A Proposal to Improve ER Efficiency, Effectiveness, and Accessibility

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1 Introduction

Emergency medicine involves the care and treatment of patients who present serious, life threatening injuries. These cases require speedy evaluation and treatment, and often non-elective admission, that is provided as a 24/7 service by hospitals. The demand for emergency care is rising worldwide due to an aging population in most countries, and rising survival rates in acute conditions[1]. Health systems that are unable to expand services or manager resources to meet rising demand, are plagued by delays[2]. Emergency medicine delays are of particular concern due to the urgency of cases presented. Additionally, the provision of emergency care is costlier than all other forms of care, with an overburdening of the department, impacting overall financial soundness of a hospital.

The problem presents in the following forms:

- Patient Queuing - Queuing is the phenomenon of long lines of patients boarding up outside emergency rooms(ER), waiting to be treated, due to the inability of the hospital staff to adequately meet patient demand. Overburdened, understaffed ERs result in long queues, that may lead patient deterioration or death[3]. The strategy employed by a hospital to manage these queues determines efficiency outcomes. The usual pattern of pooled queuing of patients may be altered by accounting for the urgency of a case.
- Moral Hazard - Even in countries that do not provide universal healthcare, ERs cannot refuse care on the basis of ones ability to pay or insurance status[4]. Further, unlike other forms of care, there is no requirement to schedule advance appointments. This makes an ER more directly accessible to patients, than other forms of care. These two phenomena make individuals more likely to pursue excessive ER care[5].
- Triaging Errors - In simple terms, triaging is the process of sorting patients according to their need for emergency medical attention. Historically, triaging has been used to tackle the problem of excessive demand and is essential to both, the effective management of a hospital ER and the provision of clinical justice to patients[6]. Triaging standards vary slightly across countries, but the process usually involves the assessment of a short questionnaire and patient vitals to determine emergency need[7]. Patients are categorized into triage categories ranging from 1 - for most urgent, to 5 - non-urgent[8]. This process, however isnt always accurate as care is sometimes over or under provided due to triaging errors. Improving triaging accuracy is an essential step towards equipping hospitals to meet patient demand.

In order to restore the efficacy of emergency services across hospitals, the optimization of emergency department utilization and the reduction of patient flow into ERs must be addressed.

2 Data Findings

Data from the Emergency Management System (EMS) deployed at Hope Hospital, a tertiary-level cancer hospital located in the Middle East, provides details regarding 31,000 patient visits from April, 2018 to April, 2019. Insights from this data helps us identify focal points for emergency department optimization.

[1] https://www.city.ac.uk/news/2017/october/demand-for-emergency-care-why-is-it-growing-so-fast
[2] https://health.usnews.com/health-care/patient-advice/articles/2018-10-26/why-do-i-have-to-wait-so-long-to-be-seen-in-the-emergency-room
[3] https://www.theguardian.com/society/2014/sep/18/ambulance-queue-death-nhs-cuts
[4] https://www.acep.org/life-as-a-physician/ethics–legal/emtala/emtala-fact-sheet/
[5] https://www.newyorker.com/magazine/2015/05/11/overkill-atul-gawande
[6] Robertson-Steel, I., 2006. Evolution of triage systems. Emergency Medicine Journal, 23(2), pp.154-155.
[7] King, D.L., BenTovim, D.I. and Bassham, J., 2006. Redesigning emergency department patient flows: application of lean thinking to health care. Emergency Medicine Australasia, 18(4), pp.391-397.
[8] The Canadian Triage and Acuity Scale: Education Manual

The data reveals patterns in emergency care demand and service. 36% of patient visits are by patients categorized as non-urgent (category 5), while only 2% of visits are categorised 1.

