Spatial Data Mining for Disease Mapping & Analysis: Flu Spread in University of Arizona 2014

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Contents

1) Introduction

About the Project

This paper is intended as an experiment in data mining process of the social network. The intention is to mine useful data related to spread of a particular disease for the purpose of further analysis and mapping. While the authenticity of the data cannot be 100% guaranteed, a lot of validations and cross-checking is performed to keep the data as accurate as possible. Additionally, mining data opens up a lot of opportunities to classify the data in to meaningful features. For the simplicity of this project all valid and meaningful data is assumed to be associated with the spread of flu, and each symptom is not classified into individual features. Data mining is a vast field, and almost all social networks can be mined with the help of correct resources. For the purpose of this study, the social network data mining is restricted to just twitter.

Also, the data is limited in it's capacity, hence the results are meaningful but not the best estimation of disease spread.

Objective

The objective of this study is to analyze and map the spread of flu for University of Arizona students in the last 3-4 months based on the data mined from social networking website, Twitter. The study is limited to University of Arizona, and about 2-3 miles from each direction from the center of the university to correctly account for all the students. Due to the limited time frame for mining data, the study does not include regions beyond the 2-3 mile radius, and hence any data from beyond those points is not considered while mapping flu spread.

For the purpose of analyzing data, a point pattern analysis followed by K-function test is carried out to confirm the spatial pattern of the mapped data. For risk estimation of the disease, ordinary kriging is carried out towards the end.

While the data is not classified into features, each useful data is given a weight based on many factors to estimate the intensity of disease for the individual in that particular area,.

Motivation

Motivation for this study comes from the growing popularity of social networking websites among individuals of all age. Kids as young as 12, and adults as old as 80 use popular social networking websites these days, thus contributing to the vast amount of data generated by these websites each day.

The most attractive feature about the use of social networking websites is keeping your friends or people in your network updated about the events in your life. Most people share the information about their well being on websites like Facebook, Twitter. This study takes advantage of this fact to mine data related to flu in the last 3 months. Given the fact that the target audience for this study is students, it is easier to gather data due to the popularity of social networking websites among students.

2) Methodology

Mining Data from Twitter

Twitter makes it easy for it's developers to extract data via various Application Programming Interfaces (APIs) written in many different programming languages. For this study, the *Tweepy* api written in **Python** was used. The API provides functionality to search for keywords, add geographic filters, like specific coordinates or city, and also gives the option of filtering results by date. There are many ways in which these APIs can be further used to search individual users, their followers and collect their tweets.

To gather data related to flu , it was important to look for the right keywords. There are many different ways in which an individual can share their illness on Twitter. They can use certain hash tags, phrases or can just be direct.

The following keywords were used while searching for relevant data:

1. **#fever**
2. **#sick**
3. **#flu**
4. **sick**
5. **flu**
6. **fever**
7. **cold**
8. **Nyquil**

9. **Tylenol**
10. **ill**
11. **under the weather**

After gathering results, the most challenging part is to clean the data and filter out noise. Most of the times, the above-mentioned keywords are used in completely different context, thus generating a lot of useless data. A specific branch of computer science, Natural Language Processing, deals with situations like this. For this study, the data was manually read and filtered. Since the data being analyzed was limited in its capacity, it made the manual filtering possible but definitely not easy.

Data from about **2,250** users was mined, and was limited to **200** tweets per user. This resulted in about **450,000** tweets in total.

These tweets were then filtered based upon the above given keywords. The filtering usually resulted in about **1000-2000** matches, and then these tweets were mined for useful data.

There were a lot of ways in which the useful data was sometimes discarded. For instance, if the data was older than September 2014 it was not considered.

If the data was useful but lacked coordinates, it was discarded because it becomes hard to map data without actual coordinates.

If the data was useful and had coordinates, but was not from the decided range (2-3mile radius) it was discarded to avoid any outliers and keep the data normalized for efficient mapping.

Lastly, if the data was not from a university student, it was discarded as the study specifically targets the students of University of Arizona.

As mentioned earlier, while the data is thoroughly checked for its authenticity, it cannot be 100% verified. Luckily most useful data was straightforward and not ambiguous, but when mining data from the social network, one cannot ignore the magnitude of informality in data. Also, almost all the data was user’s own opinion about their health, and in some cases it may just be false alarm for a temporary infection. There is no way to account for false negatives and false positives in this study, and hence it is assumed that the data found is accurate for analysis purposes.

Challenges

While Twitter is friendly with data extraction from their database, they impose a lot of limits on the APIs to avoid abuse of their resources.

Each API has rate limits, which are different based upon what the API is used for. For searching for specific keywords and obtaining tweets for just those keywords, the rate limit is **150 requests** per **15-minute** window. The API will start throwing errors after 150 requests are exceeded or after 15minutes end from the time of its use (whichever happens first). The API will then be unavailable for close to 15 minutes. If you are searching for a specific user's tweets, the API poses a rate limit of **180 requests** per 15minute window. Approximately **3,200 tweets** can be mined per user without exceeding the rate limit.

To overcome these issues, multiple twitter accounts were created, and a python script was run as a daemon in the background to make sure a change of account happened after the rate limit exceeded. If meanwhile the program is put to sleep (using sleep functionality available in time module in Python), the searching does not restart and continues from the exact place it was left off at.

Each account is authenticated using **OAuth,** and is given a specific access token and consumer key along with access token password and consumer secret token. To access the API each account needs to create an app , after which the **OAuth** credentials are granted

Another problem with the Twitter API is that it does not return results older than 7 days. At the most, it can return old results that were popular. Since this study requires analyzing data at least upto 3 months old, a different technique was adopted.

Twitter API allows scanning up to **3,200** tweets per user, and this was used as an advantage to scan each user who came up in the results for a specific coordinate specified in the filters, along with the radius. In this case the coordinates were of the center of university with radius kept to 3miles.

A blank search resulted in **18,246** tweets from users who had tweeted around those coordinates. These tweets were analyzed for duplicates user ids, and all the unique twitter ids were extracted. Multiple searches with random and popular were keywords were also carried out to extract as many users as possible. In the end the total count of unique users from the given bounding box was **2,652**.

Considering there are **40,000** students in the university, this sample is very less. A reason for such less number of users is

1) Not a lot of people have geotagging on for their twitter accounts, which is why they are never detected.
2) Not a lot of students are on Twitter, and prefer using other social networking websites.

Twitter APIs are infamous for not resulting all the tweets, and filtering out most tweets. Since the search was mainly focused on extracting twitter ids, only getting sampled tweets was not an issue because the APIs returned at most one tweet by each user, which is sufficient.

About **200** tweets were extracted from each user per request. This number was chosen to avoid data beyond the 3 month limit, and most users tweet about 200-300 times on an average in 2-3 months

Using search engine in a popular text-editor called **Sublime- Text**, these tweets were searched with specific keywords and data was extracted, cleaned and analyzed.

3) Analysis

Mapping mined data

All the clean data was mapped and created into shapefiles.

The maps below show data, which is up to 4 month old.

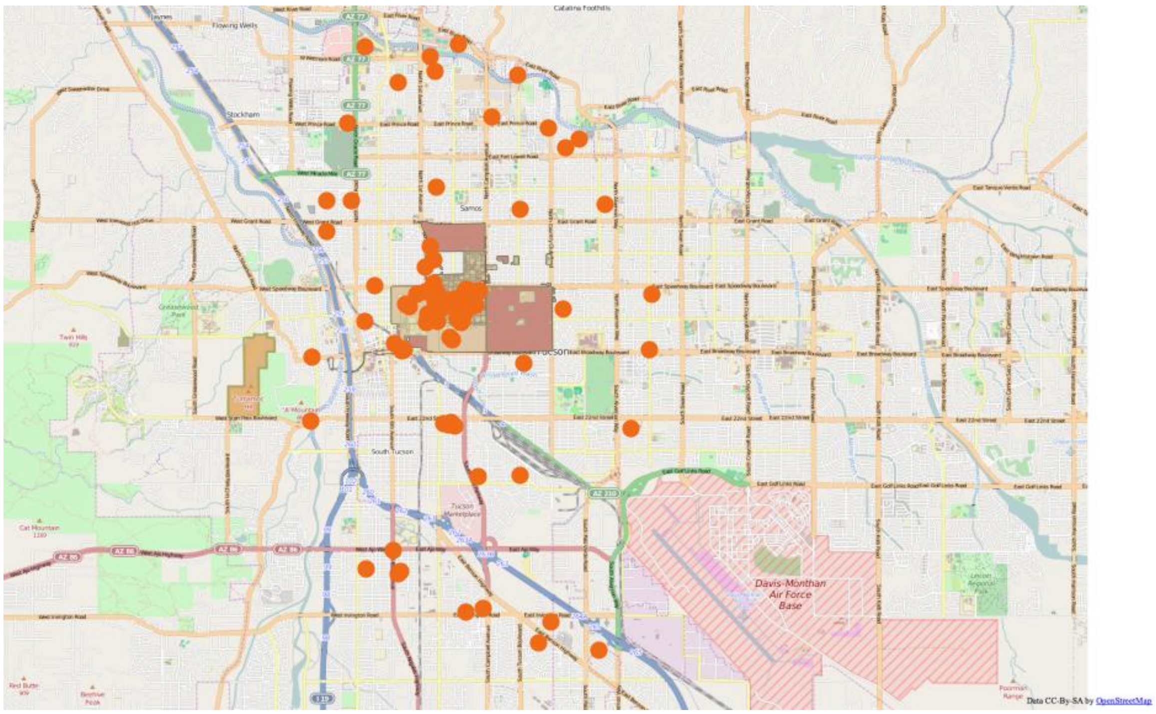

Figure 3.1: Data collected from tweets mined on map of Tucson. Brown polygon is the University area

