Creating an Accessible Network of Life-Saving Medical Devices

A Thesis Presented to the Departments of

Computer Science
and
Electrical Engineering

at the
John A. Paulson
School of Engineering and Applied Sciences

in Fulfillment for the

Joint Degree
of
Bachelor of Arts

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on
March 31, 2017

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Abstract

Acknowledgements

Contents

1 Introduction **6**

1.1 Motivation 6

1.2 Contributions 6

2 Background **8**

2.1 Prior Art 8

2.2 Population Considerations 8

2.2.1 Autoinjectors Nearby 8

2.2.2 Population Densities 11

3 Privacy and Compliance Considerations **13**

3.1 Location 13

3.1.1 Location Privacy 13

3.1.2 Data Privacy Contract 14

3.1.3 Mercator Projection Cloaking 15

3.2 Compliance 16

4 Hardware Design **17**

4.1 Goals 17

4.2 Form Factor 17

4.3 Electronics 18

4.4 Network Protocols 18

5 Software Design **20**

5.1 Goals 20

5.2 Motivation 20

5.3 Hardware Dashboard 20

5.4 Mobile App 20

6 Budget **21**

7 Conclusions **22**

A Engineering Drawings **23**

B Specification Sheets **23**

C Repository **27**

References **29**

List of Figures

1 $P(N \geq k)$ for New York City and Houston. Each line represents a different value for $P(C)$, ranging from 10% to 90%. 11

2 Comparing $P(N \geq k)$ for different population densities. As the population density increases, the chances of having more autoinjectors nearby increases. The graph on the left assumes $P(C) = 0.3$ while the right assumes $P(C) = 0.5$. The units of population density, ρ, is people/km^2. 11

3 Population of autoinjector carriers that live in areas of differing population densities. The y-axis shows the number of autoinjector carriers that lives in an area of at least the density of the value on the x-axis. 12

4 Main schematic. 19

5 Adafruit Arduino Feather M0 specification sheet with Atmel ATSAMD21318. 23

6 Adafruit 2.8" Color TFT Touchscreen specification sheet. 24

7 Adafruit Arduino Feather M0 specification sheet. 25

8 iPixel APA102 addressable LED strip specification sheet. 25

9 iPixel APA102 addressable LED strip specification sheet. 26

List of Tables

1 Population of autoinjector carriers living in areas where the probability of having at least k autoinjectors nearby $P(N \geq k)$, is at least 1/2 for different values of k and $P(C)$. 12

1 Introduction

1.1 Motivation

The field of medical devices has continued to shape the practice and perception of medical care since the invention of the stethoscope and thermometer and into the age of the CAT scan and prosthetic limbs. The world's premier hospitals are home to highly sophisticated technology capable of efficiently saving lives that could not have been saved in recent history [16]. However, despite these advancements, many life-saving medical devices often remain inaccessible in times of need. For instance, autoinjectors used to administer epinephrine during anaphylactic shock are needed immediately to counteract an allergic reaction for those who suffer from food allergies [10]; yet, if someone in need does not have an autoinjector on their person, they waste crucial time waiting on an ambulance or driving to a hospital. Emergency defibrillators recognize heart arrhythmia and can save a person's life during cardiac arrest before an ambulance has time to arrive on the scene [8]. Many buildings contain public containers with access to defibrillators in the case of an emergency, but this requires someone nearby the emergency finding the container without knowing whether one is even nearby. In the cases of anaphylactic shock and cardiac arrest, the medical technology is available for saving a life, but the device may simply be physically inaccessible during the time of need.

Compared with the inaccessibility of medical devices such as these, the Internet and crowdsourcing have made many other goods and services dramatically more accessible. Ride-sharing mobile apps such as Uber and Lyft have dramatically increased the accessibility of cars in recent years. The apps allow a user to find or request a ride nearby within seconds instead of looking for a taxi or walking to a bus stop. Websites such as Kickstarter and Go Fund Me have removed the door-to-door hassle of fundraising for a startup or personal venture and brought investors and donors directly to users—faster than any door-to-door campaign ever could. A simple PA system allows an employee at an airline terminal to quickly find a volunteer to check a bag if the overhead bin space is sure to be full by asking everyone all at once instead of individually. Innovations such as these can provide quick and easy access to nearby services and information without the need to physically search any physical area.

1.2 Contributions

The contributions of this thesis are...

The goal of this paper is to explore how the Internet and crowdsourcing can best be used to improve the accessibility of certain life-saving medical devices in time-sensitive emergency situations. We will show that, by using both web and mobile apps and containers connected to the Internet, it is possible to create such a network that significantly improves the accessibility of these devices. In Section 2, we provide background on why connecting these medical devices is important, what others have already done to address this inaccessibility problem, and which medical devices we will use for the purposes of our design and why. Section **??** gives detailed statistical analysis revealing why a crowdsourcing network is possible for finding and obtaining a medical device quickly via a mobile app. In this section, we also discuss why using strategically-placed, Internet-connected containers are favorable for creating a more useful network of devices that cannot be achieved through crowdsourcing alone.

The overall design goals and specifications are developed in Section **??**. We will discuss why the network needs a mobile platform to facilitate peer-to-peer communication in order to locate people nearby with an available device and, more specifically, what features the app must have to be functional and secure. Additionally, in this section we will discuss why connected containers that house devices are needed to improve the usefulness of the network. Requirements and specifications for the containers and the web app that will administer them will be given here, as well as discussion as to how the containers, web app, and mobile app should interact. Section **??** will present our approach to meet the design specifications developed in Section **??**.

In Section **??**, we will give an evaluation as to how well our implementation met the design specifications and addressed the overall issue of medical device inaccessibility. In general, we found that our approach was successful and could be deployed after addressing some regulatory and legal issues. Related work will be discussed in Section 6, and Section 7 details our conclusions and plans for future work.

2 Background

2.1 Prior Art

2.2 Population Considerations

In order for this crowdsourcing network to be a useful service, certain population and active-user requirements must be met. Specifically, in order for the network to be used within a particular geographic area, the population density of autoinjector carriers must be high enough to make sharing their autoinjectors logistically possible within a reasonable amount of time. Based on this necessity, the following probabilistic measure is considered:

> In the event that Person X is looking for an autoinjector in Area A, what is the probability that there exists some Autoinjector Carrier Y such that the distance between X and Y makes it possible for Y to walk to X faster than an ambulance could travel to X?

This asks whether or not the creation of this network is possible based on the population densities of people who carry autoinjectors. This probability will be used to show that the network effect of sharing autoinjectors is, in fact, possible. We address this question in the following two sections.