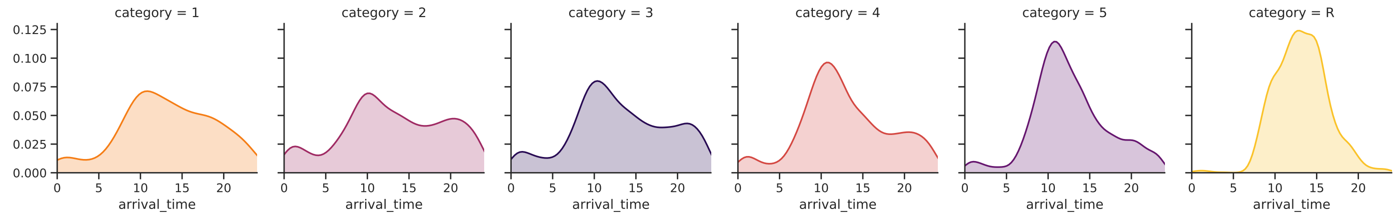


Figure 1: Patients Arrival Distribution

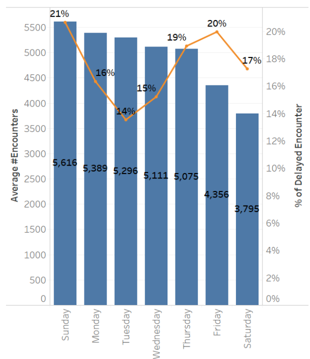


Figure 2: Average # Encounters and % of Delays for Category 1

Time trends show that 9am to 12pm are peak hours, with maximum patient in flow, with numbers dipping in the evenings and at night. Patient numbers also drop during the weekend and peak right after. It is important to note that since this data comes from a cancer hospital, the nature of cases presented tend to be medical in nature, so these trends may not be easily generalizable to general hospitals where trauma care forms a larger proportion of care demand[9]. The important insight here is that emergency care demand varies over time.

Wait time, measured as the time elapsed between the patients arrival at the ER, and the patients examination by a doctor, is an important measure of department effectiveness. Average waiting times followed the same pattern as patient demand, across hours, and days of the week. Delays can be defined as cases when a patient experiences a wait time duration that is longer than the wait threshold defined for his or her triage category. By examining the data, we found that approximately 17.3% of patient visits resulted in delays in care provision. An important insight was that delay proportion was found to be the highest for Category 1 patients, at 73%, and fell as the patient category number increased, down to 5% for category 5.

This is worrying as patients with lower triage categories require treatment without delay.However, this pattern may indicate that the Triage thresholds for wait time that have been set may be too strict for lower priority patients (category 4 and 5). This also indicates the urgent need to optimize workload by employing alternative patient queuing strategies that incorporate patient category. Additionally, an exploration of high frequency visitors revealed that approximately 1200 patients who visited the ER more than once a month were categorized 4 or 5. There were a few cases of frequent flyers, defined by at least 9 visits a month, who make unnecessary and frequent visits to the ER for care which exposes a moral hazard problem. In summary, the data suggests that staffing interventions, reduction of low urgency patients, transformation of triage thresholds, and alternative queuing strategies, are all viable interventions to tackle ER problems.

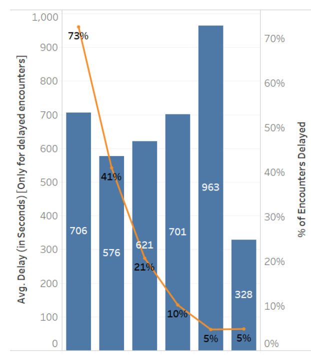


Figure 3: Delay Analysis for Triage Categories

3 Patient Flow Model

3.1 Busy Hours

The number of arriving patients variates during every day. We believe by discovering the pattern of customers can help the hospital better prepare. Therefore, I estimate the kernel density of the average arrival distribution every day.

We have also done the same visualization for each of the *Triage Category*, which appear basically in the same pattern. Therefore, we characterize : "Peak" 9:00-12:00, average 8.29 visitors; "Non-Peak" 8:00-9:00 and 12:00-15:00, average 6.05 visitors; "Medium" 6:00-8:00, average 3.21 visitors; "Extremely Low" 0:00-6:00 and 23:00-24:00, average 1.28 visitors.

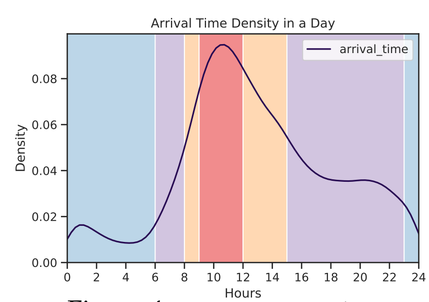


Figure 4: Average Arrival Time

3.2 Maximum Likelihood Time Estimation

The estimated percentage and average number of visitors are used in our simulation model.

The differences between the *completedtime* and *seentime* are used for conducting several lab tests and waiting the doctors to make a decision. Unlike we can estimate the time for testing time by directly calculating the difference between

[9]Cantwell, K., Morgans, A., Smith, K., Livingston, M., Spelman, T. and Dietze, P., 2015. Time of day and day of week trends in EMS demand. Prehospital Emergency Care, 19(3), pp.425-431.

seentime and *caltime*, this period of time is entangled by a set of several actions together. For example, for the *encounterid* 406, the record just shows that it took 235 minutes on three parts: *CBC*, *Blood Chemistry*, and doctor decision making.

Table 1: "encounters"

encounter id	room number	encounter time	call time	seen time	completed time	lab
406	1	4/17/18 8:36 AM	4/17/18 8:43 AM	4/17/18 8:57 AM	4/17/18 12:52 PM	CBC, Blood Chemistry

If we want to simulate the total time used in each step, we don't have enough information to calculate the real-time. So we relax the problem setting to the following linear model:

$$\overline{completed\_time(i) - seen\_time(i)} = \sum_{l \in lab(i)} t_l + r_{room(i)} + \epsilon_{mean} \tag{1}$$

For each encounter i, the total time is the sum of the time used in each procedure. Here I made the assumption that the time used for each test have no correlations with each other. Then we can add them to represent the total testing time. The error is modelled as identical Gaussian error.