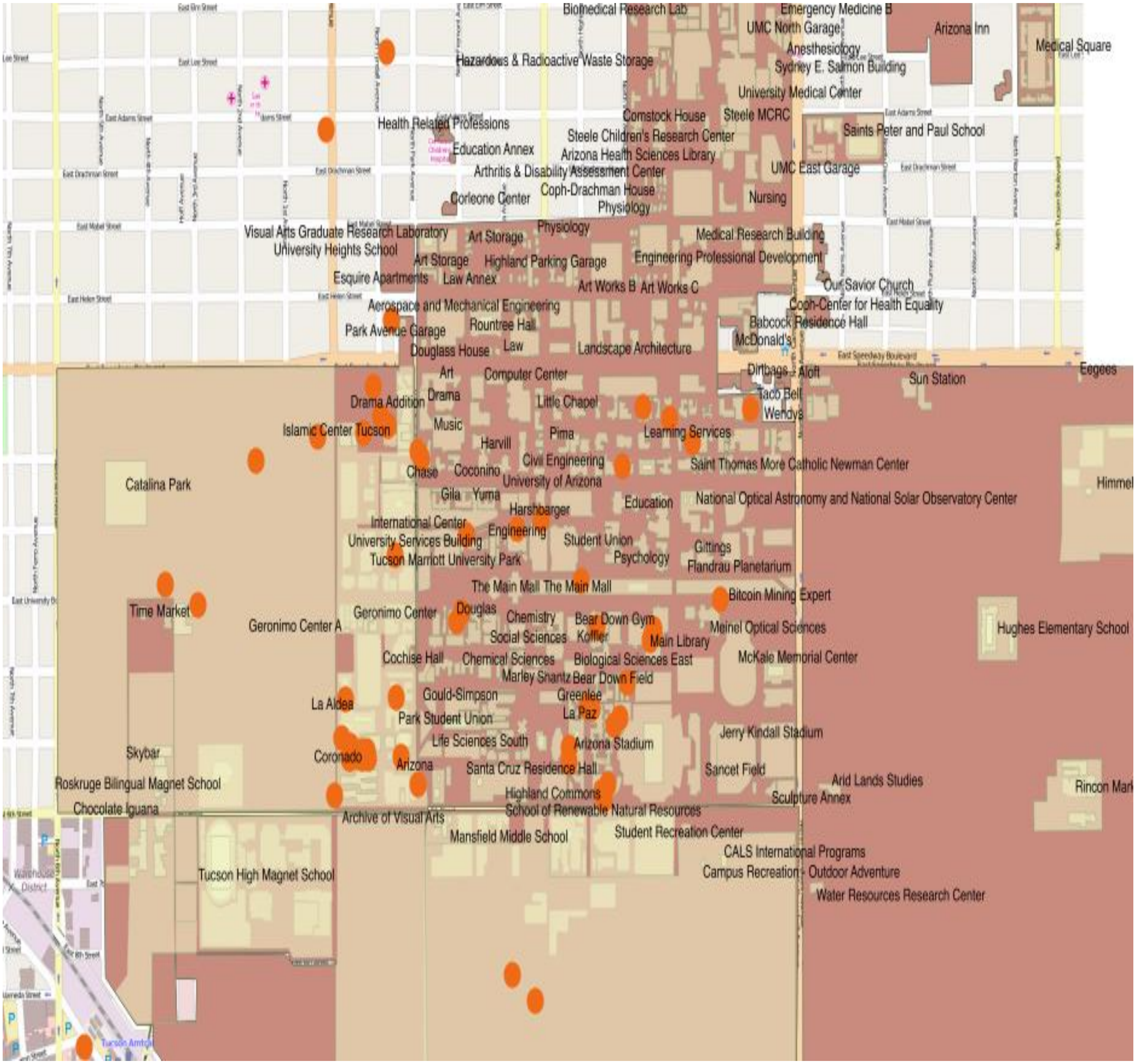

Figure 3.2: Map zoomed in closer to University area with labelled buildings

Figure 3.3: Map zoomed in on cluster newar the university area

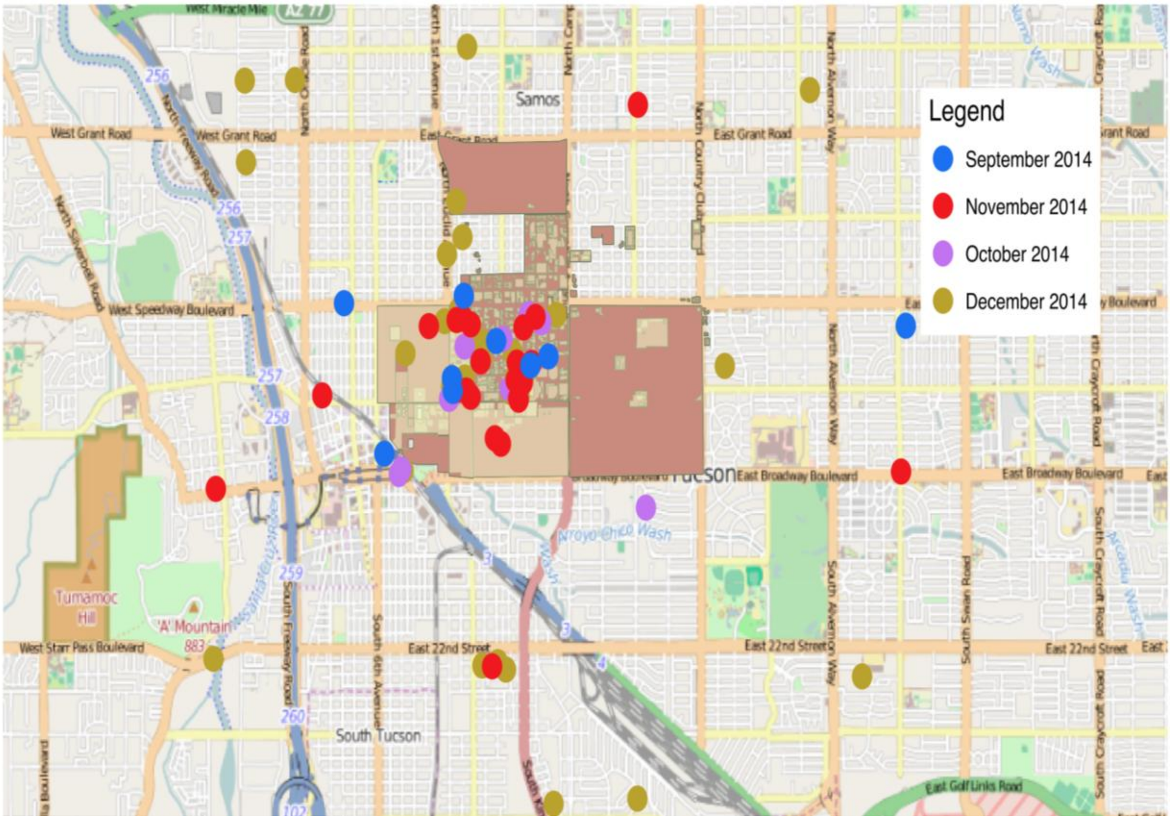

Figure 3.4: Map of data mined from tweets separated by creation date

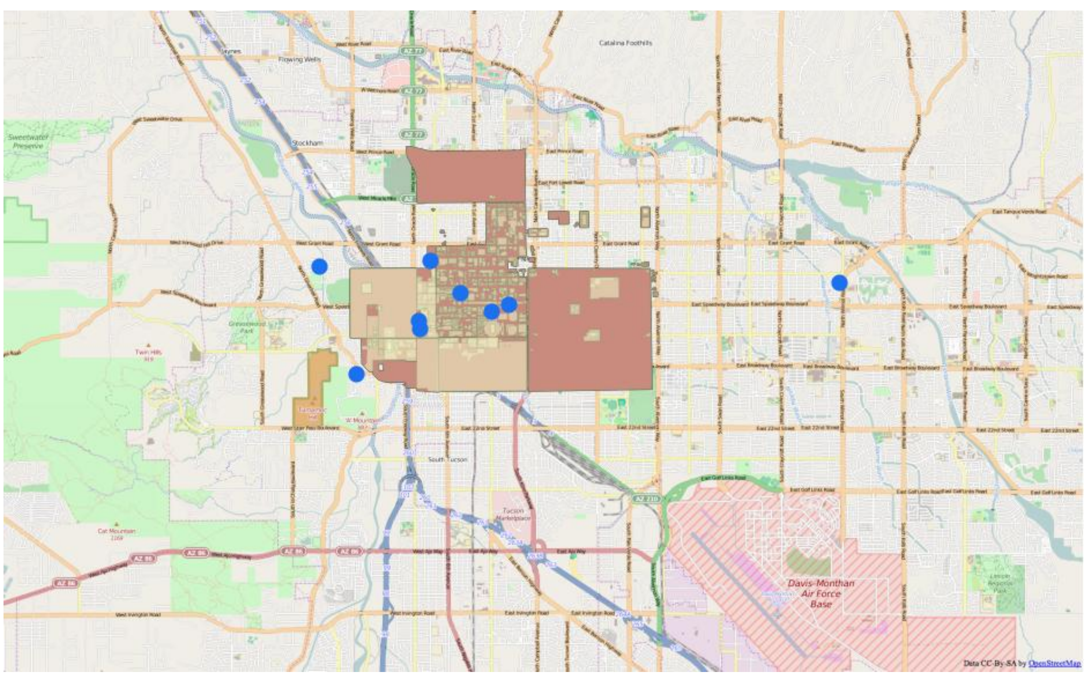

Figure 3.5: Data from September 2014

