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CS: 591

Project Report

Drone Use for Boston Medical and Protective Services

Emergency Medical Services are a vital part of any urban ecosystem. As the field rapidly changes, and new technologies make their way into the hands of first responders around the world, it is important to examine how these technologies can be used to best affect modern cityscapes. Theoretically the drones would have a 60mph top speed, 1 hour of flight time, would be remotely piloted, and come with a $15,000 price tag. This is based off proposed values for projects with a similar purpose, and news reports and serves as a baseline for the capabilities of these devices. This project aims to begin investigating the use of these drones for Medical and Protective Services in Boston.

Time is one of the most important factors in many medical emergencies. For example, patients suffering cardiac arrest deal with brain damage and death in approximately 4-6 minutes. According to the 2011 Boston EMS Annual Report, the average Priority 1 Median response time is 5.7 Minutes. If defibrillators can reach a patient within 1 minute “This response speed increases the chance of survival following a cardiac arrest from eight percent to 80 percent.“ It’s easy to imagine drones carrying epi-pens, medications, or other time sensitive emergency medical supplies, directly to patients. Further, in this age of government surveillance, one can imagine police departments using a technology that allows them to have eyes on a crime scene minutes before officers arrive. Or to follow fleeing suspects as they leave a crime scene. Drones can follow criminals into enclosed spaces or patrol areas in an effort to gather information that can help officers make the best decisions possible. These devices aren’t affected by traffic and can fly directly to wherever they are needed. Drone technology is poised to start filtering into the urban landscape in a major way in the following decades.

Data was gathered from the City of Boston Data Portal and includes: Boston Police Department 911, Hospital Locations, and Police Department Locations. The 911 dataset is the major component behind the research. It includes a date, a time of call, various event data such as location and type, and sometimes malformed location information (see page 2). To gather the preliminary datasets I created the gather.py script which uses the Boston Data Portal API to gather the desired information from each dataset. Next reform.py should run on the three gathered datasets. From these three datasets, two new datasets are created: Police Events and

Med Events which are subsets of the original 911 dataset modified to contain all events that