Under the assumption of uncorrelation, the variance of each test time can be added to get the total testing variance.

$$\mathbf{Var}(completed\_time(i) - seen\_time(i)) = \sum_{l \in lab(i)} \sigma_l + \delta_{room(i)} + \epsilon_{std} \tag{2}$$

Our problem has been reduced into linear equations. Where we can estimate the mean and variance of each different *lab*, *room number* pairs, the total number of which is 361.

X is a 0-1 matrix represent the patterns in rows. The columns correspond to tests, room number decision time, and inception. The number of functions is 361, while the number of parameters is 18. In this case, we can not use direct linear algebra techniques to solve it. Instead, we apply a maximization likelihood approach to optimize the parameters by gradient descent method.

$$Xt = y_{mean} \tag{3}$$
$$X\sigma = y_{var} \tag{4}$$

Finally, we apply a gradient descent method using tensorflow package. Because the variance of the testing time can not be negative, here we assign a minimal variance as 0.1 for each test.

Table 2: Results

Test	Mean	Variance
Urine Analysis	0.62131184	0.3841998
Urine Culture	-0.52856034	1.3210369
Bleeding Profile	-1.5207993	0.82174927
CBC	-1.3526688	0.1
Blood Chemistry	-1.3425401	0.1
Room 1	1.3596053	1.8585489
Other Labs	-0.3192535	1.0111718
...	...	...

The results show interesting patterns[10]. *CBC* is usually a sign of admission, so the contribute of them is negative to the testing time. *Bleeding Profile* occurs in emergent accidents, which will have high priority accordingly, so this test can actually reduce the testing time. Some of the tests have fixed duration, but there are time variation(high variance) regarding to the tests like *Bleeding Profile*, *Other Labs*, *Urine Analysis*, *Urine Culture*. The efficiency of doctors in *Room 1* is the wrost among all the three rooms.

3.3 Simulation

Having parameter estimated, we can use AnyLogic to simulate the queueing situation in a average day setting.

After the simulation, we have come to the following procedure design.

[10]Whole results refer to Appendix A

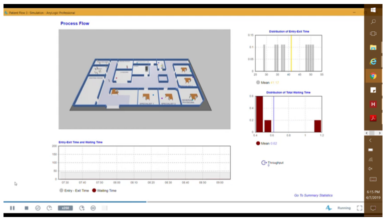


Figure 6: Simulation by AnyLogic

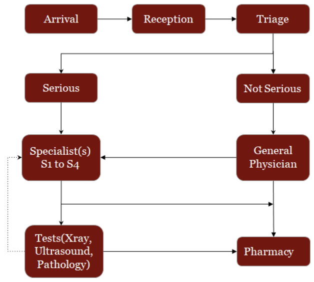


Figure 7: Designed Procedure

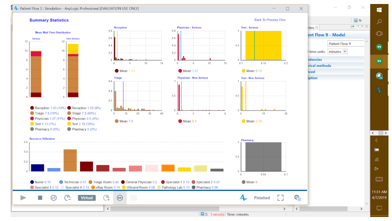


Figure 8: Simulation Result

4 Recommendations

To solve the problems of queueing, moral hazard, and triage errors, based on data insights, we have formulated the following recommendations:

1. **Primary Care and Social Health Integration** - Our first proposal suggests Primary Care integration to reduce the number of patients visiting the ER due to ease of access. We propose hiring social service staff who can address patients social needs. In order to achieve this, the hospital would coordinate with their patients primary care providers to make sure that patients in the database are attending their regularly scheduled appointments and getting necessary lipid measurements checked. This would divert patients from ending up back in the ER by using primary care to help patients better manage their chronic illnesses[11]. We would use information from EMS to determine patients who have come to the ER with chronic health issues and would work to coordinate care with those primary care physicians that are in charge of caring for the patientshttp://www.annfammed.org/content/10/5/452.full. In the next step of this policy, social workers would ensure that patients social needs are met[12]. This would involve making home visits to make sure that patients have access to healthy foods and are living in housing conditions necessary to maintain good health[13]. This is very important as the social determinants of health in many cases determine patients outcome more so than the clinical visits[14]. Finally, in order to help maximize patient health the hospital would implement the same nifty after fifty program, amongst the aforementioned patient population, that CareMore healthcare implemented to help their senior citizens stay healthy[15].