2.2.1 Autoinjectors Nearby

Let R be the event that Person X is having an allergic reaction and needs an autoinjector in area A. Let the random variable N be the number of autoinjector carriers nearby Person X in Area A. In order to determine if a peer-to-peer network of autoinjectors is possible, we need to find the probability that there are at least k autoinjector carriers nearby Person X, given that Person X has a reaction in Area A. Thus, we are looking for $P(N \geq k|R)$. For purposes of simplicity, we will assume that Person X having a reaction does not increase the probability that someone with an autoinjector nearby, and thus assume N is independent of R. Thus, we are looking for the probability that there are at least n people carrying autoinjectors in area A at any given time, or

$$P(N \geq k)$$

By taking the complement, we know that

$$\begin{aligned} P(N \geq k) &= 1 - P(N < k) \\ &= 1 - \sum_{j=0}^{k-1} P(N = j). \end{aligned}$$

Therefore, we need to determine the probability mass function (PMF) of N, $P(N = k)$. According to the U.S. Census Bureau, population varies drastically during normal working hours, so we will account for this in our model by differentiating probabilities between 8:00 AM and 5:00 PM [4]. Person X might be more likely to be eating and, thus, more likely to have a reaction during working hours. However, eating behaviors are difficult to model and vary among different populations; therefore, we will ignore eating behaviors in this model and assume independence. Let W be the event that the current time is between 8:00 AM and 5:00 PM. By the Law of Total Probability [2],

$$P(N = k) = P(N = k|W)P(W) + P(N = k|W^c)P(W^c).$$

Next, we need to clarify a few definitions. First, we will define an autoinjector carrier near Person X to be a person with an autoinjector that could walk to Person X faster than an ambulance could drive to Person X on average. While there is no federally-mandated ambulance response time standards, many cities and municipalities choose to set an 8-minute response time as the gold standard [11]. The National Fire Protection Agency also recommends that Advanced Life Support teams should aim to respond to all calls within 8 minutes [1]. In actuality, average response times vary across regions, with some cities averaging below 8 minutes and some above [6][13]. Therefore, for the purposes of analysis we will assume that the average response time of an ambulance to Person X is 8 minutes. Now, the effective nearby Area A around Person X is anywhere within an 8-minute walk from Person X. The average walking speed of adults is 5 km/h [3]. We can thus calculate A as

$$A = \pi\left((5\text{ km/h})\,(8\text{ min})\,(1/60\text{ h/min})\right)^2 = 1.40\text{ km}^2.$$

Now, we need to determine the probability that a person within Area A has an autoinjector. According to Food Allergy Research and Education, 12% of people within the U.S. have food allergies, with children and adults accounting for 8% and 4% respectively [12]; however, we are interested in people who are carrying autoinjectors, not necessarily those who have allergies. According to Dr. John Lee, director of the Food Allergy Program at Boston Children's Hospital, more than 4.5 million autoinjector twin packs were prescribed in 2015 for children and adults combined [9]. Because food allergies are on the rise [12], we will assume that the number of autoinjectors prescribed next year will at least remain the same despite recent rate increases [14]. Let m be the number of unexpired autoinjector twin packs prescribed to consumers. Most autoinjectors expire 1.5 years after the date of manufacture, so we can assume that

$$m = 1.5(4.5 \times 10^6) = 6.75 \times 10^6.$$

The population of the U.S. is $u = 321{,}418{,}820$ [4]. Let T be the event that a given person in the U.S. has a prescription for an autoinjector twin pack.

$$\begin{aligned} P(T) &= m/u \\ &= \frac{6.75 \times 10^6}{321418820} \\ &= 0.021 \end{aligned}$$

While this is a simplistic model, it serves as a decent approximation. In reality, infants should not be included in the total population. We could try and treat population of children and adults differently who might have different probabilities of having prescriptions, but parents of those children might be just as likely to carry an autoinjector as their children. Therefore, we will assume this probability for purposes of analysis. We can account for the fact that a person with a prescription may not have the autoinjector on their person at all times. Let $P(C)$ be the probability that any given owner or user of an autoinjector is actually carrying it on their person. Then, assuming independence, the probability p that any given person has an autoinjector on their person is

$$p = P(T)P(C)$$

Let ρ be the population density of Area A around Person X. The number of people, n, in Area A can be modeled as

$$n = \lfloor \rho A \rfloor .$$

Each person in Area A has probability p of having an autoinjector on their person. This is the story of the binomial distribution [2], and, thus, the number of pens during working and non-working hours both have the binomial distribution, so

$$N|W, N|W^c \sim \text{Bin}(n, p).$$

For any random variable $X \sim \text{Bin}(n, p)$, the PMF of X is

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}.$$

Therefore, we know that $P(N = k)$ is

$$\begin{aligned} P(N = k) &= P(N = k|W)P(W) + P(N = k|W^c)P(W^c) \\ &= \left(\binom{n_W}{k} p^k (1-p)^{n_W - k}\right)(1/3) + \left(\binom{n_{W^c}}{k} p^k (1-p)^{n_{W^c} - k}\right)(2/3), \end{aligned}$$

where n_W and n_{W^c} are the populations of Area A during working hours and non-working hours respectively. Now, we can use this to determine $P(N \geq k)$—the probability that there are at least k autoinjectors near Person X in Area A—if we know the population density of Area A, since $n = \lfloor \rho A \rfloor$. Using U.S. Census Bureau data for population density [4], Figure 1 shows $P(N \geq k)$ for New York City and Houston, and each line represents a different value for $P(C)$. The population density of New York City is 10908 people/km^2 while Houston is 1480 people/km^2, and as expected the number of autoinjetors likely to be in any given area is much higher in New York City.

