to their max are now seeing higher than ever patient census and influx of new patients, with little to no respite. They may consider retiring 5 to 6 years early. We expect permanent shifts in the way that hospitals recruit and retain their talent, and how they source their flexible staffing needs, and especially how they schedule them. The top priority for health systems is to protect and preserve their workforce talent, and there is no room to waste them.

Innovation: We have created an ED nurse staffing recommender tool to match future nursing resources to future unknown patient service needs. The tool produces hourly ED patient census forecasts to compute hourly ED nursing demand. It adapts existing nursing schedules, using preapproved modification constraints, to obtain hourly targeted nurse staffing levels that achieve the desired service level based on management policies and practices. The system has three layers: (1) data science core that implements predictive modeling and decision recommendation technology engine; (2) middle layer designed and implemented for secure HIPPA compliant data Input/Output; and (3) user interface.

Approach: Will adapt our existing tools ED nurse staffing tools to intake state and local data from surges such as COVID-19, and create further features and constraints to track burnout amongst ED nurses.

(1) Forecasting model

Several hospital capacity models have been developed for COVID-19, including one for Illinois. We have not seen any for emergency departments. We will retrofit the models (such as Figure 1) for ICU data to forecast patient demand. We will apply cluster analytics algorithms to find cohorts of similar patients with common staffing needs and create a common forecasting model for the cohorts. We will compute a common forecast for each patient cohort. Our approach will be a multivariate linear auto-regression with seasonality covariates that utilizes software packages such as "forecast", "rugarch" and "bft" available in the software system R. The



	All COVID	Non-ICU	ICU	Vent
03/23	27	18	10	6
03/24	39	25	14	8
03/25	55	35	19	12
03/26	77	50	28	17
03/27	109	70	39	23
03/28	154	99	55	33
03/29	217	140	77	46
03/30	307	198	109	66
03/31	433	279	154	93
04/01	612	394	218	131
04/02	864	557	308	185

Figure 1: Displays the daily bed needs by bed type (non-ICU and ICU) along with the project number of vents for IL hospitals. Source

forecast model will incorporate seasonality factors such as hour of the day, day of the week, and month of the year. We will apply (1) ETS (Exponential Smoothing) and (2) ARIMA (Autoregressive Integrated Moving Average). Moreover, other forecasting methods e.g. average, drift, and naïve will be applied based on the characteristic of the data. We will leverage variable imputation methods such as MICE (Multivariate Imputation by Chained Equations) to clean the data, impute missing values, and identify bad data through automatic use of threshold-based cut-offs.

(2) Build a model to optimize and balance resource allocation across the ED

$$\begin{aligned} \min \quad & \textstyle\sum_{h=1}^{T} (p_h U_h + c_h O_h) \\ & N_h + F_h + U_h + O_h = r_h, \\ & \quad h = 1, \dots H. \end{aligned}$$

Figure 2. Optimization model schematic for supply-demand balancing, where N_h: # RNs in the staffing grid, F_h: # RNs flexed, U_h: RN underage, O_h: RN overage, p_h: underage penalty, c_h: overage cost, at hour h. Model is optimized across planning horizon H.

Shift:		Entire Shift		Start of Shift				End of Shift			
Start	Hours:	Add	Cancel	-2 Hrs	-4 Hrs	+2 Hrs	+4 Hrs	-2 Hrs	-4 Hrs	+2 Hrs	+4 Hrs
0700	8	y	y	y	n	y	y	y	n	y	y
0700	12	y	y	y	y	y	n	y	y	y	n
0900	8	y	y	y	n	y	y	y	n	y	y
1100	12	y	y	y	y	y	n	y	y	y	n
1500	12	y	y	y	y	y	n	n	n	y	n
1700	10	y	y	y	y	y	y	y	y	y	y
1900	12	y	y	y	y	y	n	y	y	y	n

Figure 3. Acceptable flexing actions per shift type. e.g. for 0700 start 8-Hour shift, can reduce by 2 but not 4 hours.

We will revise our preliminary optimization model (Figure 2) to express supply-demand matching for ED nurses across all patient cohorts (1), based on the staffing and service thresholds defined by ED operations leadership. The forecast from (1) becomes an input to the optimization model. The model incorporates shift types allowed by the hospital's position control (e.g. 8, 10, and 12-hour shifts) and allowed shift flexing actions (Figure 3). Values for Nh and Fh are generated from the forecasting model. The model minimizes understaffing and overstaffing at each hour, where under- and over-staffing is estimated based on a target ratio. Moreover, the model enables tradeoffs between the relative importance of underage (e.g. understaffing/safety risk) and overage (overstaffing/cost risk) at any hour. The model is calibrated to meet a safe staffing level desired by the management

(3) Interactive UI/Front-end

We will create functionality within the web-based application to assign users to shifts, track edits to the shifts, and track hours to flag nurses for potential burnout. Figure 4 is the current front-end, implemented using programming language Angular JS, that enables the ED nursing manager to view and adjust future daily scheduling recommendations under various demand scenarios.

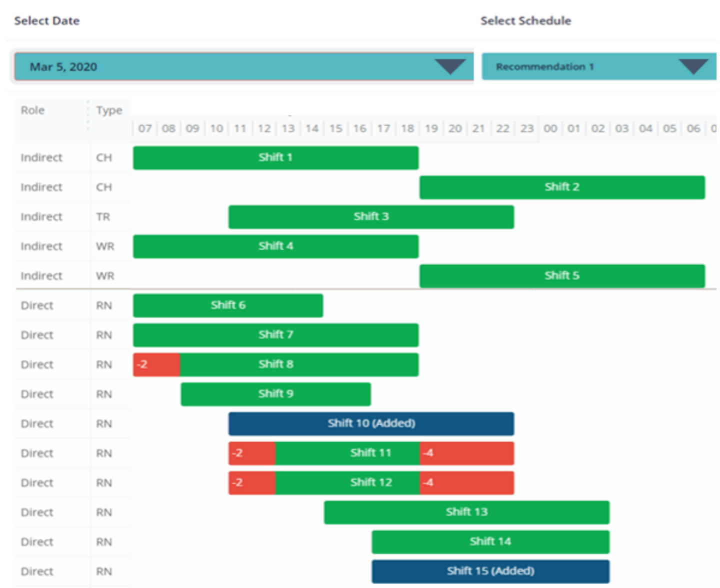


Figure 4. User Interface – optimal nurse schedule, shown for March 5, 2020.

Desired Team size: 3-5

Operations Research Analyst (2-3): Python, R, AMPL and other Solvers

Front-end Development (1-2): Angular JS

3-5 team members, regular meetings with faculty, and frequent interaction with programmer to help overcome challenges.