2. The second policy would be to have a team of primary care physicians who may choose to see the patients themselves if they feel like the issue at hand is not an emergency and wouldnt require the use of ER resources. This would help lower ER crowding by making sure that patients that are on a triage level four or five can be seen in a more effective and cheaper setting. In order to accomplish this, the hospital would employ primary care physicians and physician assistants who would be on staff in the ER[16]. These doctors would operate under what Dr. Ezekiel Emmanuel has referred to as open access scheduling[17]. In this case the doctors would have free space in their schedule dedicated to seeing patients who arent experiencing life threatening issues but need to meet with a physician.

3. **Patient Financial Incentives** - The policy that we have proposed to address the issue of moral hazard is a sliding Scale yearly hospital reimbursement program. This would function by giving all patients that are logged into the EMS system a certain reimbursement at the beginning of the calendar year. In subsequent years, the reimbursement would be reduced based on the amount of level 4 and 5 ER visits that a patient engages in[18]. This policy is based on the ACO reimbursement model that encourages healthcare organizations to save money[19]. In ACOs healthcare organizations are given a certain amount to spend on each patient and if they stay within the limit or spend less than the limit, the payor rewards them[20]. Our proposal gears this incentive model from the provider to the patient. This

[11] https://www.modernhealthcare.com/article/20170626/NEWS/170629924/dmc-gateway-program-reduces-er-visits-admissions-improves-primary-care

[12] https://validic.com/how-integrating-social-determinants-data-can-improve-care-programs/

[13] https://www.rwjf.org/en/library/research/2011/05/housing-and-health.html

[14] https://www.kff.org/disparities-policy/issue-brief/beyond-health-care-the-role-of-social-determinants-in-promoting-health-and-health-equity/

[15] https://www.commonwealthfund.org/publications/case-study/2017/mar/caremore-improving-outcomes-and-controlling-health-care-spending

[16] Twelve Transformational Practice in Care -Emmanuel

[17] https://knowledge.wharton.upenn.edu/article/prescription-health-cares-future/

[18] https://journal.ahima.org/2011/04/22/the-risks-and-rewards-of-acos/

[19] https://www.healthaffairs.org/do/10.1377/hblog20180906.711463/full/

[20] https://khn.org/news/aco-accountable-care-organization-faq/

policy can work as a behavioral nudge to prevent excess use of hospital resources due to the effect of loss aversion[21]. This is because patients would avoid using the ER as a place to come and get their social needs addressed and would be more likely to try and seek a primary care physician if the patient knows that he or she may lose on some possible rebates if one isnt prudent with ones ER visits.

4. **Strategic Queuing and Triage Adjustments** - Our final policy proposal involves segmenting the ER based on the the triage number that a patient is given. These patients are then assigned either to a specialist (category 1 and 2) or a generalist physician (categories 3,4 and 5) based on their category. Lower priority patients are referred to a specialist upon need. This queue model has been noted to bring about efficiency gains by inculcating a sense of ownership amongst physicians[22]. From a physician standpoint those who have 1s and 2s would be seated closer to the operating area and those with 3s, 4s and 5s would be seated further and further away. In addition to this, the triage wait times for 4s and 5s would be doubled in order to put more priority on those who fall within triage levels 1, 2, and 3. This would lower delays for those who fall within triage levels 1, 2, and 3. In addition to this, nurses would be notified a minute before the triage wait time expires for a certain patient. This would help nurses remember the exact order of patients to prioritize for admittance within a certain triage. From a behavioral standpoint this would serve to address the cognitive limits that people have and would help the nurse get the high priority ER patients as quick as possible[23]. It would also help the nurse remember the order of patients that were admitted but may reside in the same triage[24].

5. **Staffing interventions** - Staffing Interventions of the nature of staffing to demand, and strategic hiring, would be employed to better equip hospitals to address patient demand. By tracking patient demand over time, peak hours and days can be identified to alter shift timings, and number of staff employed at a particular time. The high proportion of low urgency cases in the ER also indicates that strategic hiring of less specialized staff, that is well equipped to handle non-life threatening cases, may be done. Such staff is likely to be relatively inexpensive compared to specialized emergency trained staff, and could help ease the burden on the latter, allowing them to treat a larger proportion of urgent cases.

5 Conclusion

These reccomendations could go a long way towards addressing the problems of queuing, moral hazard and triage errors. Though they have been derived from the data in this case, these recommendations are generalizable to hospitals across geographies, that are facing similar challenges in the provision of emergency care. Though these improvements require some investment from the hospitals end, the potential for eventual cost savings is large due to the high cost of providing emergency care. One can look at the costs savings, about 2.3 million that BlueCross BlueShield of Illinois, Montana, New Mexico, Oklahoma and Texas achieved through an ACO model[25]. I assume with the high costs of ER services, about $150-3$,000 depending on the extent of the injuries sustained that one can expect even larger cost savings from these reforms[26]. Thus, these steps would help reduce the burden on the hospital ER, improving the quality of care provided, reducing the probability of mishaps due to excessive delays, and providing overall cost savings to hospitals. Despite the expanded provision of healthcare through the Affordable Care Act, many still lack health coverage which makes it imperative that those who go to the ER get the best care possible[27].