As can be see, a higher population density corresponds to an increase in the expected number of autoinjectors neraby. As shown in Figure 1, even if 50% of people with autoinjector prescriptions carry it on their person, there is only a 50% chance there will be at least 25 autoinjectors nearby

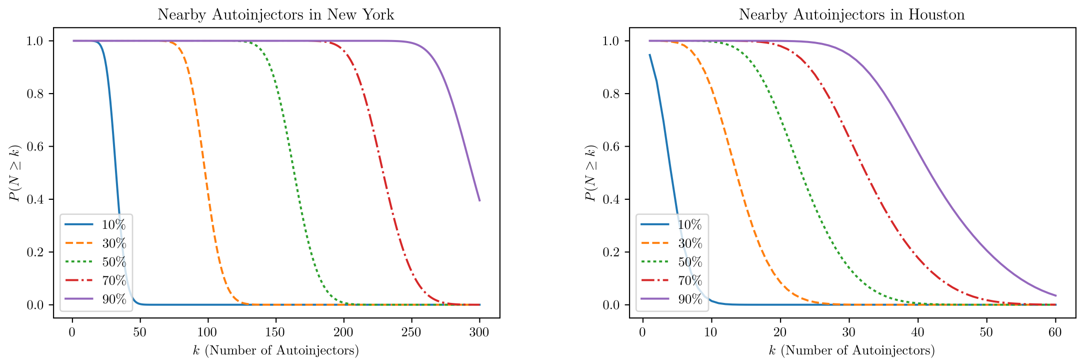


Figure 1: $P(N \geq k)$ for New York City and Houston. Each line represents a different value for $P(C)$, ranging from 10% to 90%.

in Houston compared to New York's 160. New York and Houston are the first and fourth largest populated cities in the U.S. respectively [4], yet there is a significant difference in likelihood due to their differing populatino densities. We next consider this effect more formally and determine the number of people living in different population densities in the U.S. and the resulting effect on $P(N \geq k)$.

2.2.2 Population Densities

As shown in Section 2.2.1 through the cities of New York and Houston, a higher population density corresponds to an increase in the expected number of autoinjectors nearby. Figure 2 shows this effect of population density on $P(N \geq k)$ for two different values of $P(C)$. As expected, the probability of having an autoinjector nearby is proportional to population density.

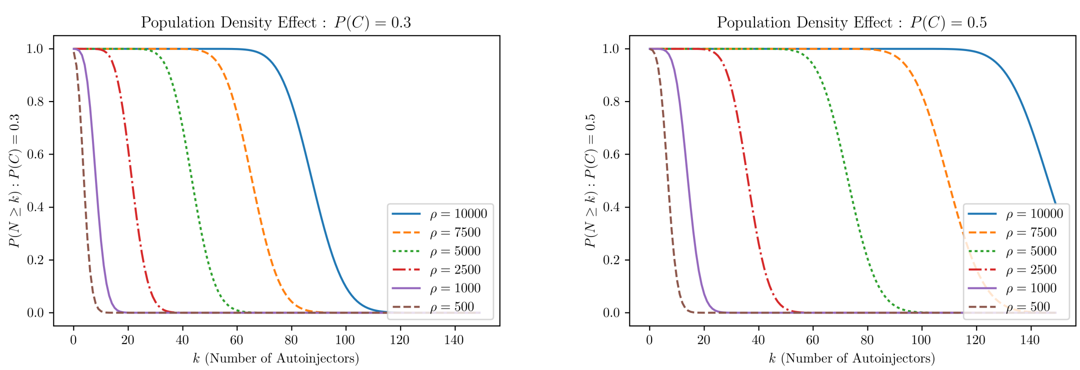


Figure 2: Comparing $P(N \geq k)$ for different population densities. As the population density increases, the chances of having more autoinjectors nearby increases. The graph on the left assumes $P(C) = 0.3$ while the right assumes $P(C) = 0.5$. The units of population density, ρ, is people/km^2.

An important consideration that arrises from this analysis is determining how many people in the U.S. live in an area with a population density that allows a reasonable probability of having an autoinjector nearby. If the number is too low, then an implementation of this network might not be fiscally practical. Figure 3 shows $uP(T)P(C)$—the number of people in the U.S. population that live have prescriptions for autoinjectors and carry them on their person—living in different population densities. The y-axis shows the number that live in an area of at least the density of the value on the x-axis.

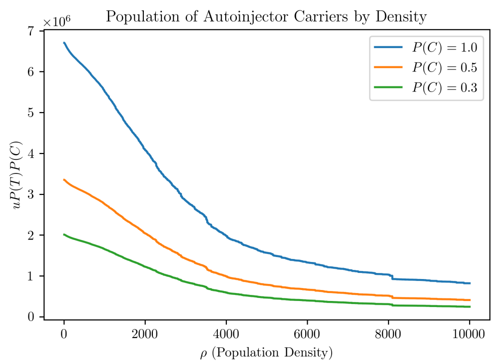


Figure 3: Population of autoinjector carriers that live in areas of differing population densities. The y-axis shows the number of autoinjector carriers that lives in an area of at least the density of the value on the x-axis.

The relationship between Figures 2 and 3 combine to show how many autoinjector prescribers live in areas where $P(N \geq k) > 0.5$ for different values of k. These results are shown in Table 1. Recall that $P(C) = 1.0$ means that everyone with an autoinjector carrying it on their person, and thus $uP(T)P(C)$ represents the total number of people with autoinjector prescriptions. Thus, for any value of k in Table 1, $uP(T) : P(N \geq k) > 0.5$ indicates of the total number of people *who might need* an autoinjector in living in areas where $P(N \geq k) > 0.5$. As can be seen, over 6 million people who might need an autoinjector live an area where it is more likely than not that there are at least 10 autoinjectors within walking distance if at least 30% of prescribers are carrying their autoinjector.

	$uP(T) : P(N \geq k) > 0.5$	
k	$P(C) = 0.3$	$P(C) = 0.5$
10	6.06×10^6	6.31×10^6
20	4.89×10^6	5.09×10^6
50	3.11×10^6	3.34×10^6
90	9.89×10^5	1.50×10^6

Table 1: Population of autoinjector carriers living in areas where the probability of having at least k autoinjectors nearby $P(N \geq k)$, is at least 1/2 for different values of k and $P(C)$.

These results indicate that millions of people who might need an autoinjector in an emergency live in areas where a crowdsourcing app could, on average, supply one faster than an ambulance. Based on these results, we can conclude that creating such a crowdsourcing network is indeed possible.

3 Privacy and Compliance Considerations

3.1 Location

Leveraging the crowdsourcing network in emergencies does not necessarily require the system to process or store user locations. For instance, if Person X in Area A is looking for an autoinjector and sends a request to the service without any location information, the system can simply send contact info for Person X to all other users, or contact info for all other users to Person X, and allow the location sharing to happen via non-system communication methods. However, even with a very small number of users this is highly impractical and provides very little benefit.

On the other hand, if the system can process user locations, then the service can become more streamlined and useful. Suppose the service does not persistently store any user location information. If Person X in Area A sends a request to find an autoinjector with their current location information, then all other users on the network can be notified of that location and opt to respond if they are able. This method is much better than sharing no location information with the service at all, yet, if there are n users on the network, $n-1$ users will always be notified for every emergency, regardless of their location or proximity. This protocol creates many useless notifications and still requires $n-1$ users to manually check if they are nearby the emergency. The number of notifications involved and work required disincentivizes users from taking notifications seriously.