A	B	C	D	E	F	G	H	I	J	K	L
Start Calendar Date	Start Standard Tir	CAD Agen	Measure By CAD Event	CAD Event	CAD Event Type	CAD Event Numl	UDO Event Locatio	Latitude	Longitude	UDO SAM Neighborhood	
2/23/2015 0:00	1:00:23 AM	BPD	ABAN	201	ABANDONED CALL (P)	P150094185		42.27744	-71.0973	Mattapan	
2/23/2015 0:00	1:00:27 PM	BPD	MVA	201	MOTOR VEHICLE ACCIDENT	P150094992	142 ROSSETER ST	42.30009	-71.0732	Dorchester	
2/23/2015 0:00	1:00:30 AM	BPD	TS	201	TRAFFIC STOP	P150094184				Other	
2/23/2015 0:00	1:00:36 PM	BPD	ABAN	201	ABANDONED CALL (P)	P150094988				Other	
2/23/2015 0:00	1:00:48 PM	BPD	MVA	201	MOTOR VEHICLE ACCIDENT	P150094987	342 BLUE HILL AVE	42.31276	-71.0798	Roxbury	
2/23/2015 0:00	1:00:53 PM	BPD	MISC	201	MISCELLANEOUS CALLS	P150094989		42.31874	-71.0922	Roxbury	
2/23/2015 0:00	1:00:59 PM	BPD	ABAN	201	ABANDONED CALL (P)	P150094991	1 BEACON ST	42.35788	-71.0608	Boston	
2/23/2015 0:00	1:01:06 PM	BPD	MISC	201	MISCELLANEOUS CALLS	P150094996	35 KNEELAND ST	42.35053	-71.0619	Boston	
2/23/2015 0:00	1:02:20 PM	BPD	MISSING	201	INVESTIGATE PERSON	P150094993	794 MASSACHUSETTS AVE			South End	
2/23/2015 0:00	1:02:47 AM	BPD	MISC	201	MISCELLANEOUS CALLS	P150094186		42.37808	-71.0586	Charlestown	
2/23/2015 0:00	1:02:56 PM	BPD	CD9	201	Station Assignment	P150094994	135 HUMBOLDT AV	42.31475	-71.088	Roxbury	
2/23/2015 0:00	1:02:57 AM	BPD	ABAN	201	ABANDONED CALL (P)	P150094187		42.37808	-71.0586	Charlestown	
2/23/2015 0:00	1:03:29 PM	BPD	IVMV	201	INVESTIGATE MOTOR VEHICLE	P150094998				Other	
2/23/2015 0:00	1:03:34 PM	BPD	MISC	201	MISCELLANEOUS CALLS	P150094997	1497 TREMONT ST			Mission Hill	
2/23/2015 0:00	1:03:50 AM	BPD	CD19	201	Walk and Talk	P150094188				Other	
2/23/2015 0:00	1:04:56 PM	BPD	TS	201	TRAFFIC STOP	P150094999	974 HYDE PARK AV	42.26605	-71.1208	Hyde Park	
2/23/2015 0:00	1:05:36 PM	BPD	CD19	201	Walk and Talk	P150095000				Other	
2/23/2015 0:00	1:06:39 AM	BPD	DISTRB	201	DISTURBANCE	P150094189	711 WASHINGTON	42.28668	-71.071	Dorchester	
2/23/2015 0:00	1:07:02 AM	BPD	IVMV	201	INVESTIGATE MOTOR VEHICLE	P150094191	50 LYON ST	42.30615	-71.059	Dorchester	
2/23/2015 0:00	1:07:41 PM	BPD	ABAN	201	ABANDONED CALL (P)	P150095002	35 KNEELAND ST	42.35053	-71.0619	Boston	
2/23/2015 0:00	1:07:54 AM	BPD	CD23	201	Guarding Prisoner	P150094190				Other	
2/23/2015 0:00	1:08:24 PM	BPD	ABAN	201	ABANDONED CALL (P)	P150095001		42.31156	-71.0871	Roxbury	
2/23/2015 0:00	1:09:59 AM	BPD	ARREST	201	ARREST REPORT	P150094192	768 MORTON ST	42.28319	-71.0888	Mattapan	
2/23/2015 0:00	1:10:10 PM	BPD	CD8	201	School Crossing	P150095003	65 MALCOLM X BLVD			Roxbury	

could potentially be aided by drones. The events are as follows:

MEDICAL:

['Request EMS and BPD Response', 'UNABLE TO DETERMINE IF CONS/MOVING (E) (F) (P)', 'UNCONSCIOUS PERSON (E) (F) (P)', 'CARDIAC EVENT','ASSIST EMS OFFICIALS ONSCENE (E) (P)','BURNS','PERSON STABBED (P) (E)','MOTOR VEHICLE ACCIDENT','INJURY']

POLICE:

['TRAFFIC PURSUIT','PROTESTERS GATHERING','PERSON SCREAMING FOR HELP','PERSON WITH A KNIFE','SHOTS FIRED', 'PERSON WITH A GUN', 'ROBBERY','Traffic Enforcement', 'TRAFFIC STOP','Tagging','VANDALISM','ALARM', 'DISTURBANCE', 'ASSAULT IN PROGRESS','KIDNAPPING','HOME INVASION']

As this is more of a theoretical exploration rather than a survey with explicit goals these events that are selected could easily be modified in reform.py to change the subset of 911 calls saved for each dataset. Further reform.py modifies the Hospital Location and Police Department Location datasets to include a metric of how many events each hospital and police station are one of the 3 closest stations to. Importantly reform.py also measures the vincenty distance between all events and all hospitals (or stations for police events) using the latitude and longitude of each event and of each hospital. This calculates the distance between two coordinate sets across the curvature of the earth. Unfortunately many of the precise location values required are missing and need to be entered into each document using a Nominatim or GoogleV3 geocode reference search based off the address of the event. This takes a bit of time because the 911 dataset contains thousands of entries and the geocoders tend to be easy to overload with requests. A more sophisticated solution would use a geocoder with an api key that would allow a higher limit on requests and wouldn't need to be manually changed in the script if requests start timing out.

