Final Presentation

The Dapper Squirrels

Liqian Ma Wentao Yao Xingbang Liu



Theme

Misconduct analysis in terms of different locations and communities can be valuable. Is there over-policing in low socio-eco status neighborhoods? We could compare the low-income area data with high income area data. The income of the neighbor could be a factor to influence the "victim" narrative (complaint report). We plan to dive deep into the relationship between location, income level, and police misconduct.

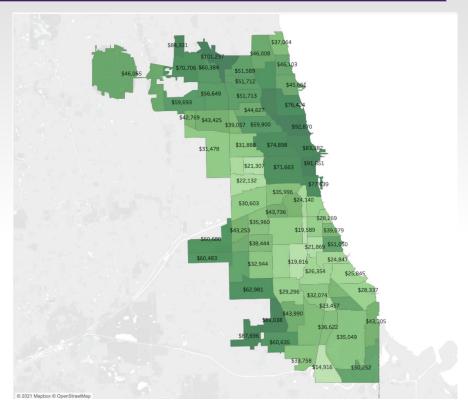
- What are the TOP 5 richest and lowest income neighborhoods?
 - Riverdale Fuller Park Englewood East Garfield Park Washington Park
 - Forest Glen Lincoln Park Loop North Center Beverly
- What are the neighborhoods' income and CRs(complaint record) per capita?
- What is the TRRS(tactical response report) per capita?
 - N/A can't associate income with beat areas

- What is the percentage of each race in the community?
 - From data_area and data_racepopulation
- What are the top 5 streets in allegation counts for each beat area?

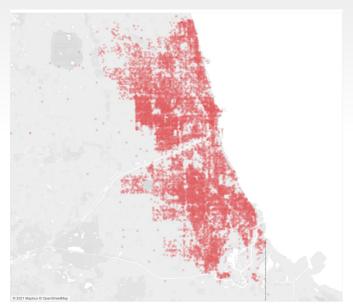
id	name	race	ratio
435	Roger Park	Asian	0.06435425168192346
435	Roger Park	Black	0.24484393956104555
435	Roger Park	Hispanic	0.24144332928936435
435	Roger Park	White	0.41853240689680526
435	Roger Park	Other	0.030826072570861365

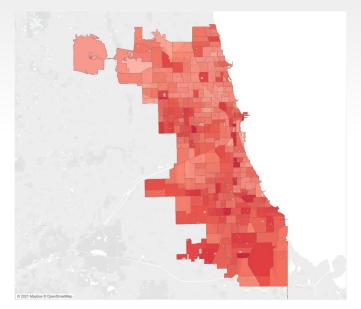
beat_id	add2	allegation_count	rank
6	N WESTERN AVE	26	1
6	W IRVING PARK RD	9	3
6	W ADDISON ST	7	4
6	W BERTEAU AVE	5	5
6	N WESTERN AV	5	5
6	North CLARK ST	5	5

Heatmap of the Income in different community



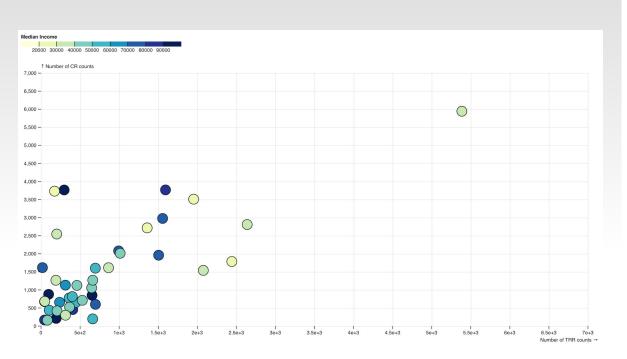
• Scatterplot of Complaint Report per capita V.S. Tactical Response Report per capita. We could also consider lawsuits between "victims" and police officers; search warrants granted in each complaint?





Beat_id to Community

Highlighting the high and low socio-economic status communities with different colors and plot TRRs on them. Set up a time slider to see how it changes over time. Using color code(heat map) of A&A (dara_officer assignment attendance) in different neighborhoods. Set up a time slider to see how it changes over time.