Persistent system knowledge of all users' locations, however, can improve the service drastically: when Person X requests an autoinjector, the system can only send notifications to users within a reasonable proximity to Person X. Users who receive a notification will immediately know they are within reasonable distance of someone in need of an autoinjector and can opt to respond. This protocol will be taken more seriously be users and does not require any unreasonable communication of users' locations. However, storing users' locations comes at a price: privacy. Users might be reluctant or unwilling to have their locations stored in or processed by the system. If the system did store user locations and became compromised, location information would be exposed. In the next section, we discuss different methods to store user locations while providing some degree of anonymity in the event of a breach and still retaining the usefulness of the location data.

3.1.1 Location Privacy

In the context of protecting privacy for the public or private release of any data set for purposes of research, Sweeney [15] presents a model known as k-anonymity, where any data set released "provides k-anonymity protection if the information for each person contained in the release cannot be distinguished from at least $k-1$ other individuals in the data set" [15]. This model can be adopted to the storage and processing of user information in network databases. If a database is k-anonymized and later breached, then the users whose information was compromised still retain some form of privacy: namely, anonymity amongst k other users.

Gedik and Liu [7] describe a k-anonymity model for protecting user privacy in mobile systems that allows for each user to indicate the level of k-anonymity desired for each message sent to a particular service. The k-anonymity is achieved by either decreasing location accuracy until $k-1$

other users share the same spatial location or delaying message processing until $k-1$ other messages have been received from the same spatial region.

Cheng et. al [5] present a different scheme that uses a more probabilistic approach. They argue that k-anonymity may not be used if there are fewer than k users in the system, and that even if there are more than k users, "they may span in a large area over an extended time period, in which case the cloaked location can be very large and cause a severe degradation of service quality." They instead provide a framework that stores cloaked geometric areas for each user, where the users' true location is somewhere in the area stored. The framework lets each user decide on the size and boundaries of the cloaked location stored, and the larger the area, the more anonymity. k-anonymity may be achieved as a side effect in this framework if cloaked locations overlap, but it does not dictate how locations are anonymized. Location-based search queries find cloaked areas that overlap with a given query range, and queries have a runtime in the worst case of $O(e^2 \log e)$ and best case of $O(m+e)$, where e is the number of sides of the geometric shapes stored and m is the number of sides of any polygon used for the query computation.

These frameworks (and others) have their advantages, but neither is the best fit for this particular application. k-anonymity is not a good option for reasons described by Cheng et. al [5]: if there are too few users within a given region, then the size of the cloaked location stored would be too large to provide useful data to the service. Similarly, letting each user specify the size of the cloaked region might cause the service to run into problems as discussed previously if they specify a large area. Instead, we present the following location privacy contract to the user of the application and an implementation differing from those above to achieve it.

3.1.2 Data Privacy Contract

1. A user's exact location will never be stored in any system database.
2. For any user $u_i \in U$, let the stored location of that user in the system be $L(u_i)$. The granularity of $L(u_i)$ will be no less than 1.4 km^2, where $\text{Area}(L(u_i)) \geq 1.4 \text{ km}^2 \;\; \forall\, i$, and the true location of user u_i will be uniformly distributed across $\text{Area}(L(u_i))$.
3. Only the most recently received location will be stored for each user and location history will never be stored.
4. User locations will be stored separately from other user information, including user IDs. The IDs for each user location entry will be hashed using a secure hash function. An adversary would need the user ID, hash function, and entire location table to find a specific user's entry.

This contract ensures that in the event of a data breach or compromise, even if an adversary had full knowledge of the source code, any user locations would only be known within 1.4 km^2 of the true locations. If an adversary only had access to the locations table, then the hashed user IDs would prevent them from knowing which cloaked location belonged to who without knowledge of user ID's and the secure hash function. Additionally, this granularity of locations stored allows the service to retain the functionality it needs. Next, we present a method for implementing this contract.

3.1.3 Mercator Projection Cloaking

To store the location of the user while maintaining no more than 1.4 km^2 granularity, we opt to take a grid-based approach. We conceptually divide the Earth into a grid, where each square in the grid has area 1.4 km^2. When the system receives a latitude and longitude from a user, it maps this latitude and longitude on to the grid and stores which square the user reported. As distances between adjacent meridians and parallels on the globe are not constant, the mapping is non-trivial but can easily be solved with a Mercator projection. As Weisstein [17] shows, for any (latitude, longitude) pair (λ, ϕ), where λ and ϕ are measured in radians, (λ, ϕ) can be mapped to a Cartesian (x, y) point such that $x \in (-1, 1)$ and $y \in (-1, 1)$, where

$$x = \lambda - \lambda_0$$
$$y = \ln \tan\left(\frac{\pi}{4} + \frac{\phi}{2}\right)$$

and λ_0 represents the reference meridian is equal to 0 when used with standard latitude and longitude systems. To scale these components into units of kilometers, we multiply each component by the radius of the Earth, R_E, and to decrease the granularity in the x and y directions, we can take the floor of each component divided by α and β respectively, where α and β are the granularities desired in each direction. Based on our privacy contract, α and β will each be 1.4 km. Now, our cloaked components take the form

$$x_{\text{cloaked}} = \left\lfloor \frac{R_E \lambda}{\alpha} \right\rfloor$$
$$y_{\text{cloaked}} = \left\lfloor \frac{R_E}{\beta} \ln \tan\left(\frac{\pi}{4} + \frac{\phi}{2}\right) \right\rfloor$$

Note that any (λ, ϕ) pair such that $\phi = \pm\pi$, the y component value is undefined. To store any user location in or query for users that within proximity to a particular location, we present Algorithms 1, 2, and 3. In Algorithm 3, U is the set of all users and τ is used as a constant to eliminate any entries in the database that have expired.

The runtime for MPCloak is $O(1)$, assuming the multiplications and division run in constant time. Under most systems and (λ, ϕ) values, this a reasonable approximation. The runtime of StoreLocation and QueryLocation depend on the storage implementation. Assuming a binary heap, we achieve $O(n \log n)$ for both, where n is the total number of users.