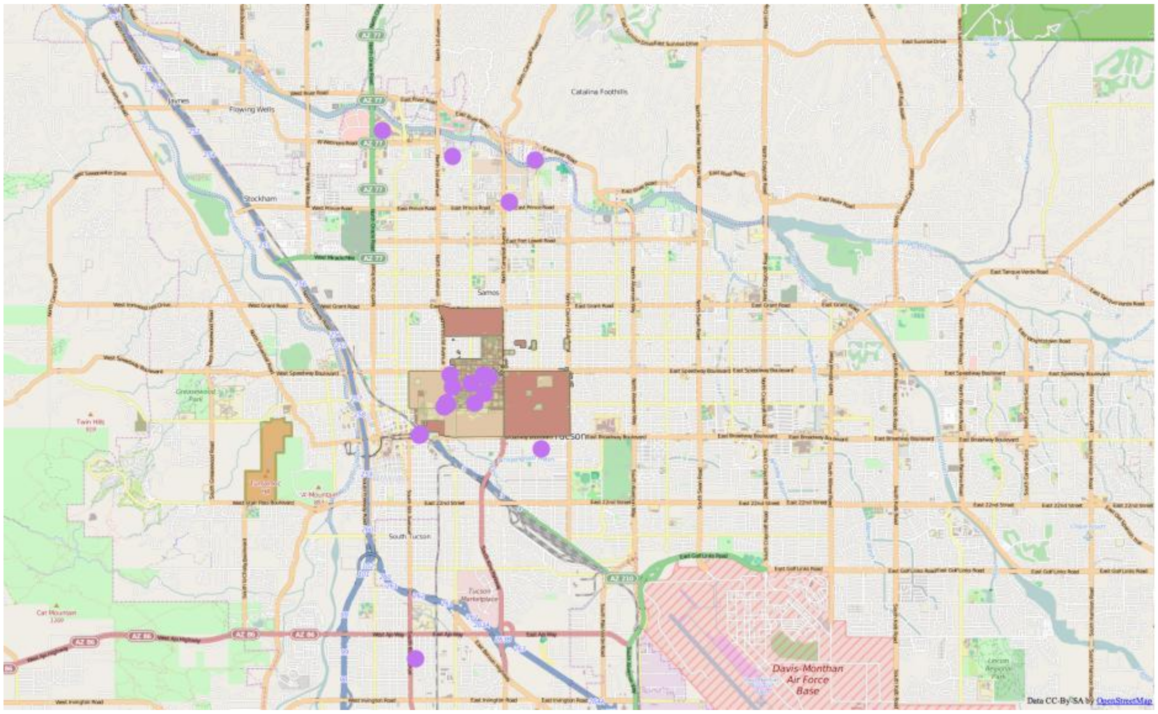

Figure 3.6: Data from October 2014

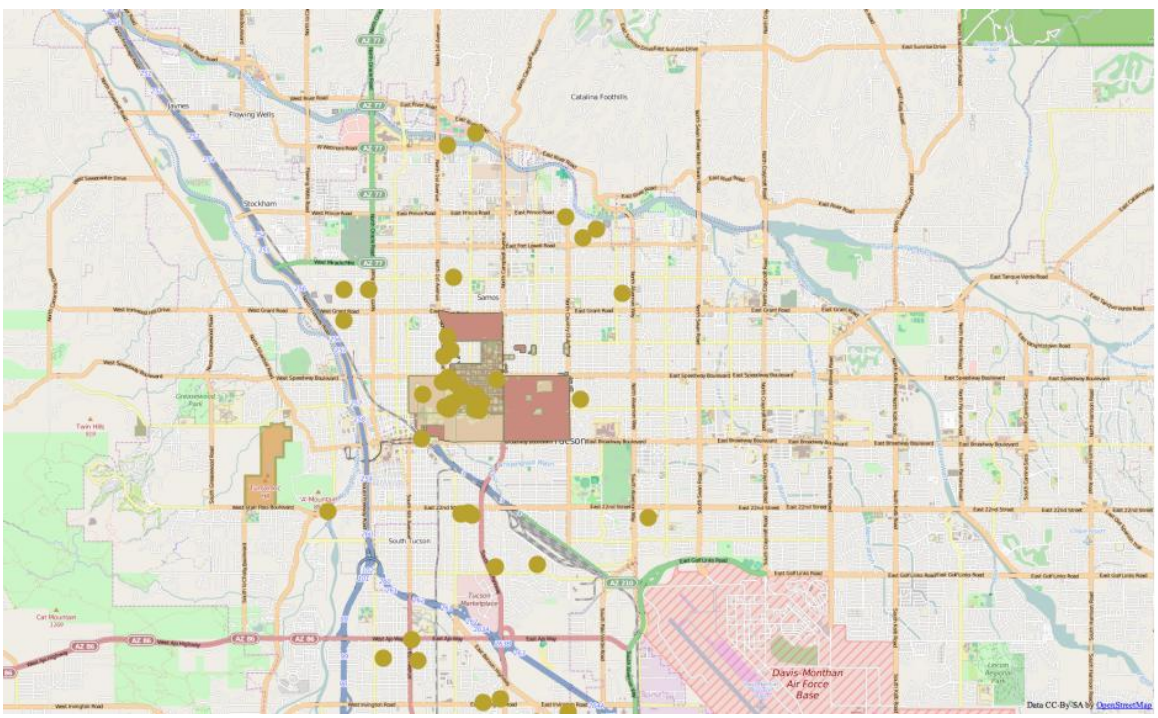

Figure 3.7: Data from November 2014

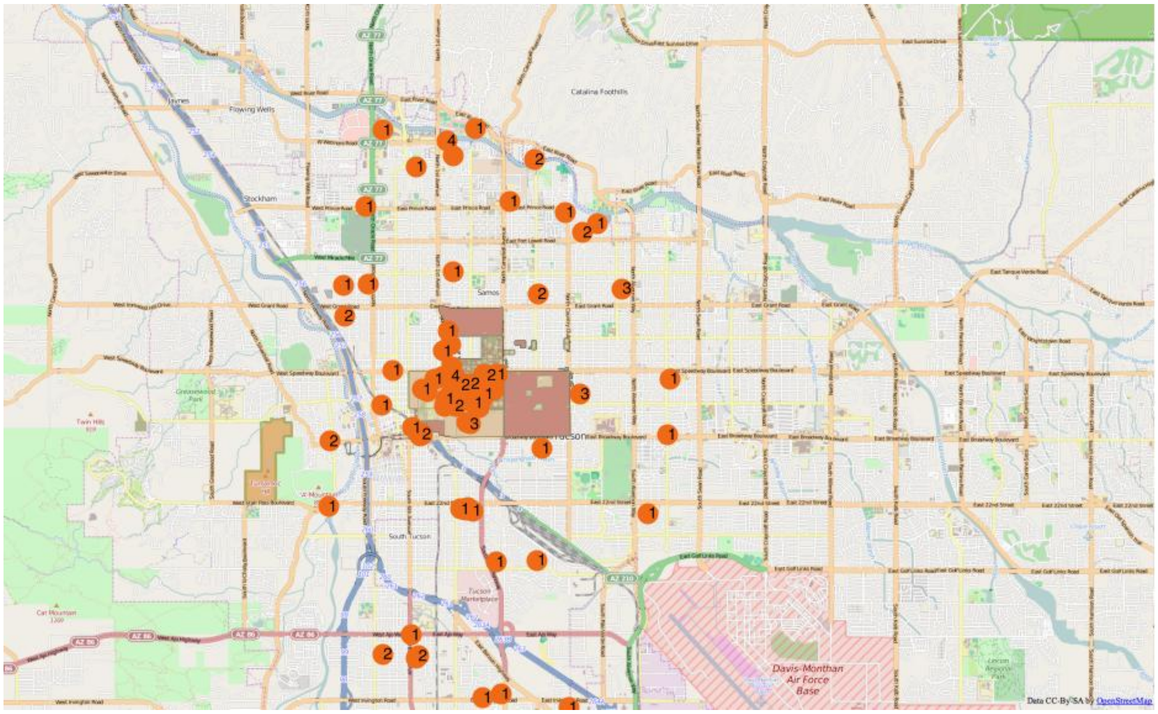

Figure 3.8: Data from December 2014 labeled with intensities

Point Pattern Analysis

The point pattern analysis of the data was carried out in R, and the results are pasted below. They will be discussed at length in the next section.