Now that we have the Police Events(PS_EVENTS) and Medical Events(HS_EVENTS) we can start to actually investigate the problem. Using stat_analysis.py we can investigate some basic correlations, namely time of call and its location. I correlated time of day and x coordinate and time of day and y coordinate in an attempt to separate potential differences between all cardinal directions and time of day. I suspected there may have been a correlation that 911 calls moved towards the city center during the day as people move into the city or some other interesting correlation. This information could be used in order to build optimization for drone hosting centers and their inventory, for example if more calls came from outside the city center at night more drones could be moved to those locations at that time. However the results show that for both medical and protective 911 calls there is little correlation between time of day and location.

Med Events

For latitude vs minutes past 6 AM

Original correlation and covari 0.04401672783043568 0.47545501869363527

Cov and p value (0.044016727830435677, 0.24145280911548125)

For longitude vs minutes past 6 AM

Original correlation and covari 0.01846399489901063 0.21530080732292606

Cov and p value (0.018463994899010568, 0.62331090282289747)

Police Events

For latitude vs minutes past 6 AM

Original correlation and covari 0.0016579976159801528 0.021147033292677607

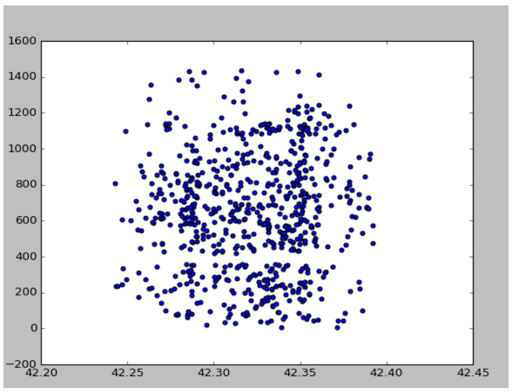
Cov and p value (0.001657997615980184, 0.94680233115602674)

For longitude vs minutes past 6 AM

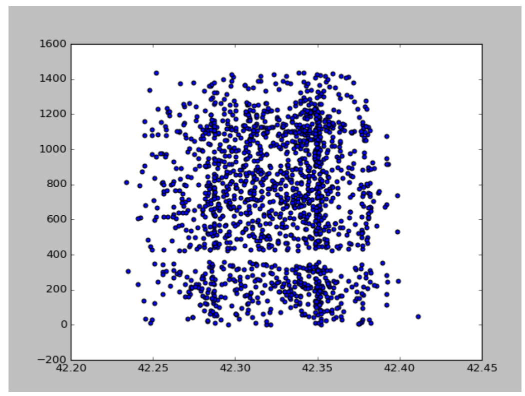
Original correlation and covari 0.025042342037381777 0.31851411894169307

Cov and p value (0.025042342037381742, 0.31348453874881232)

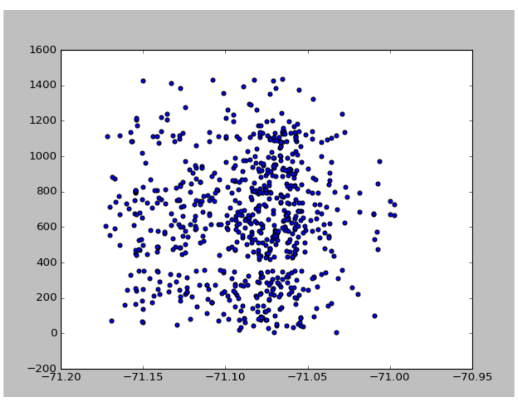
These results show very little correlation (as can be seen on the graphs on page 4) and p values that support no correlation between the dimensions. Further because there are no correlations regarding these dimensions I was not able to modify the optimization function with these dimensions in mind specifically. It would have been very interesting to also perform these statistical analysis with a day of the week analysis, and month of the year analysis however the 911 dataset was very limiting in that regard as it only contains data from one week in 2015 which wouldn't have been very significant. The stat_analysis.py script also generates mat_plot_lib graphs of the dimensions and saves this data to two new datasets PS_EVENTS_STATS and HS_EVENTS_STATS.