Algorithm 1 Mercator Projection Cloaking

```
procedure MPCloak((λ, φ))
    if φ is ±π then
        reject
    x ← ⌊R_E λ/α⌋
    y ← ⌊R_E ln tan(π/4 + φ/2) /β⌋
    return (x, y)
```

Algorithm 2 Mercator Projection Storage

procedure StoreLocation(u_{id}, $(\lambda, \phi), t$)
    $(x, y) \leftarrow \text{MPCloak}((\lambda, \phi))$
    $\text{store}(h(u_{\text{id}}), (x, y), t)$

Algorithm 3 Mercator Projection Query

procedure QueryLocations((λ, ϕ))
    $(x, y) \leftarrow \text{MPCloak}((\lambda, \phi))$
    $R \leftarrow u_i \in U : h(u_i).\text{location} = (x, y)$
    $S \leftarrow u_i \in U : h(u_i).t - t_{\text{cur}} < \tau$
    $\text{retrieve}(R \cap S)$

Using these algorithms with α and β values of 1.4 km, we fulfilled point 2 in the location privacy contract. Points 1, 3, and 4 depend strictly on implementation, and care to ensure they are met is needed.

One way to ensure that the granularity requirement is met by an application is to move the location cloaking logic to a trusted third party. The third party can handle cloaking and storage, and the application can simply make queries and handle requests to and from the third party. This is not always practical for end user experience, and in our implementation we perform the cloaking an storage ourselves while respecting abstraction barriers.

3.2 Compliance

4 Hardware Design

4.1 Goals

The smart containers that will house emergency medical devices are meant to resemble existing Automated Emergency Defibrillator (AED) units that are currently in use. This existing type of container is well-known in most communities and will serve as a familiar interface for users when using the new containers. The new, smart containers (henceforth referred to as “containers”) are designed to perform a variety of functions to assist users who are trying to locate an emergency medical device. For purposes of discussion, we will assume that the containers will house both autoinjectors and defibrillators. In the following sections, we discuss the features and design choices of the smart container.

4.2 Form Factor

Current AED defibrillator containers come in a variety of sizes and models depending on how the container is mounted to the wall, but the interior of most boxes measures around $12'' \times 12'' \times 5''$, with the defibrillators themselves measuring around $8'' \times 6'' \times 3''$. We will assume that the autoinjectors we store in the containers are the same size as those purchased with a prescription (approximately $5'' \times 1'' \times 1''$), but in practice it might be prudent to create a larger autoinjector form factor that would be harder to steal from the container. Current AED defibrillator containers store one defibrillator per container, and we will do the same. We will also store two autoinjectors per container, as most autoinjector manufacturers recommend carrying two at all times in case one should fail.

Besides simply storing the medical devices, we also wish to assist users who are looking for the containers and make it as easy as possible to locate. Instead of only providing the location of a container through the mobile app, we also use physical light and sound signals on a container to help direct users to the correct location. The container will feature LED lights that will flash and speakers that will make noise when a user is looking for a container. In addition to these signals, a touch screen will also provide a user interface that will allow users to control the lights and sounds of the box. Furthermore, a screen could be used to show the location of a user who is looking for the container, allowing people nearby to assist in getting the necessary medical devices to the use in need. Because the epinephrine used in autoinjectors is sensitive to temperature changes and must be kept within a specified temperature range, we use a discrete temperature sensor inside the container to monitor the containers temperature an ensure that these temperature requirements are not broken.

In order to facilitate the communication between the container and the server, we use an Internet-connected microcontroller (μC) and a network controller. These will be discretely located within the container and used to control the peripherals based on messages received from the server and commands received from the user-facing touch screen.

4.3 Electronics

The circuitry consists of five main components:

1. Microcontroller
2. Touch screen
3. Temperature, humidity, and air pressure sensors
4. Lights
5. Speakers

The microcontroller selected was the Atmel ATSAMD21G18. This chip has 256 kB of flash, 32 kB of SRAM, 6 serial communication modules, and 20 output pins. This is enough memory and I/O capability to allow for multiple peripherals, including the touch screen, temperature sensor, LEDs, and speakers while remaining comparatively inexpensive. The network controller selected was the Atmel ATWINC1500, an IEEE 802.11 b/g/n WiFi chip with a single-band 2.3 GHz channel that supports WPA/WPA2 Personal and SSL security protocols. The Adafruit Arduino Feather M0 was selected as the breakout board for prototyping and contains both the ATSAMD21G18 and ATWINC1500 chips. The Arduino IDE and bootloader were used for programming the microcontroller.

The touch screen used for the container was the Adafruit 2.8″ TFT LCD Touchscreen Breakout Board. This board is capable of simple SPI communication and allows for minimal microcontroller pin usage. The board is also has a self-contained controller, so minimal graphic computations are required on the main microcontroller. This screen is small compared to most mobile phone touch screens but is large enough to provide a simple user interface for controlling the container.

The temperature sensor selected was the Bosch BME280, an environmental sensor that measures temperature, humidity, and air pressure with $\pm$ 1.0°C, $\pm$ 3%, and $\pm$ 1 hPa accuracies respectively. When measuring only temperature and humidity, it draws only 1.8 μA of current, dissipating 5.94 μW of power when used with 3.3 V logic. For lighting, an iPixel APA102 addressable 1m LED light strip was selected. This allows for unique light patterns to be generated by the microcontroller that can be used to direct users to the container. Two, 3″ 4 Ω 3 W speakers were used for sound signals.