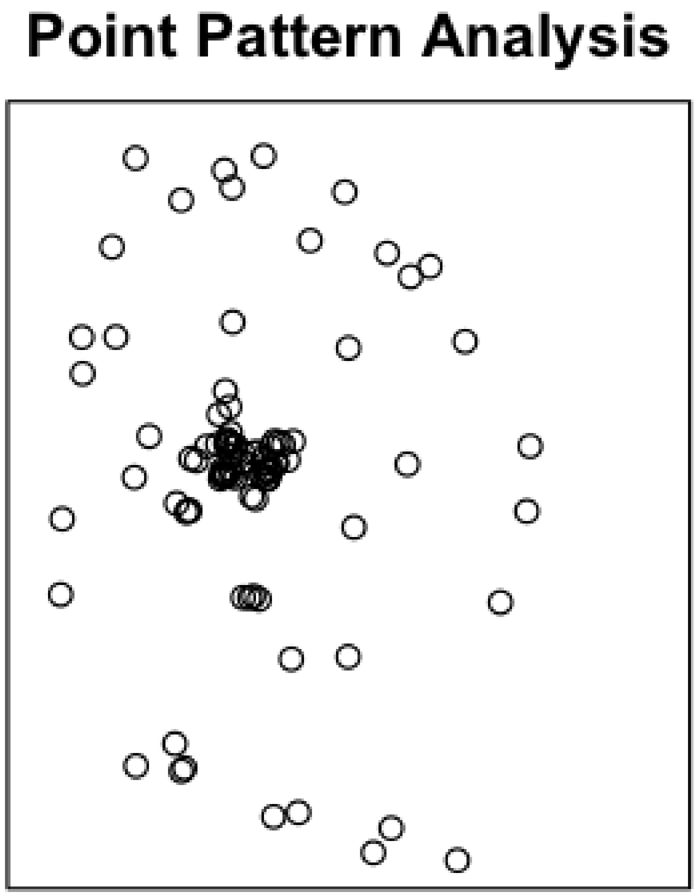

Figure 3.9: Point Pattern Analysis of the data

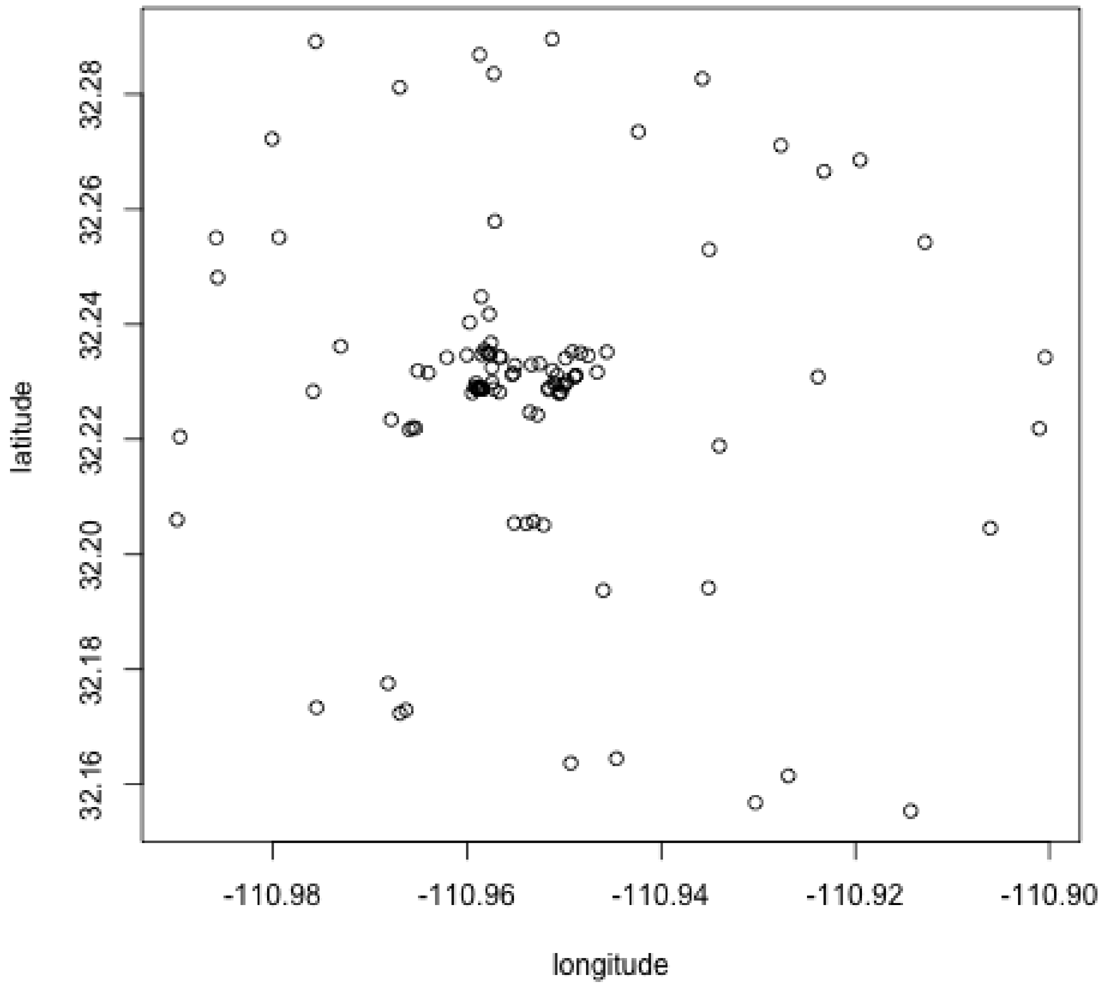

Figure 3.10: Point Pattern Analysis on a smaller range

<u>K-Function Test</u>

The point pattern analysis of the data was carried out in R, and the results are pasted below. They will be discussed at length in the next section.