[21] Nudge-Sunstein

[22] http://whartonmagazine.com/issues/spring-2017/shorter-er-wait-times-through-smarter-queues/sthash.Bu6YSI0x.qqQLMoJO.dpbs

[23] Behavioral Insights Travel Kit-Hiscox

[24] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4755193/

[25] https://www.rand.org/news/press/2019/03/04.html

[26] https://www.thebalance.com/average-cost-of-an-er-visit-4176166

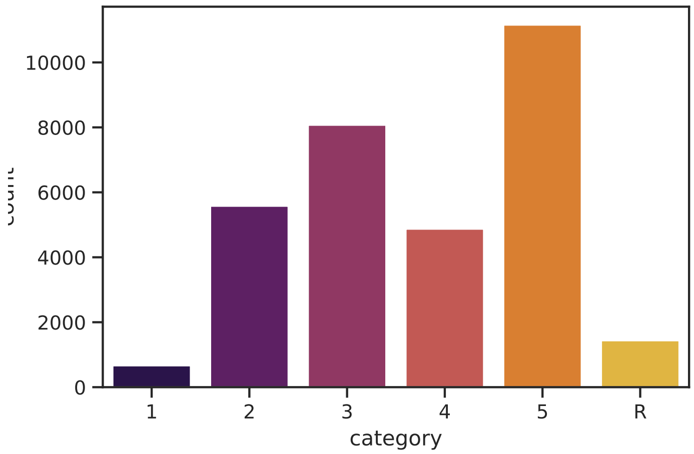
[27] https://www.healthaffairs.org/doi/abs/10.1377/hlthaff.2017.1505?journalCode=hlthaff

Appendices

A Exploratory Data Analysis

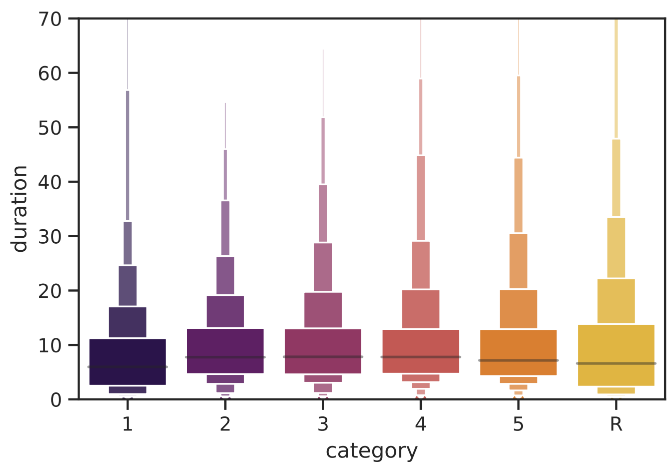
A.1 Triage Category

Figure 8: Triage Category




```
sns.countplot(encounters.category, order=['1', '2', '3', '4', '5', 'R'])
plt.xticks(rotation=0)
plt.show()
```

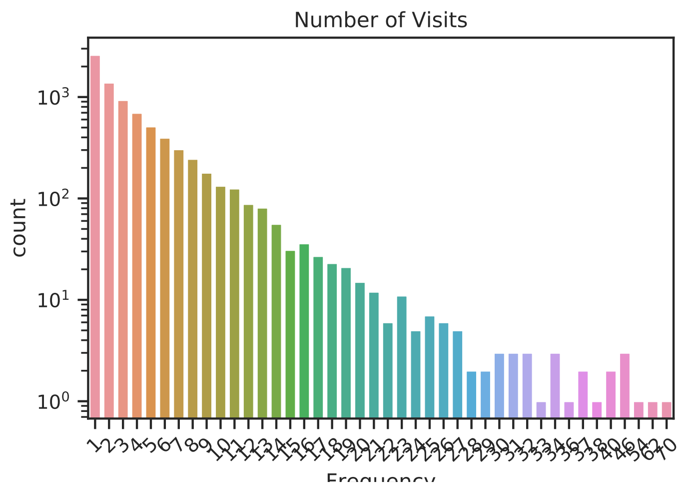
Figure 9: Higher Triage Category, Longer Seeing Time




```
sns.boxenplot(y="see_min", x="category", data=encounters, order=['1', '2', '3', '4', '5', 'R'])
plt.xlabel("category")
plt.ylabel('duration')
plt.ylim(0, 70)
plt.show()
```