4.4 Network Protocols

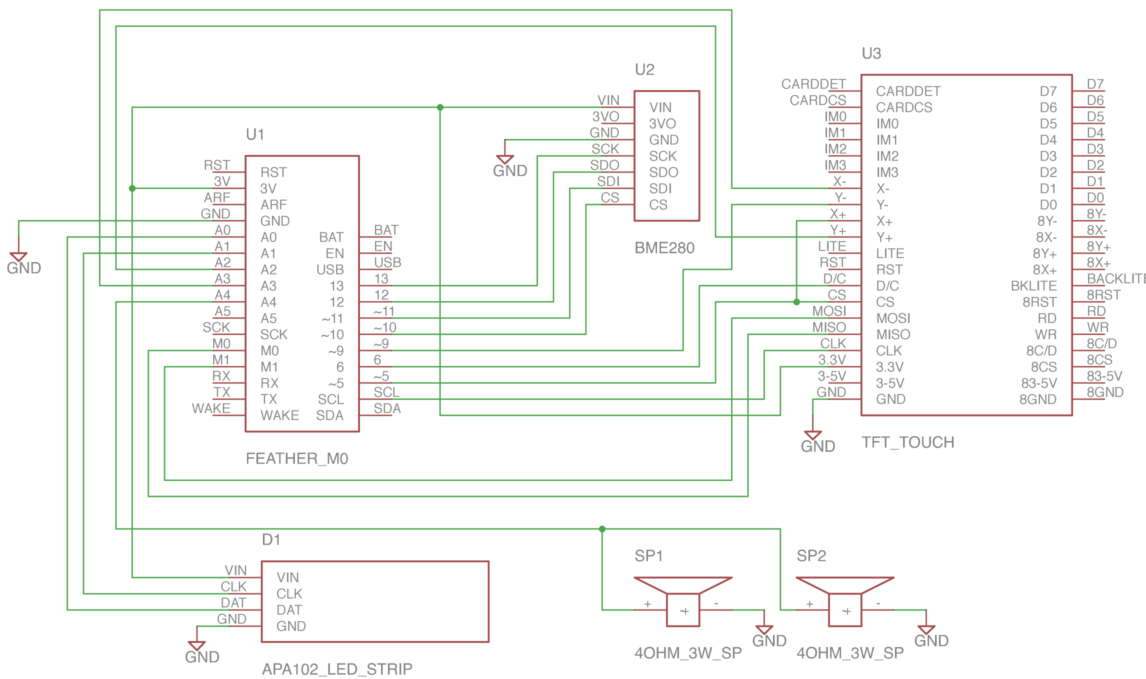


Figure 4: Main schematic.

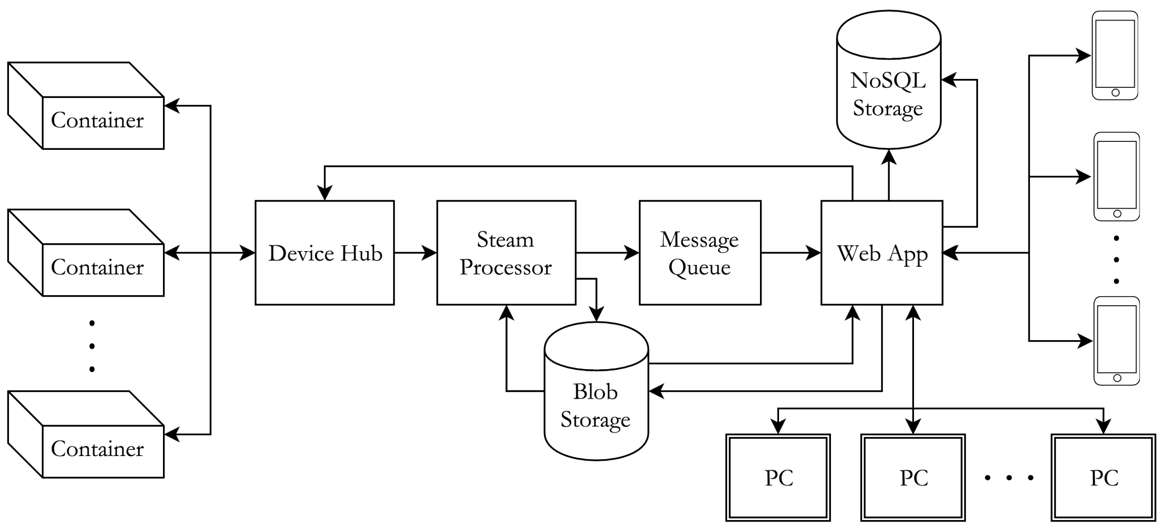
5 Software Design

5.1 Goals

5.2 Motivation

5.3 Hardware Dashboard

5.4 Mobile App



6 Budget

7 Conclusions

A Engineering Drawings

B Specification Sheets

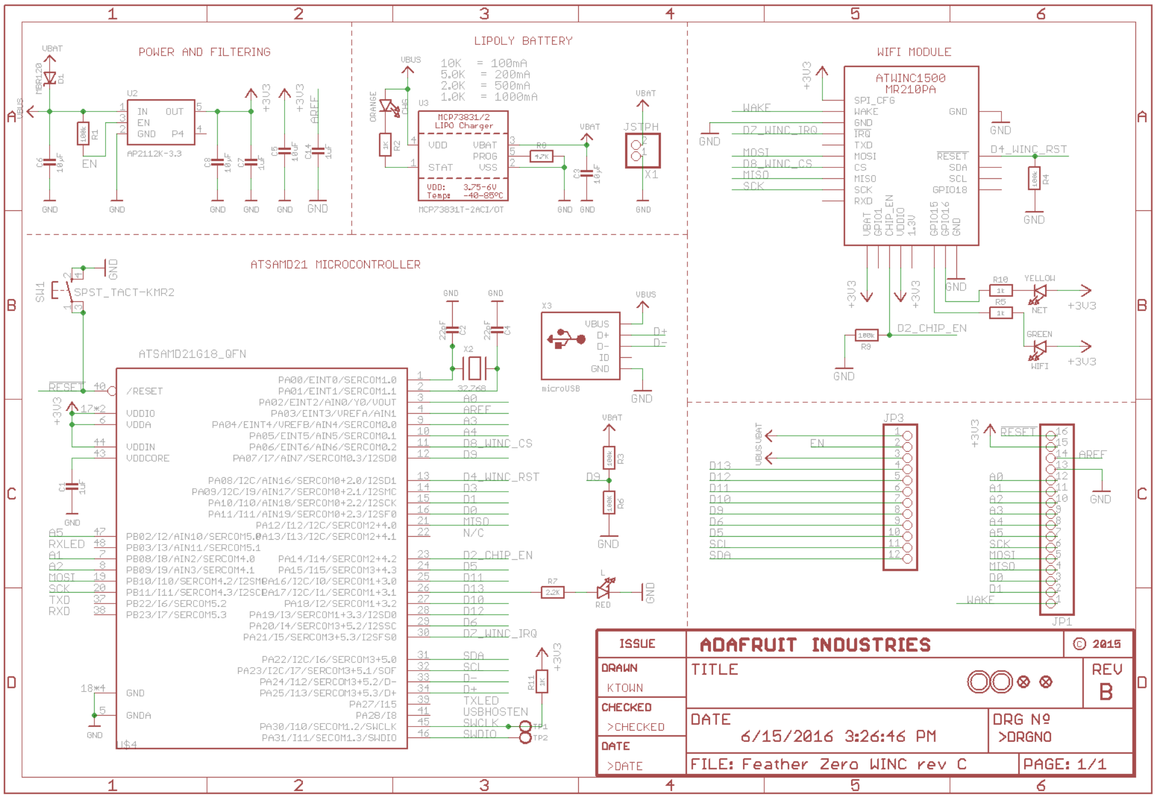


Figure 5: Adafruit Arduino Feather M0 specification sheet with Atmel ATSAMD21318.