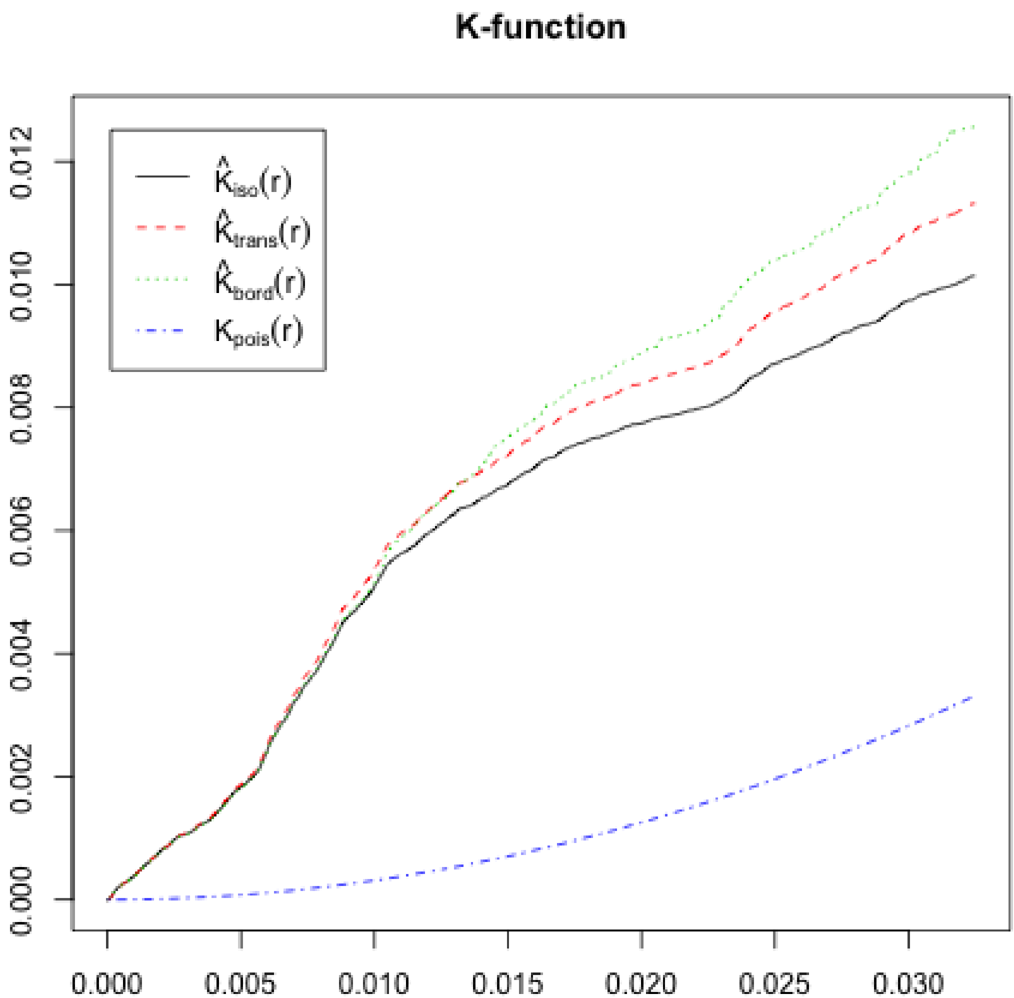

Figure 3.11: K-function test

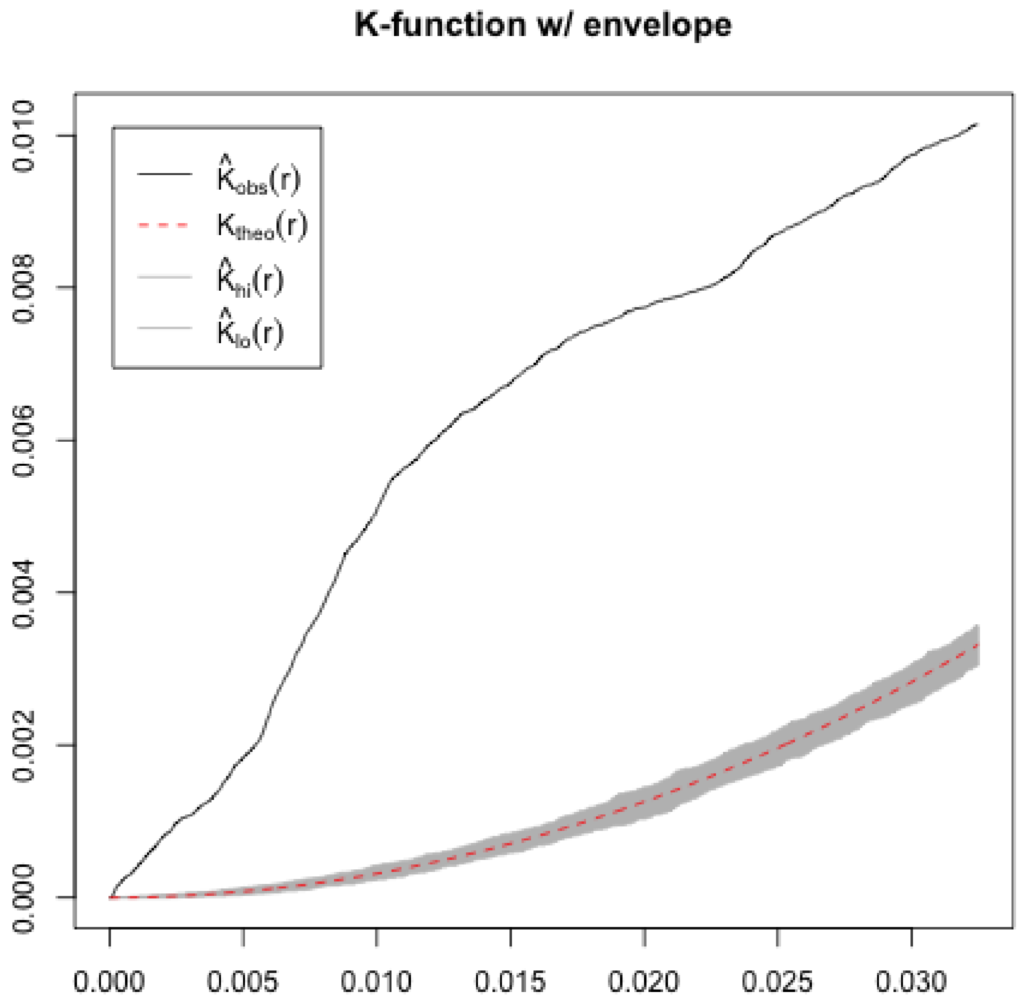

Figure 3.12: K-test with envelopes

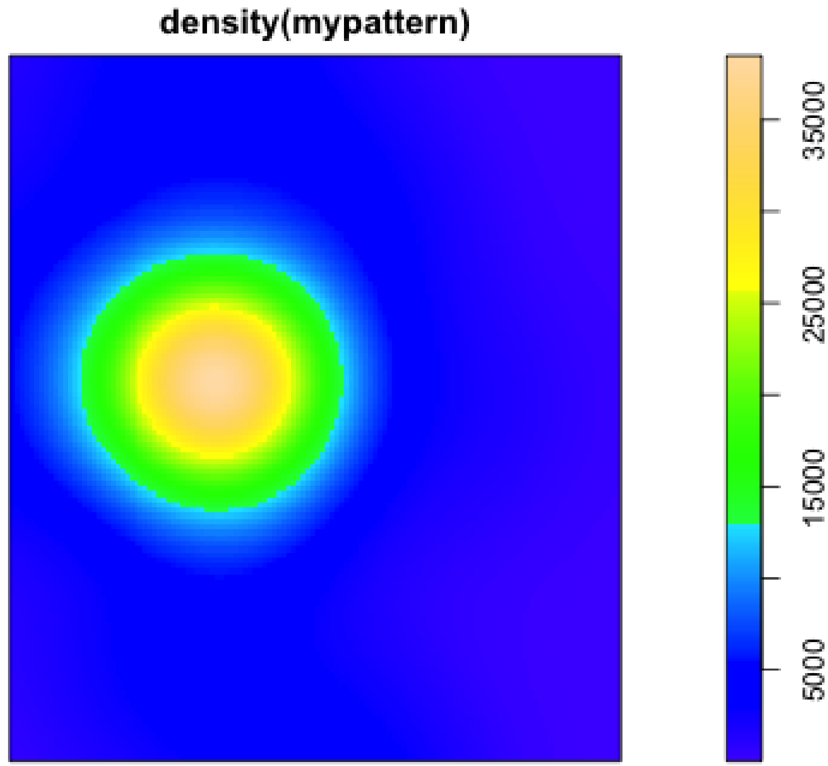

Figure 3.13: Density map of data

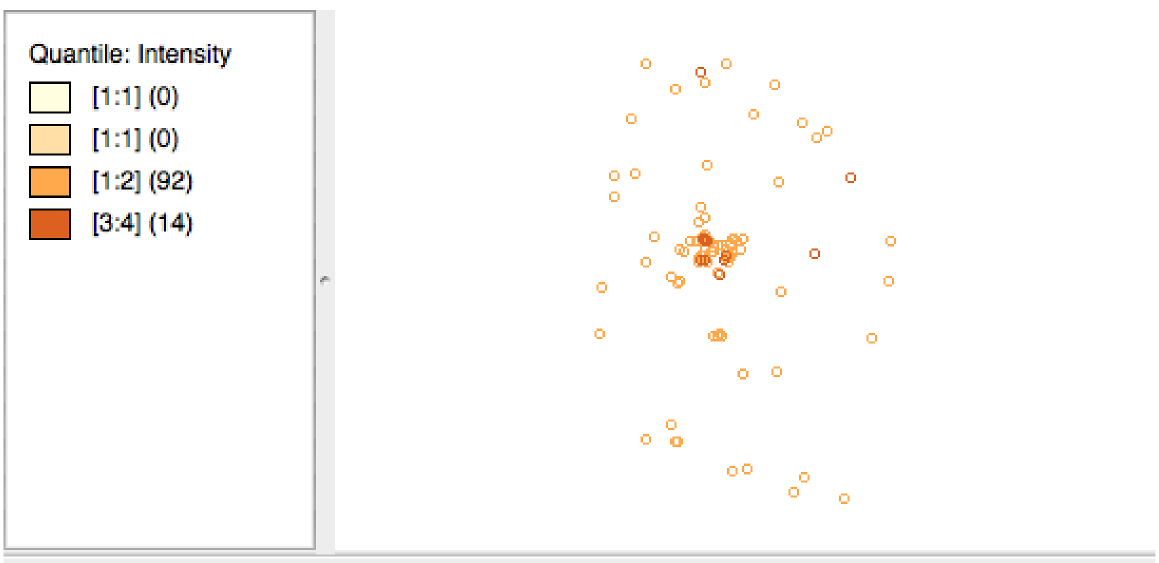

Figure 3.14: Quantile map based on intensity

Ordinary Kriging

While Baye's estimation was the first choice for risk estimation for flu spread, the acquired data lacks important features like population count per region. Hence, Ordinary Kriging is carried out for interpolation after regression.