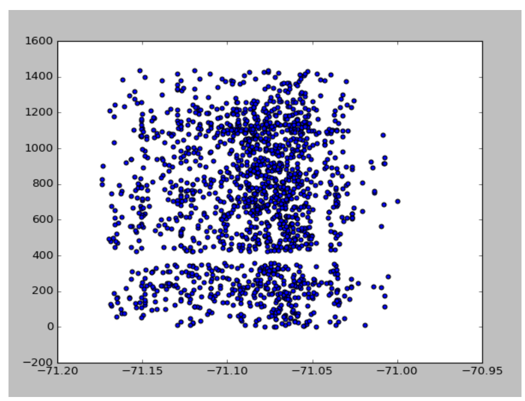
Latitude vs Minutes past 6 AM Medical Events



Latitude vs Minutes past 6 AM Police Events



Longitude vs Minutes past 6 AM Medical Events



Longitude vs Minutes past 6 AM Police Events

From the HS_EVENTS dataset I also attempted to optimize a theoretical placement of drones in hospitals to be of greatest use. I used the lingprog module from scipy.optimize to perform the actual calculations and created the matrices for constraints and bounds as well as the minimization function. Currently my implementation bounds the number of drones that can be stored at an individual hospital with a fixed upper bound and the number of drones that can be stored in close proximity to one another with another bound in order to reduce the number of drones serving the same subset of events. There is also a constraint for the number of missions a hospital can fly each day. All of these values could be customized to a specific degree if there was a more specific plan for storing drones at hospitals. For example if hospitals were given a specific budget to spend on drone systems that information could be taken into account, however as this is an exploration of the topic and no real data exists in this category I will leave it to future explorations to hone in on more specific bounds. The calculation takes into account a theoretical max number of drones to be spread around (30 in my example), a patrol radius (2 mi), a max and min drones as upper and lower bounds in each hospital(5 and 0 respectively) and a max flights per drone(5). These values are completely theoretical and arbitrary and serve to help define the problem. The constraint function currently only factors in the number of reachable events per day for each hospital and treats every medical event as equal. This is a very wide-grain function and its scope could be narrowed if we included information such as potential danger to each drone and if we gave each different type of event a score representing how useful a drone would be in that situation. The values reported for this optimization function for the first day of data are:

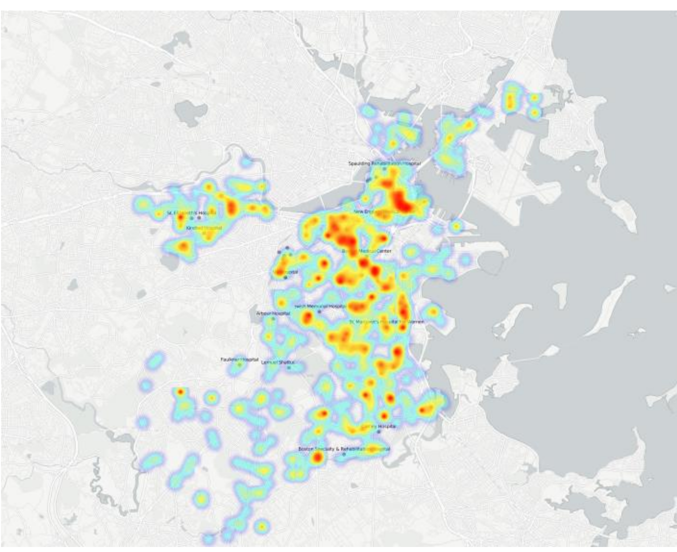
([4.6, 5. , 1.4, 0. , 0.4, 4.6, 0. , 0. , 0. , 0. , 0. , 5. , 0. , 0. , 0. , 0. , 0. , 4.6, 0. , 0. , 0. , 4.4, 0. , 0.])