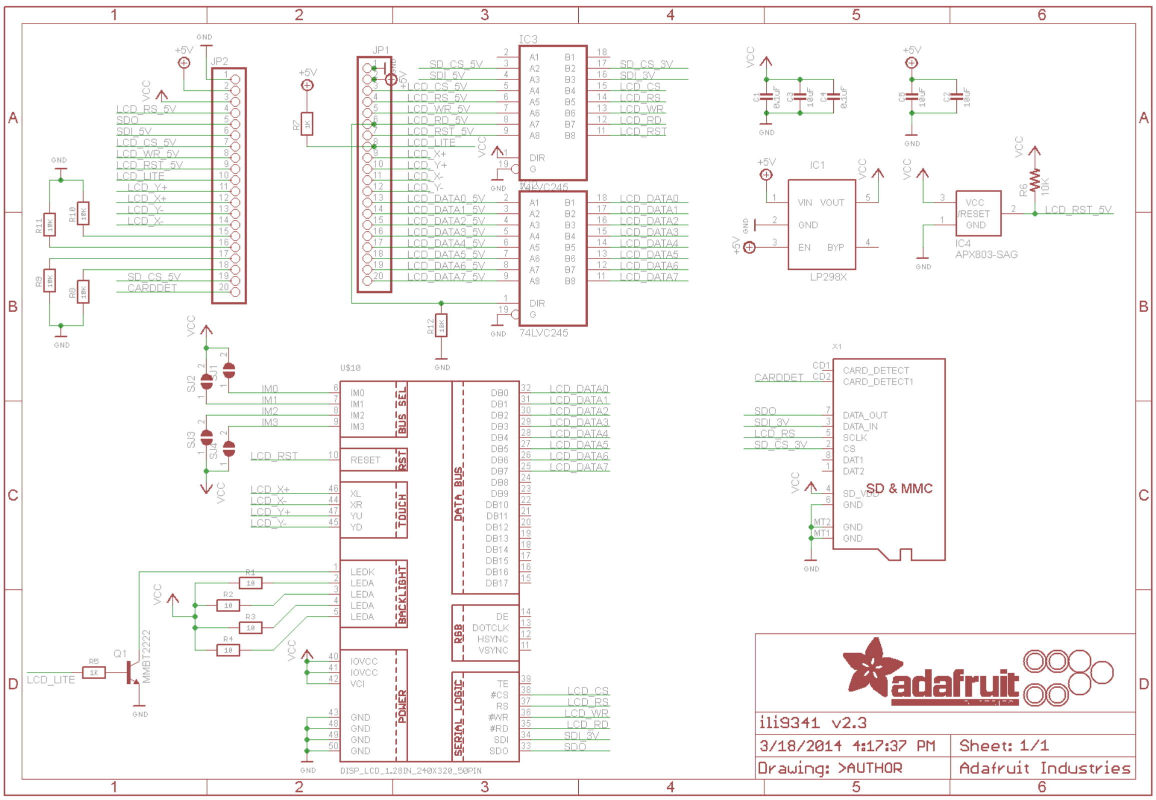


Figure 6: Adafruit 2.8” Color TFT Touchscreen specification sheet.

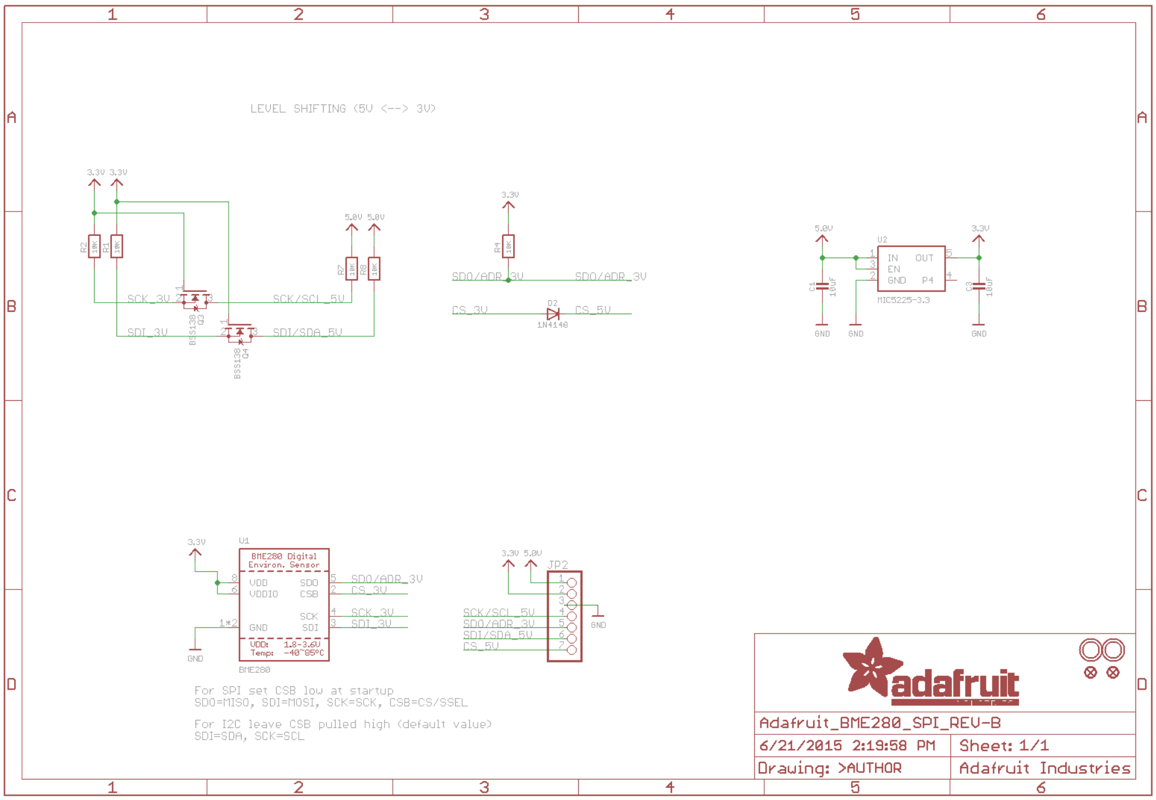


Figure 7: Adafruit Arduino Feather M0 specification sheet.