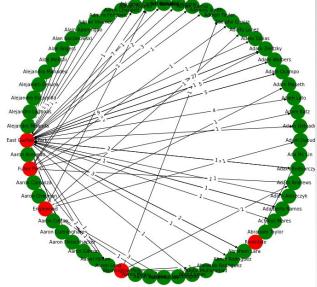


2020

How CRs TRRs changes over time in different income communities.

Beat 212: 50.88 % Attendance

- Making nodes of officers and victims by their income, race, locations, and even unsupervised machine learning models to learn the cluster and see if there is a potential connection between officers and victims.
- Network dynamics of co-accused in each cohort can be interesting. The analytics can be done with the following:
 - Make use of Triangle Count Algorithms for each cohort.
 - Make use of the Page Rank Algorithm to find the most connected officer in all cohorts.
 - How many CRs that officers have and how many co-accused for each cohort.
 - Compare the top k largest cohort of police officers in high and low socio-economy status.



	Aaron Cunningha	e de la companya della companya della companya de la companya della companya dell		Abraham Taylor		
	Aaror	Gilka	Abrahan	Lara		
		Agron Long Washington Park	Abelardo Rodriguez	22		
		A NAME A OF A	MARKUL KEASHOWLODES			
src	dst	relationship	id	inDegree	+ id	outDegree
l Austin	Alan Krok	CR	Joe Parker	129	+ Austin	10470
Englewood			Jerome Finnigan		West Englewood	
Chicago Lawn	B B - B - B - B - B - B - B - B -		Edward May		Loop	
South Deering	Nora Collins	CRI	Charles Toussas		Near West Side	
Woodlawn	Tracy Quarles	CR	David Brown		Near North Side	
East Garfield Park	Gerard Murphy	CRI	Kevin Osborn	108	Auburn Gresham	
Near North Side	Jose Zuniga	i CR i	Maurice Clayton	107	Humboldt Park	
Near North Side	Frank Cool	[CR	Glenn Evans	106	North Lawndale	
Norwood Park	Jeffrey Fronczak	[CR	Adam Zelitzky	105	Englewood	
Garfield Ridge	George Mc Murray	[CR	Jerome Turbyville	99	West Town	
Near West Side	Debra Ippolito	[CR]	Robert Smith	98	South Shore	
Lower West Side	Jack Dedore	[CR	James Grubbs	93	East Garfield Park	
Pullman	Joseph Buss	[CR]	Robert Johnson	93	New City	4891
Belmont Cragin			John Carney	88	Roseland	4763
Lincoln Square	Gail Martin	CR	Gregory Jackson	87	Chicago Lawn	4741
Austin	Marienne Perry	[CR	Tyrone Jenkins	87	Logan Square	4368
Englewood	Marilyn Uldrych	[CR]	Broderick Jones	87	Lake View	4114
Auburn Gresham		[CR	Kevin Ryan	85	Greater Grand Cro	4088
Beverly			Eugene Bikulcius	85	Uptown	3833
Ashburn	Nicola Zodo	[CR	Edward Howard	83	Woodlawn	3752

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label		
17372	8316	
3744	1636	
29511	1224	
11980	652	
28273	596	
28838	450	
32014	364	
32068	323	
32382	257	
	257	
13631	2561	
14106	243 211 207	
32274	211	
32041	207	
6534	187	
18915	186	
23787	173	
2981	162	
21912	155	
23033	115	

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- Compare the Bigram and Trigram in the top 5 highest and lowest socio-economy status communities.
- For similar(in contents) complaint summary texts, are they having similar socio-eco status to each other?
- Is there any bias in the complaint report? In other words, is the complaint report narrative different from the incident summary?

Conclusion

- Social-economic status is closely related to over-policing.
- Richer areas tend to file more complaints than poorer areas.
- Poorer areas tend to receive more tactical responses from police officers.
- The over-policing problem need more evidences to be supported. We find there are more law enforcement in low-income communities, but more data and work are needed to prove there is a logical correlation.

Future Work

- High rate of complaints in high-income areas needs to be verified by detecting the potential bias in complaint summaries.
- The legality of tactical response needs to be verified by detecting the severity of incident or is the crime rate matches the tactical response rate.

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