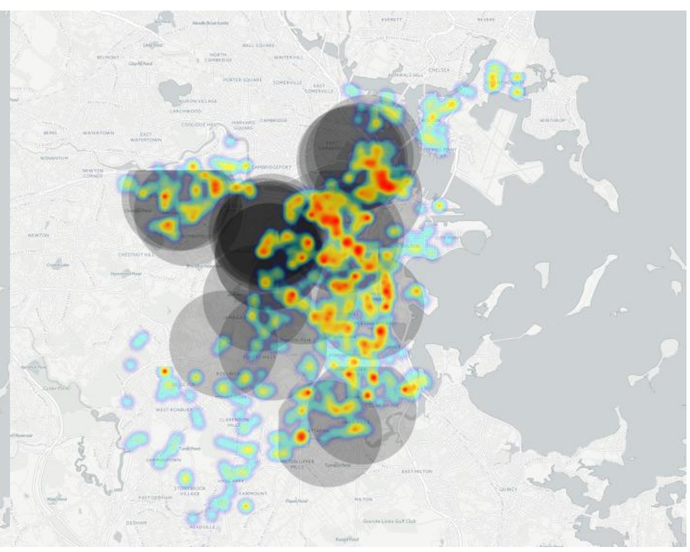
Where the index of each value in the area corresponds to the hos_stations array

hos_stations=['Beth Israel Deaconess Medical Center East Cam', 'Boston City Hospital', 'Boston Specialty & Rehabilitation Hospital', 'Boston Medical Center',"Brigham And Women's Hospital",'Carney Hospital',"Children's Hospital",'Dana-farber Cancer Institute','Faulkner Hospital',"Franciscan Children's Hospital",'Kindred Hospital','Jewish Memorial Hospital','Lemuel Shattuck Hospital','Massachusetts Eye & Ear Infirmary','Massachusetts General Hospital','New England Baptist Hospital','Beth Israel Deaconess Medical Center West Cam','New England Medical Center','Shriners Burns Institute','Spaulding Rehabilitation Hospital','Arbour Hospital','Va Hospital', 'VA Hospital','Hebrew Rehabilitation Center']

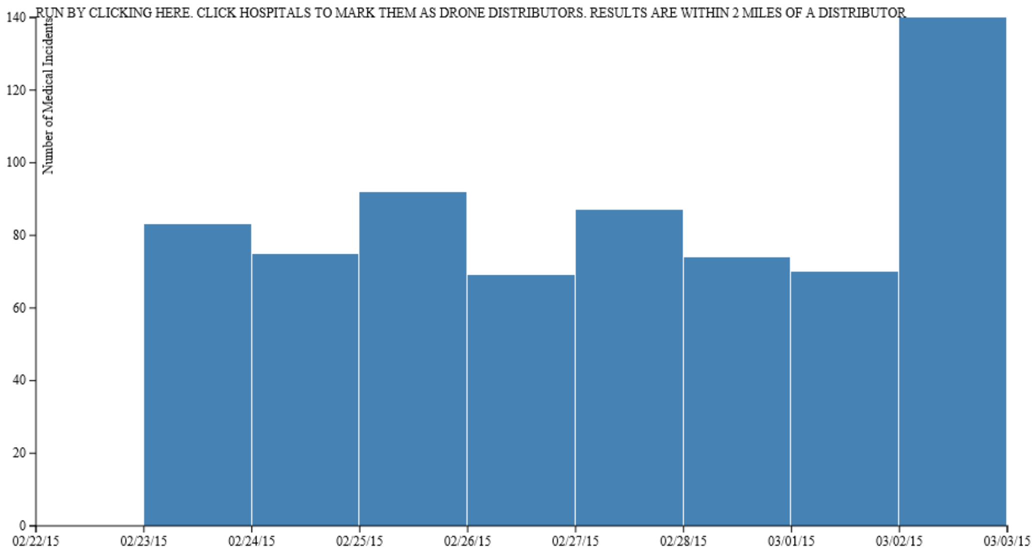
However as you can see the optimization values did not result in particularly informative data. As a result my script ends here instead of averaging over days of the week to create a schedule of drone placements. My work represents a theoretical jumping off point for more focused research on this topic. Instead of linear programming future research on this topic should use integer programming. Z3 solver is another technology that could satisfy this requirement however I did not manage to get it installed and functioning.