A.2 Frequency Long-Tail Distribution

Figure 10: Number of Visits

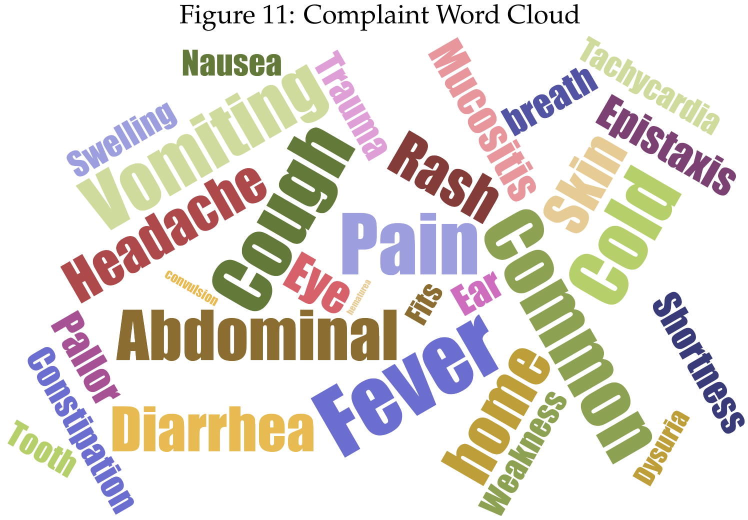



```
count = encounters["Hash"].value_counts()
sns.countplot(count)
plt.xticks(rotation=45)
plt.yscale('log')
plt.xlabel("Frequency")
plt.savefig("num_visits.pdf")
plt.show()
```

A.3 Complaint

The size of each word is process in $log(n)$ scale[28].

Figure 11: Complaint Word Cloud

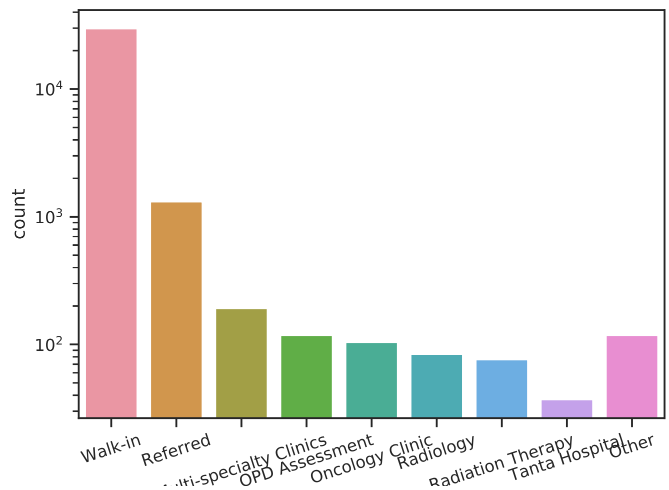



```
" ".join(list(encounters["complaint"].dropna()))
```

[28] https://www.jasondavies.com/wordcloud/

A.4 Refer From

Figure 12: Referred From




```
plt.figure(figsize=(7,5))
sns.countplot(encounters.referredfrom, order=['Walk-in','Referred','Multi-specialty Clinics',
                                'OPD Assessment', 'Oncology Clinic','Radiology',
                                'Radiation Therapy','Tanta Hospital', 'Other'])
plt.xticks(rotation=18)
plt.xlabel("")
plt.yscale('log')
plt.savefig("referredfrom.pdf")
plt.show()
```

B Discriminate Busy Hours

B.1 Method

The number of arriving patients variates during every day. We believe by discovering the pattern of customers can help the hospital better prepare. Therefore, I estimate the kernel density of the average arrival distribution every day.

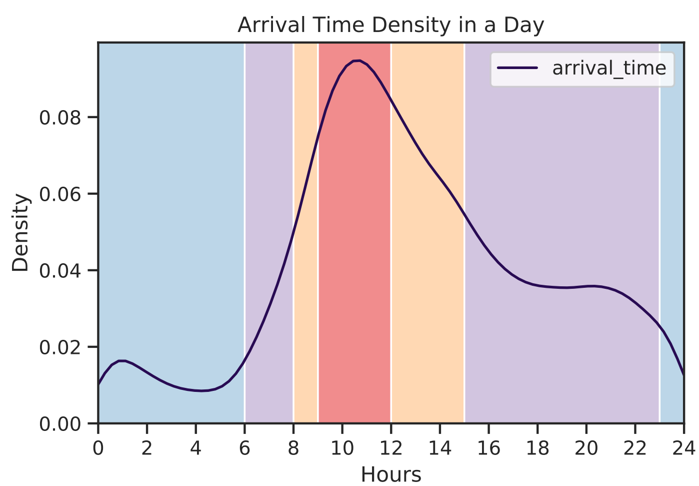


Figure 13: Patient Arrival Distribution

I have also done the same visualization for each of the *Triage Category*, which appear basically in the same pattern.

