

Network-Based Spatiotemporal Predictive Model for Car Crash Risk Assessment

Background

Introduction, to the Issue

 Every year around 1.3 million lives are lost globally due to road traffic accidents making it the primary cause of death for children and young adults.

Impact on Progress

 These accidents not result in significant personal tragedies but also hinder sustainable development, particularly in low and middle income nations where a majority of these incidents take place. UN General Assembly Resolution 74/299 declared a **Decade of Action for Road Safety 2021-2030**, with the target to reduce road traffic deaths & injuries

BY AT LEAST 50% during that period

Background

Advancements in Predictive Models

 Utilizing network-based spatiotemporal predictive models marks a significant advancement in urban road safety, allowing us to identify and predict potential crash hotspots more effectively.

Supporting Policy Making

 These sophisticated models provide essential insights into the interaction of demographic factors and road network characteristics, helping policymakers implement targeted safety measures more effectively.

Long-term Benefits

• Continued research and improvement of these predictive models are vital. They serve as foundational tools in reducing traffic-related fatalities and injuries, ultimately leading to safer urban environments.

Problem Statement

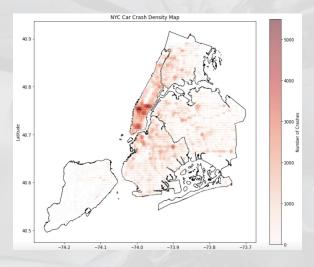
The Study is aim to:

- Explore the temporal and spatial distribution of car crashes
- Analyze the spatio-temporal autoregressive of traffic collisions
- Build a network-based predict model for Car Crash Risk

Literature Review

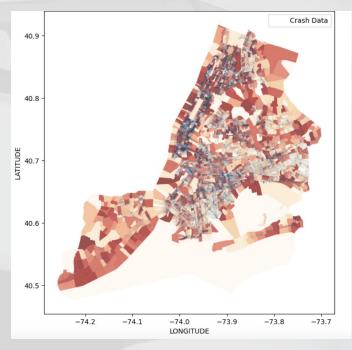
Data-Car Collision

```
collison22_23 = collison.loc[(collison['DATETIME'] > pd.Timestamp('2022-1-1 00:00'))]
collison22_23.shape
collison = collison22_23
```



NYC Open Data: Motor Vehicle Collisions - Crashes

Data-Demographic

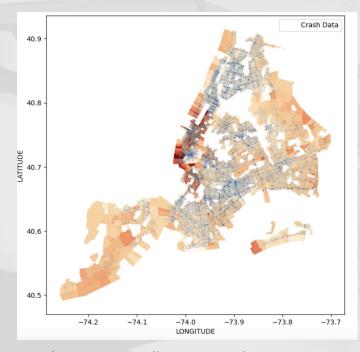


Crush Data vs Population by Census Tract
-NYC Planning

	GeoID	Pop1	geometry
0	36005000100	3,772	POLYGON ((-73.89772 40.79514, -73.89611 40.796

https://www.nyc.gov/site/planning/planning-level/nyc-population/2020-census.page

Data-Demographic

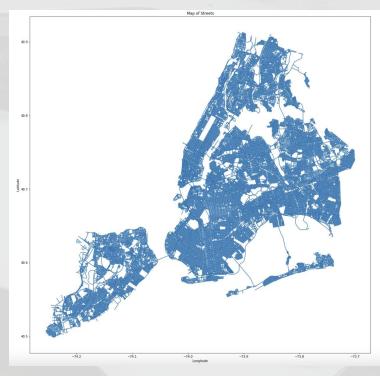


Crush Data vs Median Income by Census Tract
-NYU Furman Center

short_name	short_name	long_name		Census Tract 2009-2013		GEOID	geometry		
	0 hh_inc_med_adj Median household	income (2022\$)	36005041900	43887.524204	36984.666450	36005041900	POLYGON ((-73.88527 40.87923,	-73.88466 40.879	

https://app.coredata.nyc/?mlb=false&ntr=&mz=16&vtl=https%3A%2F%2Fthefurmancenter.carto.co m%2Fu%2Fnyufc%2Fapi%2Fv2%2Fviz/%2F98dlf1f6e-95fd-4e52-a2b1-b7abaf634828%2Fviz/json&mln=false&mlp=true&mlat=40.709955&nty=&mb=roadmap&pf=%7B%22subsidies%22%3Atrue%7D&md=map&mlv=false&mlng=-74.009866&btl=Borough&atp=neighborhoods

Data-Street Network



NYC Open Data

network													
street_nm	honorarynm	old_st_nm	streetwidt	route_type	roadwaytyp	build_stat	record st	paper_st	stair_st	cco_st	marg_wharf	edit date	geometry
													LINESTRING
Arthur Kill Road	None	NaN	irreg>80	Mjr_st	Surface_ST	Improved	NaN	NaN	NaN	NaN	NaN	NaN	(-74.22128 40.55025
Hour													-74.22128 40.5