To help explain my problem I created a variety of data visualizations, some static and some dynamic html pages. Below are static heatmaps of medical events, and a heatmap with radii of 2mi from each hospital in Boston. This is an effective visualization tool because it shows

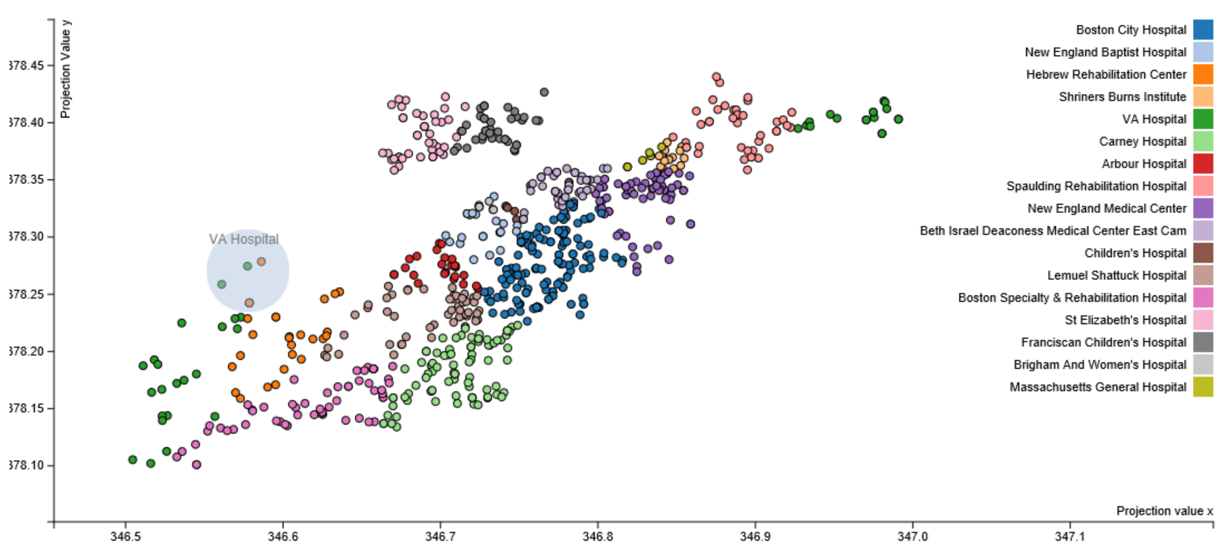




that using hospital locations as drone centers covers the vast majority of medical events in the city. These were generated using CartoDB to map the data points exported from our mongo database. CartoDB was a particularly user-friendly and intuitive resource and created very nice visualizations with the exception of occasional render issues. Additionally in my github repository there are heatmaps with varying radii from hospitals. Below is a screencap of a dynamic histogram one of my html pages generates. Users can select which hospitals they want to include and the y axis represents how many medical events per day are within 2mi of one of the hospitals selected. This could be used to gain an idea of which groups of hospitals have the highest probability of being able to reach medical events if given drones.



Below is an interactive scatterplot of all events where the cursor represents approximately a 1 mile radius around the event as well as colors representing the closest hospital to each event. This visualization could have been more robust and was intended to have temporary place able circles that highlight points within their radii and count the number of events they satisfy.



In conclusion, using hospitals and police stations to serve drones for medical and protective services has the potential to reach hundreds of events and be of definitive benefit to the people of boston. Even a single location serving drones in the center of Boston could reach many medical events faster than an ambulance and has the potential to provide help that could mean the difference between life and death. Future research on this subject should attempt to acquire more specific data both in terms of 911 calls and the ability of each hospital and police station to actually serve drones. Though this conclusion is fairly broad, the application of more specific data and lines of questionings could be quickly applied in order to solve specific problems.

SOURCES:

https://data.cityofboston.gov/ , https://www.cityofboston.gov/images_documents/2011_Boston_EMS_Annual_Report_tcm3-32900.pdf , http://www.mayoclinic.org/medical-professionals/clinical-updates/trauma/medical-drones-poised-to-take-off , http://www.alecmomont.com/projects/dronesforgood , http://www.cnet.com/news/ambulance-drone-delivers-help-to-heart-attack-victims/