Algorithm 1: Arrival Time Period Design

```
sns.kdeplot(encounters["arrival_time"])
plt.xlim(right=24, left=0)
plt.xticks(np.arange(0, 25, 2))
plt.xlabel("Hours")
plt.ylabel("Density")

# peak
plt.axvspan(9, 12, facecolor=(0.8901960784313725, 0.10196078431372549,
                        0.10980392156862745), alpha=0.5)

# non-peak
plt.axvspan(8, 9, facecolor=(1.0, 0.4980392156862745, 0.0), alpha=0.3)
plt.axvspan(12, 15, facecolor=(1.0, 0.4980392156862745, 0.0), alpha=0.3)

# medium
plt.axvspan(15, 23, facecolor=(0.41568627450980394, 0.23921568627450981,
                        0.6039215686274509), alpha=0.3)
plt.axvspan(6, 8, facecolor=(0.41568627450980394, 0.23921568627450981,
                        0.6039215686274509), alpha=0.3)

# extremely low
plt.axvspan(0, 6, facecolor=(0.12156862745098039, 0.47058823529411764,
                        0.7058823529411765), alpha=0.3)
plt.axvspan(23, 24, facecolor=(0.12156862745098039, 0.47058823529411764,
                        0.7058823529411765), alpha=0.3)

plt.title("Arrival Time Density in a Day")
plt.savefig("arrival_time.png")
plt.show()
```

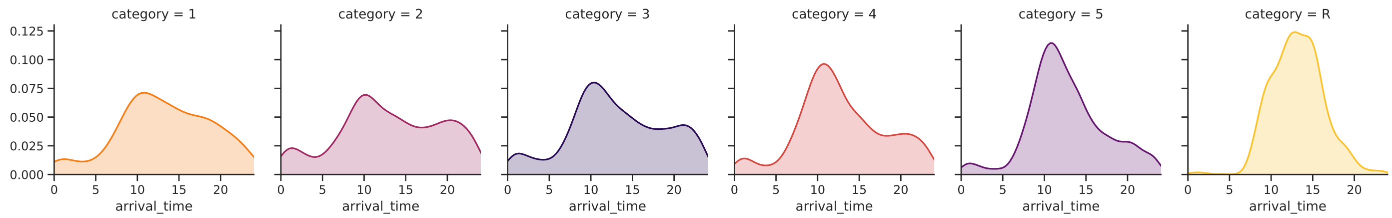


Figure 14: Patient Arrival Distribution

```
g = sns.FacetGrid(encounters, col="category", col_order=['1', '2', '3', '4', '5', 'R'],
                  hue="category", xlim=[0, 24], palette = "inferno")
g = g.map(sns.kdeplot, "arrival_time", shade=True)
plt.savefig("arrival_time_cat.pdf")
plt.show(g)
```

B.2 Results

Table 3: Results

Name	Period	Percentage	Average Number of Visits
Peak	9-12	0.27613536294	8.29084041549
Non-Peak	8-9, 12-15	0.26861869418	6.04886685552
Medium	6-8, 15-23	0.35583092213	3.20509915014
Extremely Low	0-6, 23-24	0.09941502076	1.27923917442

The estimated percentage and average number of visitors are used in our simulation model.

C Estimation of Lab Time

C.1 Problem Statement

The differences between the *completedtime* and *seentime* are used for conducting several lab tests and waiting the doctors to make a decision. Unlike we can estimate the time for testing time by directly calculating the difference between *seentime* and *caltime*, this period of time is entangled by a set of several actions together. For example, for the *encounterid* 406, the record just shows that it took 235 minutes on three parts: *CBC*, *Blood Chemistry*, and doctor decision making.

Table 4: "encounters"

encounter id	room number	encounter time	call time	seen time	completed time	lab
406	1	4/17/18 8:36 AM	4/17/18 8:43 AM	4/17/18 8:57 AM	4/17/18 12:52 PM	CBC, Blood Chemistry

C.2 Model

If we want to simulate the total time used in each step, we don't have enough information to calculate the real-time. So I relax the problem setting to the following linear model:

$$\overline{completed\_time(i) - seen\_time(i)} = \sum_{l \in lab(i)} t_l + r_{room(i)} + \epsilon_{mean} \tag{5}$$

For each encounter i, the total time is the sum of the time used in each procedure. Here I made the assumption that the time used for each test have no correlations with each other. Then we can add them to represent the total testing time. The error is modelled as identical Gaussian error.

Under the assumption of uncorrelation, the variance of each test time can be added to get the total testing variance.

$$\mathbf{Var}(completed\_time(i) - seen\_time(i)) = \sum_{l \in lab(i)} \sigma_l + \delta_{room(i)} + \epsilon_{std} \tag{6}$$

C.3 Solution

Our problem has been reduced into linear equations. Where we can estimate the mean and variance of each different *lab*, *room number* pairs, the total number of which is 361.