Spatial Analysis

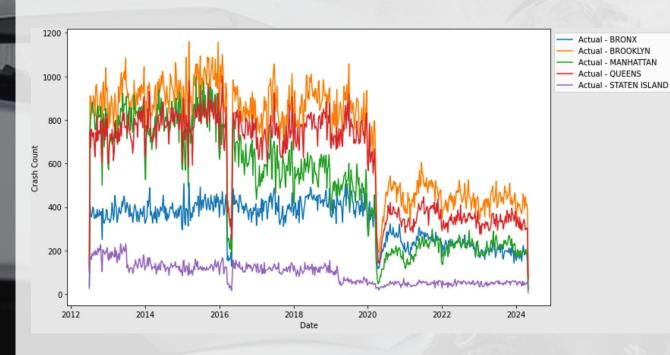


-73.8

-74.1

Longitude

Time-series Analysis

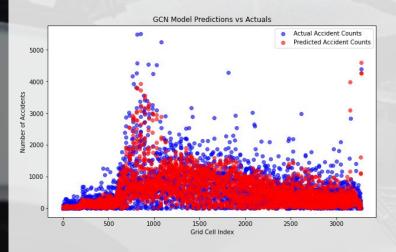


Significant drop after COVID-19

Strong seasonal pattern

Time series regression prediction is not very meaningful

GCN (Graph Convolutional Network)





GCN limitation:

Temporal autocorrelation (combine with LSTM or LSTnet, etc.)

Transportation network effect

Black box model

The logistic regression function

$$Logit(p) = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_k X_k$$

- Able to capture the many details relating to the crash occurrence;
- Have rigid assumptions about dependent with multiple categories;
- The logistic regression function is bounded by 0.0 and 1.0.

Dependent variable: Vulnerability of Crash

OF VEHICLE * 0.4 + # OF PERSONS INJURED * 0.6 + # OF PERSONS KILLED *1+ NO CRASH *0

Variable: Spatiotemporal Index

$$Gravity[i]^r = \sum_{j \in G - \{i\}, d[i,j] \le r}^n W[j] / e^{\beta * d[i,j] - plateau}$$

- W[j] is the weight of destination j, measured in hours of time interval;
- beta = 0.001 to control an exponential travel distance decay;
- Plateau radius = 0 ensure that distance decay is always included;
- For each i, the destinations j is the location where a crash happened within one month and within 3 kilometers travel distance;
- The index measures the attractive force from previous collisions around.

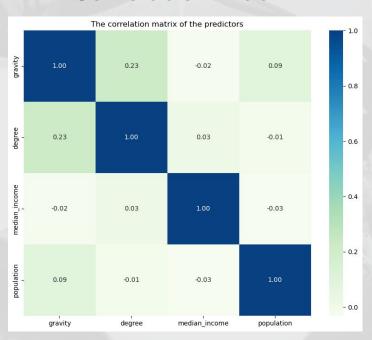
Model

R2: 0.774 In-sample MSE: 0.97 Out-of-sample MSE: 1.00

 	coef	std err	t	P> t	[0.025	0.975]
gravity	5.241e-06	4.59e-07	11.412	0.000	4.34e-06	6.14e-06
median_income	1.149e-06	6.89e-08	16.665	0.000	1.01e-06	1.28e-06
population	4.17e-05	1.34e-06	31.012	0.000	3.91e-05	4.43e-05
degree	0.2792	0.002	158.626	0.000	0.276	0.283

Model

Correlation Matrix

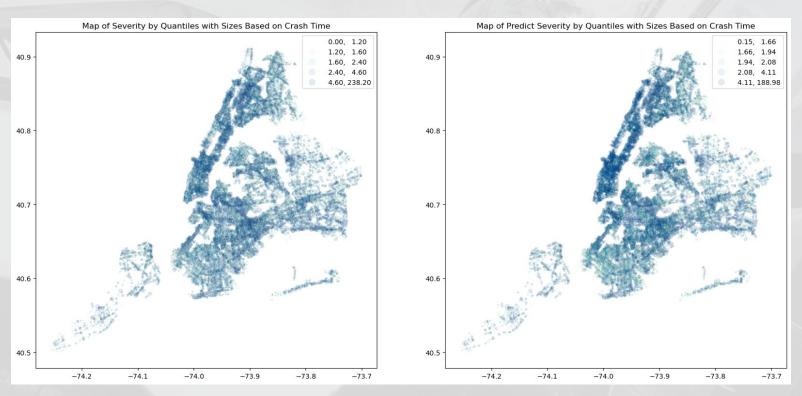


Variance Inflation Factor

Feature	VIF
Gravity	4.968909
Degree	10.182904
Median Income	3.965423
Population	4.942782

The VIF for 'degree' is slightly above the threshold at 10.18, but its statistical significance and substantial contribution to the model justify retaining it.

Model



Conclusion

- Downtown Manhattan has the highest car crash density
- After Covid-19 there has a significant drop of car crash occurrence, this pattern continue to nowadays
- Build a network-based
 predict model for Car Crash
 Risk with 0.774 R2

Limitations

- Calculate of Gravity Index is highly time costs even with Dask
- Did not take other important network factors like betweenness centrality into account due to the limit computility

Recommendation

- Use betweenness centrality instead of degree to capture the structure of street network.
- Combine the idea of gravity index into the GNN structure to get a better model.