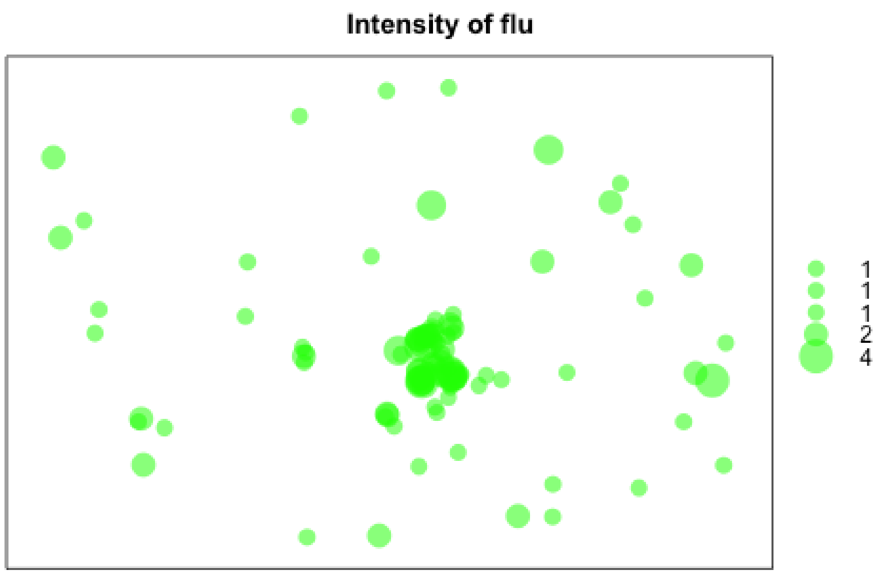

Figure 3.15: Bubble sort based on intensity

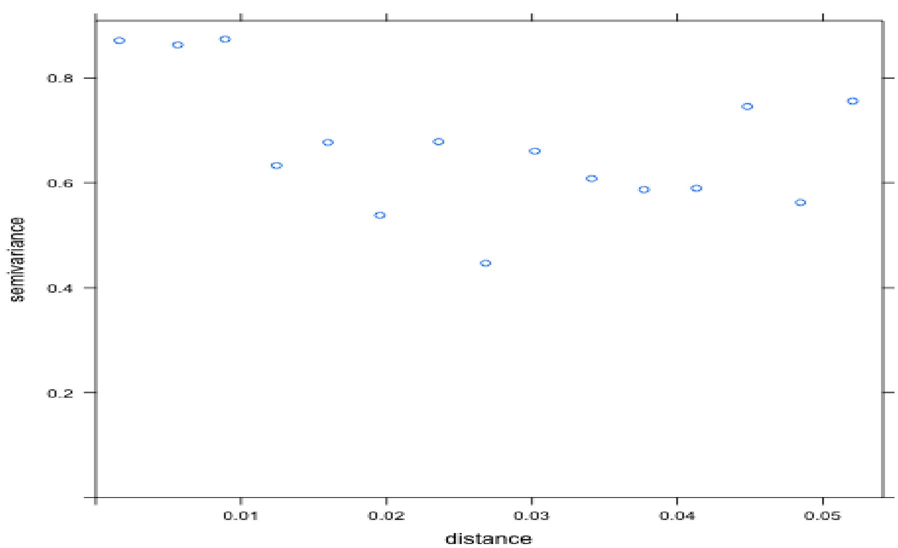

Figure 3.16: Variogram based on intensity

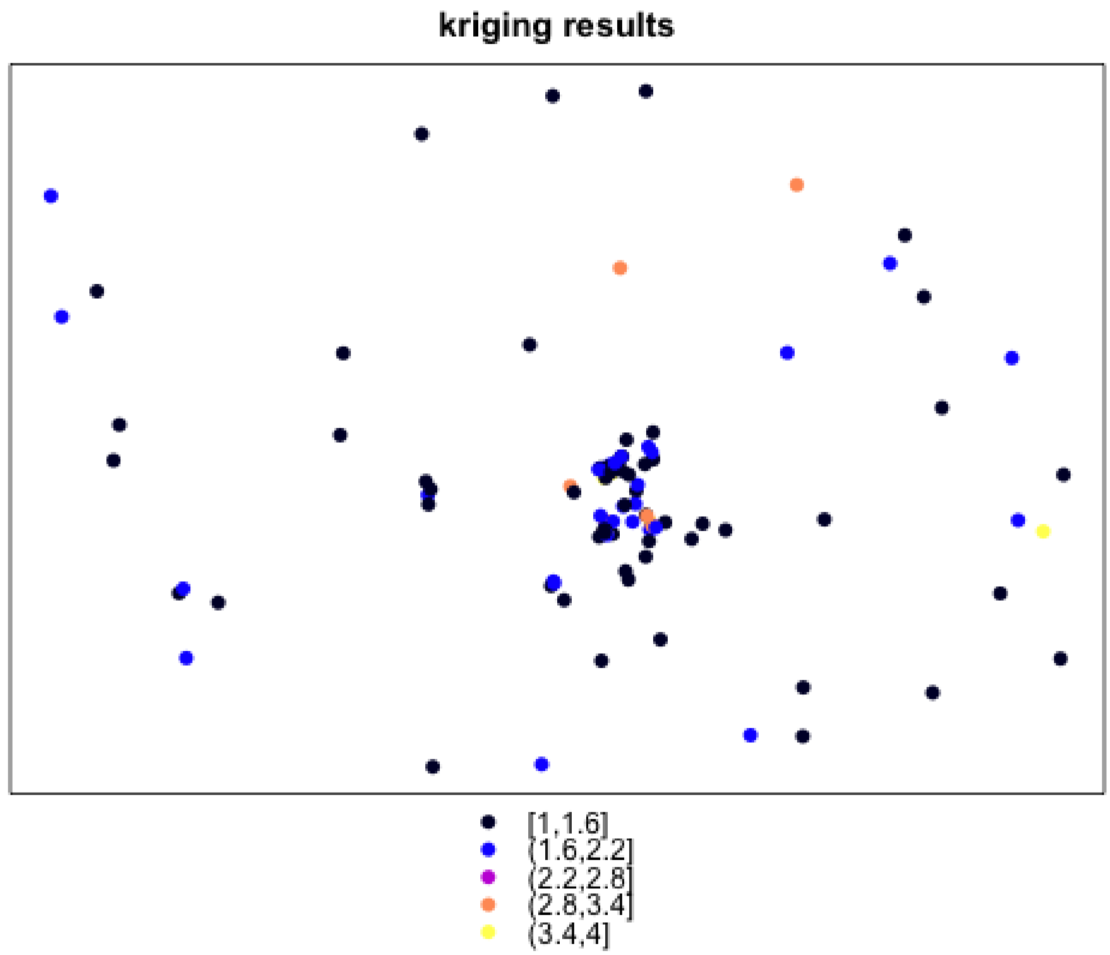

Figure 3.17: Oridinary Kriging results based on intensity

4) Conclusion

Conclusions based on Analysis and Mapping

From figure 3.1 it is clear that the points are more concentrated near the university area, and are fairly spread out as we move away from the university area. This is because most people tweeted from around the university, which also helped confirm their identity as students. Additionally most points were discarded if they were not confirmed to be students (after going through their tweet history). Zooming in on the university area shows that the points are actually much more spread out around the university.

One would expect more data to be around dorms, but most dorms did not generate much data. The major cluster near the university area (fig 3.3) comes from the area around Cornardo dorm. This could be a result of 3 dorms in that area, and the student population which frequents the area due to Park Student Union and volleyball courts.