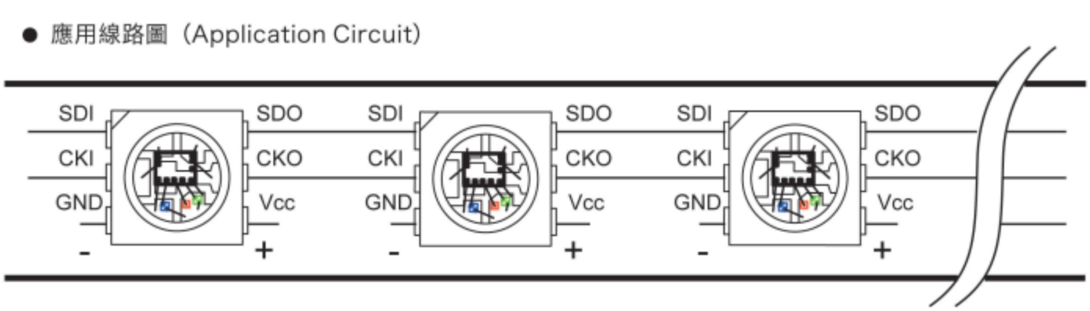


Figure 8: iPixel APA102 addressable LED strip specification sheet.

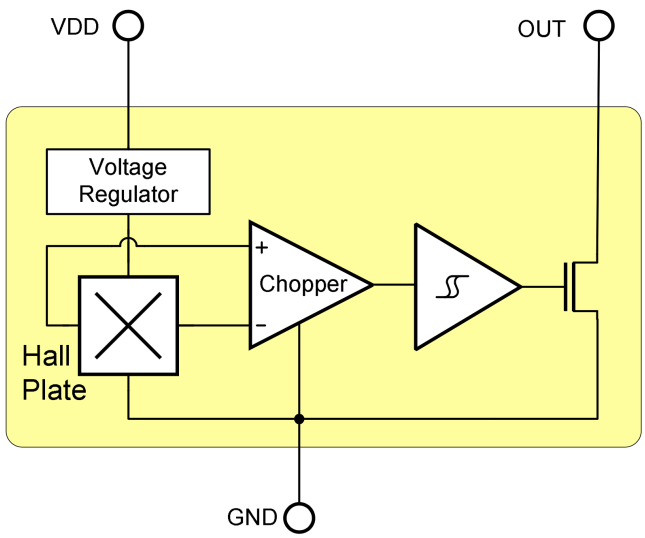


Figure 9: iPixel APA102 addressable LED strip specification sheet.

C Repository

The source files for this project are far to numerous to include in this paper. Instead, the following GitHub repository will be maintained for as circumstances allow. The repository can be found at

`https`

References

[1] National Fire Protection Association. NFPA 1710, standard for the organization and deployment of fire suppression operations, emergency medical operations, and special operations to the public by career fire departments, 2016.

[2] Joseph K. Blitzstein and Jessica Hwang. *Introduction to Probability*. CRC Press, Boca Raton, Florida, 2014.

[3] Raymond C. Browning, Emily A. Baker, Jessica A. Herron, and Rodger Kram. Effects of obesity and sex on the energetic cost and preferred speed of walking. *Journal of Applied Physiology*, 100(2):390–398, 2006. URL: `http://dx.doi.org/10.1152/japplphysiol.00767.2005`.

[4] US Census Bureau. American community survey 1-year data (2011-2015) api. Generated by Gregory Hewett. Accessed 1 November 2016. URL: `https://www.census.gov/data/developers/data-sets/acs-1year.html`.

[5] Reynold Cheng, Yu Zhang, Elisa Bertino, and Sunil Prabhakar. *Preserving User Location Privacy in Mobile Data Management Infrastructures*, pages 393–412. Springer Berlin Heidelberg, Berlin, Heidelberg, 2006. URL: `http://dx.doi.org/10.1007/11957454_23`, `doi:10.1007/11957454_23`.

[6] Erin Durkin. Longer 911 response times stir city council. *New York Daily News*, March 2014. URL: `http://www.nydailynews.com/news/politics/longer-911-response-times-stir-city-council-article-1.1737399`.

[7] Bugra Gedik and Ling Liu. Location privacy in mobile systems: A personalized anonymization model. *Distributed Computing Systems, 2005. ICDCS 2005. Proceedings. 25th IEEE International Conference*, pages 620–629, 2005.

[8] Richard E. Kerber, Lance B. Becker, Joseph D. Bourland, Richard O. Cummins, Alfred P. Hallstrom, Mary B. Michos, Graham Nichol, Joseph P. Ornato, William H. Thies, Roger D. White, and Bram D. Zuckerman. Automatic external defibrillators for public access defibrillation: Recommendations for specifying and reporting arrhythmia analysis algorithm performance, incorporating new waveforms, and enhancing safety. *Circulation*, 95(6):1677–1682, 1997. URL: `http://circ.ahajournals.org/content/95/6/1677`, `arXiv:http://circ.ahajournals.org/content/95/6/1677`, `doi:10.1161/01.CIR.95.6.1677`.

[9] John Lee MD. Boston Children's Hospital. Phone Interview. 27 October 2016.

[10] Mylan. Accessed: 2017-01-03. URL: `https://www.epipen.com/en/what-is-anaphylaxis`.

[11] Peter T Pons and Vincent J Markovchick. Eight minutes or less: does the ambulance response time guideline impact trauma patient outcome? *Journal of Emergency Medince*, 23(1), 2002. URL: `http://dx.doi.org/10.1016/S0736-4679(02)00460-2`.

[12] Food Allergy Research and Education. Food allergy facts and statistics for the u.s. *Journal of Applied Physiology*, 100(2):390–398, 2016. URL: `http://dx.doi.org/10.1152/japplphysiol.00767.2005`.

[13] Matt Rocheleau. Boston ems response times slow amid 911 call surge. *Boston Globe*, November 2015.

[14] Jonathan D. Rockoff. Mylan faces scrutiny over epipen price increases. *Wall Street Journal*, August 2016. Online. URL: `http://www.wsj.com/articles/mylan-faces-scrutiny-over-epipen-price-increases-1472074823`.

[15] L Sweeney. k-anonymity: A model for protecting privacy. *International Journal Of Uncertainty, Fuzziness & Knowledge-Based Systems*, 10(5):557, October 2001.

[16] TMHC. URL: `http://www.topmastersinhealthcare.com/30-most-technologically-advanced-hospitals-in-the-world/`.

[17] Eric W. Weisstein. Mercator projection. *MathWorld*–A Wolfram Web Resource. URL: `http://mathworld.wolfram.com/MercatorProjection.html`.