X is a 0-1 matrix represent the patterns in rows. The columns correspond to tests, room number decision time, and inception. The number of functions is 361, while the number of parameters is 18. In this case, we can not use direct linear algebra techniques to solve it. Instead, I apply a maximization likelihood approach to optimize the parameters by gradient descent method.

$$Xt = y_{mean} \tag{7}$$

$$X\sigma = y_{var} \tag{8}$$

Algorithm 2: Calculating X, y_{mean}, and y_{var}

```
types_dict = {}
list_tests = []
for idx, c in encounters.iterrows():
    key = list(set(str(c['lab']).split(", ")))
    try:
        key.remove('nan')
    except:
        pass
    list_tests = list_tests + key
    list_tests = list(set(list_tests))
    try:
        key.append(str(int(c['roomnumber'])))
        key = ",".join(key)
        try:
            types_dict[key].append(c['test_min'])
```

```
        except:
            types_dict[key] = [c['test_min']]
    except:
        pass
list_tests = list_tests + ['1', '2', '3', 'c']

n = len(types_dict)
X = np.zeros(shape=(n, 18))
y_mean = np.zeros(shape=(n, 1))
y_var = np.zeros(shape=(n, 1))

idx = 0
for i, q in types_dict.items():
    tests = i.split(',')
    for t in tests:
        X[idx, list_tests.index(t)] = 1
    y_mean[idx][0] = np.mean(q)
    y_var[idx][0] = np.std(q) * np.std(q)
    idx += 1
```

Finally, I apply a gradient descent method using tensorflow package. Because the variance of the testing time can not be negative, here I assign a minimal variance as 0.1 for each test.

Algorithm 3: Optimization

```
def train(X_input, y_input, lr, num_epochs, relu=True):
    tf.reset_default_graph()

    # define input placeholders
    X_inp = tf.placeholder("float", [n, 18], name="X_inp")
    y_inp = tf.placeholder("float", [n, 1], name="y_inp")
    t = tf.Variable(tf.truncated_normal([18, 1]))
    if relu:
        t = tf.nn.relu(t)
        t = tf.maximum(t, tf.constant(0.1))
    e = y_inp - tf.matmul(X_inp, t)
    loss = tf.reduce_sum(tf.square(e), name="l2_mean")

    # optimizer
    optimizer_op = tf.train.GradientDescentOptimizer(lr).minimize(loss)

    best_loss = 1e6
    best_t = None

    with tf.Session(config=tf.ConfigProto(log_device_placement=True)) as sess:
        init = tf.global_variables_initializer()
        sess.run(init)
        start_time = time.time()

        for step in range(num_epochs):
            sess.run(optimizer_op, feed_dict={X_inp: X_input, y_inp:y_input})
            e_cur = sess.run(e, feed_dict={X_inp: X_input, y_inp:y_input})
            loss_cur = sess.run(loss, feed_dict={X_inp: X_input, y_inp:y_input})
            t_cur = sess.run(t, feed_dict={X_inp: X_input, y_inp:y_input})

            if best_loss>loss_cur:
                best_loss = loss_cur
                best_t = t_cur
            if((step+1)%100==0):
                print("step {} / {}, loss {}, time {}".format(
                step+1, num_epochs, loss_cur, time.time()-start_time))
    return best_loss, best_t
```

C.4 Results

Table 5: Results

Test	Mean	Variance
Urine Analysis	0.62131184	0.3841998
Urine Culture	-0.52856034	1.3210369
VIRAL SWAB	0.38158008	0.1
ABG	-1.1003572	0.1
Blood Culture	1.160526	0.1
Other Labs	-0.3192535	1.0111718
PT	0.14623423	0.1
Stool Panel	-0.4725617	0.1
CRP	0.034993492	0.1
Bleeding Profile	-1.5207993	0.82174927
CBC	-1.3526688	0.1
Other	-1.1311041	0.1
PTT	-1.357972	0.1
Blood Chemistry	-1.3425401	0.1
Room 1	1.3596053	1.8585489
Room 2	1.0736116	0.1
Room 3	0.20024449	0.1
constant	0.7303601	0.39519298

The means and variances are used in our simulation model. I have also found some interpretation regarding the resulting testing durations. *CBC* is usually a sign of admission, so the contribute of them is negative to the testing time. *Bleeding Profile* occurs in emergent accidents, which will have high priority accordingly. The time of most of the tests are fixed, but there are uncertain(high variance) regarding to the tests like *Bleeding Profile*, *Other Labs*, *Urine Analysis*, *Urine Culture*. The efficiency of doctors in *Room 1* is the wrost among all the rooms.