Surprisingly not a lot of data came from highland avenue dorms, which is closer to Campus Health and has more dorms than the Cornardo area. Eitherway, just by looking at the maps it can be said that most sick students came from the Cornardo area.

Looking at the data time in Fig3.4 wise shows how the tweets increased progressively in a span of 3 months. This could be a result of weather changing from extremely hot in September to extremely cold in December. The September data is not much reliable intensity wise as the tweets mostly came from October, November and December, which was also a result of taking only 200 tweets per user.

These results are analytically proved by the Point pattern analysis in figure 3.9 and 3.10. Fig 3.10 shows a zoomed in point pattern analyses. The overlapping points are around the cornardo dorm and neighboring areas. They look clustered due to shorter range on the plot.

K function estiamtes show perceived clustering around the university area as well. The desnity function is another proof.

The Quantile map is based on the intensity values. Intensity for a particular data is calculated based upon certain factors which involve – multiple problems like fever, cold, headache earn an intensity of 4, recurring problems earn an intensity of 3 unless they have been going on for a very long time. Problems, which cause a lot of discomfort like not being able to sleep at night because of fever, earn an intensity of 2 and mild to less troublesome problems are 1. These intensities have been carefully calculated after evaluating each and every data source from their previous tweets. The quantile maps shows larger densities around university area, and the intensities decrease as we move away from university. This can also be confirmed by the bubble sort which shows higher radius in the center (fig 3.15)

Estimation of risk from disease is analyzed by ordinary kriging, by essentially interpolating the data based on given intensities. The variogram plotted with the intensity variable is a singular matrix, which shows a very vague horizontal line implying an almost negative correlation, which states that intensities are mostly random.

The kriging shows predicted intensities. It is easy to observe that most intensities are predicted to be between 1 and 2 , and are clustered around the university area. Rarely does the predicton go over 2, and most of it is not even near the university area. The highest intensity is very rare in the prediction map, and is away from the university.

Kriging shows that most intensities around the university area were 1 or 2, and hence there is chance of people getting mild to medium flu like symptoms around the university in coming months.

Once again, the data is credible but only to an extent, and these analysis and estimations are based on the same credibility.

Future Work

Future work for disease mapping by mining data from social network includes exploring more social networking websites like Facebook, Google+, etc.. and gathering as much data as possible for establishing credibility. Of course there are limitations on these social networking websites, so we also need to rely on advanced technology for hacks.

Disease mapping can be useful for a variety of reasons, but most importantly it is necessary for people to be aware of the disease-spread rate around them and their chances of catching the infection. Hence, it is important to enhance technology in disease mapping.

Appendicies

Appendix A:

a) September 2014:

id	text	creation_date	creation_time	longitude	latitude
tiffanersz	sick and soaking wet and late to class	9/8/2014	20:38:57	-110.9533747	32.232959
JennaBellinger	Of course the weekend Car leaves me I wake up sick □	9/27/2014	20:01:14	-110.9590912	32.22981262
JChuckIsButts	Being sick is straight up lame. Been sleeping all day. Really wish I didn't get sick so often.	9/6/2014	4:40:09	-110.9669414	32.28118408
majitobonitaa	I hate being sick	9/18/2014	20:07:17	-110.9730361	32.236167
djjonjon1	It's Friday and of course i feel sick :((@ Madden Media in Tucson AZ w/ @_arexis) https://t.co/hCDAXgTVcz	9/12/2014	15:05:48	-110.9678275	32.22340526
stone_sydney	I love being sick :-)	9/21/2014	17:03:16	-110.9589897	32.22873728
haycmcshane	No rain gear to walk to class in this rain and now I'm about to get even more sick □	9/8/2014	16:07:27	-110.9575503	32.2368001
Courty_Cat	When you're sick and you ask your best friend to bring you food and she says no. http://t.co/5avwc7QjpE	9/21/2014	23:45:19	-110.9801061	32.2722507
veeheymann	Sick girl □	9/11/2014	2:17:12	-110.900437	32.23425922
danielle_claud	Soup couch and a blanket. I refuse to get sick!	9/24/2014	3:23:38	-110.9466098	32.23165659
cassidyfknapp	hate being sick..	9/29/2014	1:00:01	-110.9489448	32.23089779

b) October 2014

id	text	creation_date	creation_time	longitude	latitude
sambam158575	I really need to stop getting sick I'm at campus health wayy too much 馃槕	10/15/2014	18:02:53	-110.9579283	32.23502829
Alexamunson	true friends come over late at night when you're sick to take care of you #solucky	10/6/2014	6:48:50	-110.9572476	32.28356866
Beahmr	Being sick in college is one of the worst things in the world	10/27/2014	18:26:59	-110.9491611	32.23521843
JosieeEck	Don't go to college kids you never sleep and then you get sick and still don't ever sleep.	10/23/2014	17:49:19	-110.9525458	32.23313692
afimbres94	Literally no matter how sick I get wilbur will always make me laugh and smile. 馃樆 http://t.co/CrGo6Al2T0	10/20/2014	16:49:06	-110.9669124	32.17238082
mkavanaugh_	it sucks being so sick and not at home馃樣	10/27/2014	5:17:19	-110.9588732	32.22874598
Rehya66	I'm feeling sick.	10/2/2014	1:46:47	-110.9755928	32.2891732
christinajtobin	I've been sick for two moths straight #thankscollege	10/7/2014	23:11:54	-110.9589255	32.22895038
RachelThaxton	The fact that I've been sick for over a week is getting really old.	10/28/2014	16:12:13	-110.9516279	32.22891622
TheDaveMarr	I'm so sick and tired but AHS comes back tonight so I have to make it through.	10/8/2014	18:29:28	-110.9574509	32.23249071
mollysupple	It's ironic that I got sick while studying for my Lymphatic/Immune system exam.. #brokenimmunesystem	10/13/2014	14:11:58	-110.9340208	32.21883397
arkmuntasser	I'm sick and @BeccaBummer	10/4/2014	23:08:25	-110.942347	32.27347361

	came over poured tea down my throat shoved medicine in my face and made soup. She's really the best.				
callmetashaaaa	There's no better feeling than taking a hot bath where you're sick 倮泙	10/13/2014	21:11:11	-110.965954	32.22168093
Savannuhhx3	Haven't been this sick in awhile 倮槖	10/10/2014	0:28:43	-110.9357663	32.28272367
enriv_	I love how I'm sick as hell and I'm still going to the career fair 倮楕	10/1/2014	15:27:07	-110.9475205	32.2345615
krystaldlo	Besides being sick...Not to shabby of a day	10/9/2014	18:46:31	-110.9594574	32.22805554
jkarmannn	Spiking a fever again 倮槍 #blessed	10/30/2014	4:12:10	-110.9656176	32.22206027
moniquwah	Emma is bringing Max soup bc he's sick college love is real	10/21/2014	23:10:19	-110.9585488	32.22872059
kenzie_bev	I keep getting sick. Should probably stop licking doorknobs	10/1/2014	16:07:21	-110.9488151	32.23100493
caitlinbarner	Why does my Nyquil have to be at nado and my sick ass in my real home #ebolagotmelike 倮樂	10/12/2014	6:40:41	-110.9588954	32.22876024

c) November 2014

id	text	creation_date	creation_time	longitude	latitude
JenniPURRm	Taking a 8am midterm with the flu/cold is not ideal but I'll just have to suck it up	11/4/2014	14:05:59	-110.9576773	32.23487691
Bitchflakes	Fucking Flu is killing me can barely breath	11/6/2014	14:09:36	-110.9577022	32.23485744
abellitter	Have the flu on thanksgiving but I know it's for having so many good people & things in my life ❤□ #ItWouldn'tBeFairToHaveHealthToo	11/27/2014	18:07:13	-110.9553852	32.23123692
KristennKearney	I hate the flu □	11/8/2014	1:22:17	-110.9538995	32.20537751
ShendlxSinger	#flu	11/29/2014	5:08:19	-110.9584803	32.23473972
toriginsburg	How is it possible to always be sick □	11/10/2014	20:16:07	-110.9589208	32.22873183
becca_noya	Being sick= watching every Harry Potter movie and never leaving bed	11/17/2014	22:52:08	-110.9487996	32.23110494
KoralPreiss	I got my bf sick & now I feel bad □	11/10/2014	20:55:45	-110.9499259	32.22946196
tatum_kyle	Being sick during the school week sucks.	11/17/2014	18:34:47	-110.9010473	32.22189449
OfficialRuben_	I hate being sick	11/12/2014	20:21:56	-110.9507074	32.231132
nicoleeoley	I woke up 100x more sick □	11/27/2014	19:19:08	-110.9572457	32.22875939
_davissofia	I feel so sick □	11/21/2014	22:05:55	-110.9758537	32.2283475
a_pfotenhauer	Everything hurts. #sick	11/12/2014	17:01:14	-110.952764	32.2242456

kenzweller	Being sick in college is the worst. I just want my bed & my mom□	11/24/2014	0:01:41	-110.9482871	32.23500971
emilysill13	Being sick away from your mom is the worst □	11/15/2014	7:31:36	-110.9498511	32.23411846
julesburd	Whenever I'm done being sick I get sick again	11/5/2014	19:41:59	-110.9620718	32.23422392
haleykaatee	@nawtbob i'll cuddle you i'm sick already□	11/15/2014	5:45:51	-110.9501574	32.22932793
katieszymanskk	there is nothing worse than being sick in college	11/16/2014	18:37:18	-110.9566652	32.22823174
mthalg	I hate that I'm getting sick again...	11/11/2014	4:54:28	-110.9302939	32.15682977
rachjfranks	Literally when am I not sick□	11/17/2014	17:06:55	-110.9504723	32.22798028
theresadelaney	It's been cold in Tucson for 1 day and I am getting sick. The world is cruel.	11/4/2014	17:25:37	-110.9350581	32.25299063
Luna_princess11	Not only am I hurting because of heart break I'm sick too □	11/6/2014	16:19:03	-110.9895992	32.22042622
TTesten	Coughing a lung out on Homecoming week and being sick...#notcool #fomo □	11/5/2014	7:56:57	-110.9583712	32.22885712
reynapesquera	It's become normal to get sick at least once a month□	11/24/2014	7:32:46	-110.9566662	32.23437386
BreaCicinelli	If you weren't sick before you went to campus health I can guarantee you will be by the time you leave □□□	11/13/2014	16:21:07	-110.9585357	32.22886441
hello_emily95	Being sick made me sleep all day so now I'm up □	11/11/2014	8:14:37	-110.9535377	32.2247156
marimac08	So much homework still so sick	11/19/2014	6:46:16	-110.9505339	32.22811212
lauren_hen	been sick all day so that means binge watching desperate housewives	11/18/2014	5:37:18	-110.9508557	32.22963708

d) December 2014

id	text	creation_date	creation_time	longitude	latitude
Brother_Brew	Currently dying once again at Urgent Care with the flu	12/7/2014	0:16:32	-110.9510269	32.22966693
remydanger	Woke up from a flu near death nap only to find my #49ers lose to the gaddamm Oakland Raiders. I should have stayed in bed. #FML	12/8/2014	0:22:45	-110.9755031	32.1733545
PrinceTom007	Fuck this flu and this bs spasms. Back to doc tomorow. Possible pneumonia	12/3/2014	2:14:06	-110.9516198	32.22866883
27_ariell	Freaken hate to be sick i cant even sleep good.	12/4/2014	9:30:52	-110.9857013	32.24811181
Samshooo	Even though I'm still sick after almost 5 weeks...and haven't run in a month #iwillsurvive	12/2/2014	22:38:32	-110.958687	32.228764
samantakoro	WHOEVER GOT ME SICK IS GOING 2 DIE	12/9/2014	14:22:06	-110.9577326	32.24176538
itshope_nothoe	When you're sick and your friend brings you all kinds of stuff to make you better plus THIS soup □□□ @lisunderwood http://t.co/Xtrm25c5u8	12/4/2014	1:12:01	-110.958544	32.24480251
livelove_kari	I woke up super super sick... □□	12/15/2014	14:35:24	-110.9142985	32.15539271
saul_mancinas30	And I'm getting sick shitty way to start the week	12/8/2014	22:17:19	-110.9512353	32.2895977
JLoFo_	“@ImEmilioParedes: Yep.. I would get painfully sick on the day of my 8 AM final..” RFT	12/15/2014	13:55:11	-110.9565445	32.23425565

Ermergerd_Alina	I haven't felt this sick in a LONG time. □	12/5/2014	7:57:14	-110.966313	32.172934
MaryJaneEichenb	Why does my body decide to get sick NOW	12/12/2014	23:47:05	-110.9583317	32.22872059
Pheromone27cvlt	I only get sick maybe once a year. Why? Because I don't think about being sick. Nor am I concerned who is or isn't. Mind over immune system.	12/8/2014	14:38:05	-110.9195218	32.26855208
highdreams_Bert	Fuck being sick!!!	12/11/2014	15:04:22	-110.9681442	32.1775644
ceeairuhhhhhhh	I feel so sick	12/4/2014	8:13:26	-110.9571312	32.2579097
terrangrace	Man. Why do I feel sick.	12/2/2014	4:14:45	-110.9651042	32.23191829
joshhmayo	I've never felt this sick in my life.	12/9/2014	14:10:15	-110.9858594	32.25503946
xoxo_gabbbyy	I don't wanna be sick □□	12/14/2014	3:55:16	-110.9899074	32.20600809
brwnai	When sick days turn into emotional days http://t.co/wIbKKQKPIZ	12/9/2014	22:18:51	-110.9493206	32.16370689
brielledeclercq	Super cool that all semester I would get like 10 hours of work a week but now that it's finals I'm working every day #nice #sick #cool □	12/12/2014	20:15:44	-110.9456009	32.23518685
stephieduf	I don't know what's worse about being sick feeling like shit or not being able to taste my food.	12/12/2014	2:20:10	-110.9653232	32.22198002
HollyyLark	I would like to thank laura the whora for getting me sick during finals week. Thanks babe. You rock. ✌□	12/11/2014	23:57:03	-110.9597396	32.24032347
rigoomurillo	Smh viejon my fault I was hella sick that I didn't even leave my house pero este fin de	12/8/2014	4:38:48	-110.912822	32.2542353

	semana si le hecho un grito @BraulioGee				
dchapsss	I would be getting sick right before finals week□	12/9/2014	20:35:26	-110.9512324	32.2319885
rileyylyons	Came downstairs this morning and Heather was making me tea cause I'm sick. What a good friend□ (even though you punched me in the throat)	12/13/2014	17:01:33	-110.9531567	32.20572905
tnatalie_	The worst part about being sick is that I only feel better after sleeping a lot.□	12/10/2014	20:36:02	-110.9588262	32.22887261
thomasanoth	Still sick □	12/16/2014	5:35:44	-110.9276757	32.27107307
lexxiramiirez_	Great I'm sick □	12/14/2014	3:27:53	-110.9060864	32.20452516
K_phanthao	How the fuck did i get sick so fast in one day	12/1/2014	0:35:59	-110.9351204	32.19414996
__Zulay03	Im getting sick □	12/13/2014	17:47:46	-110.9269081	32.1615033
SamanthaTGail	Of course I get sick just in time for finals	12/9/2014	1:29:50	-110.9521153	32.20510012
JamieCelia	Times like these I wish I had someone to take care of me when I'm sick □ http://t.co/2osFpQe470	12/10/2014	3:42:14	-110.9446051	32.16447792
Annaa_Bannanerr	Going to classes sick is dreadful □□	12/1/2014	21:02:06	-110.9550724	32.2328519
kelseygriffinn	why do I have to be sick during finals□	12/13/2014	16:27:58	-110.9600248	32.234648
everythingtosay	I may be sick but at least I didn't have a stroke.	12/12/2014	2:15:12	-110.9459562	32.1937223
julbearr	I'm really sick now :(	12/3/2014	4:56:05	-110.95741	32.22985957
_Shells7	I feel so sick rn.	12/10/2014	0:47:34	-110.9793737	32.2550926

siaweleski	@lantz_a might've got you sick □	12/12/2014	6:27:14	-110.9551498	32.20544242
kaarlafernanda4	fuck this headache. And this nausea. And this fever.	12/8/2014	3:34:56	-110.9587138	32.28689387
lunalightsout	Dying of a fever but at least there's tinder✌□ http://t.co/xgS0ZEH4vA	12/5/2014	3:30:09	-110.923831	32.23084838
ChloeWetzel	Can't sleep cause this fever is melting my brain tissue	12/10/2014	5:38:21	-110.923234	32.26658163
BahAnthony	I have a cold and a headache. I don't have time for this shit	12/2/2014	5:57:52	-110.9581918	32.23557202
Chelle_Dance94	I'm sick...it's raining..I'm hungry...who wants to bring me food ? AURORA?□□	12/17/2014	19:37:18	-110.9503294	32.2282378
lenalaaa	Too sick to study □	12/17/2014	23:11:20	-110.9592057	32.2290978
danielcorrales	At least I'm getting sick after juries but still :/	12/12/2014	17:45:24	-110.9552271	32.23143292
Keewinkrazy12	Now I just missed the first part of my exam because I'm out sick. NOW IM GONNA FAIL OUT	12/10/2014	20:39:10	-110.9496918	32.23011455