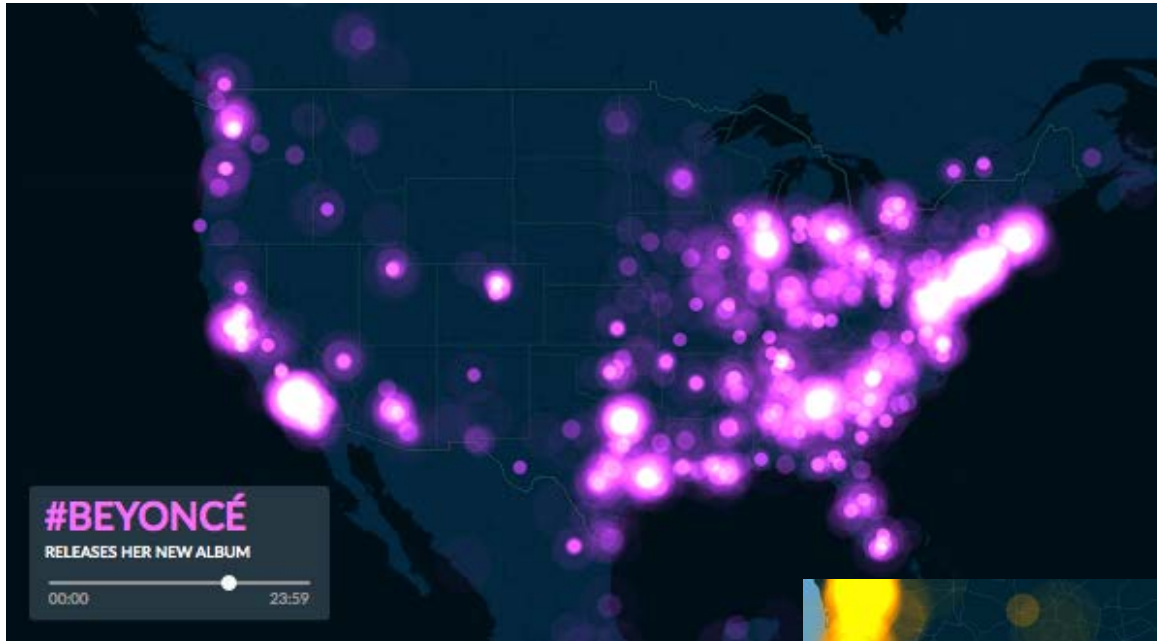


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Place for Spatial Big Data Analytics

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<https://cartodb.com/solutions/twitter-maps/>





Difficult
to grasp

Data are deluging;

Places are emerging.



Visible
Perceivable
Locatable

Peter Fisher and David Unwin (2005) Representing GIS

- **Space vs. place**
 - Euclidean spaces; containers
 - Socially-produced and continually changing notion of place
- **The social world that people experience**



Time



Human
activities and
events

Yi-Fu Tuan (1979): Space and Place from the Humanistic Perspective

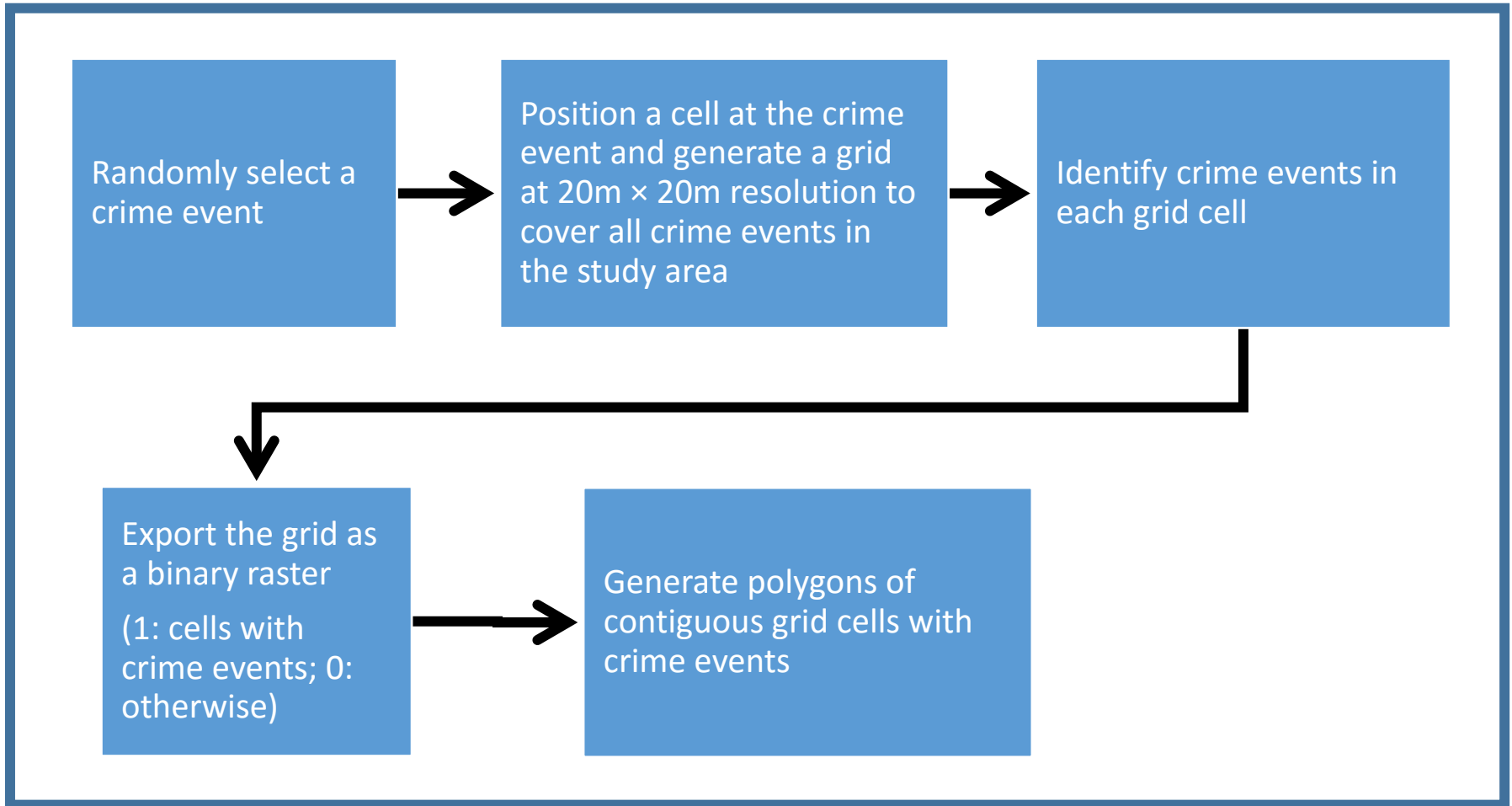
Space and place together define the nature of geography

- **Place: a unique entity, a “special assemble”**
 - ✓ History and meaning
 - ✓ Experiences and aspiration of a people
 - ✓ A fact to be explained in the broader frame of space
 - ✓ A reality to be clarified and understood from the perspective of the people who have given it meaning

Data prescribe experiences and drive emergence of places.

Places summarize data and synthesize experiences.

events as experiences to define places



Iterate 15 times to create 15 sets of polygons.



first contacting May Yuan at myuan@utdallas.edu

Polygons generated from 15 iterations



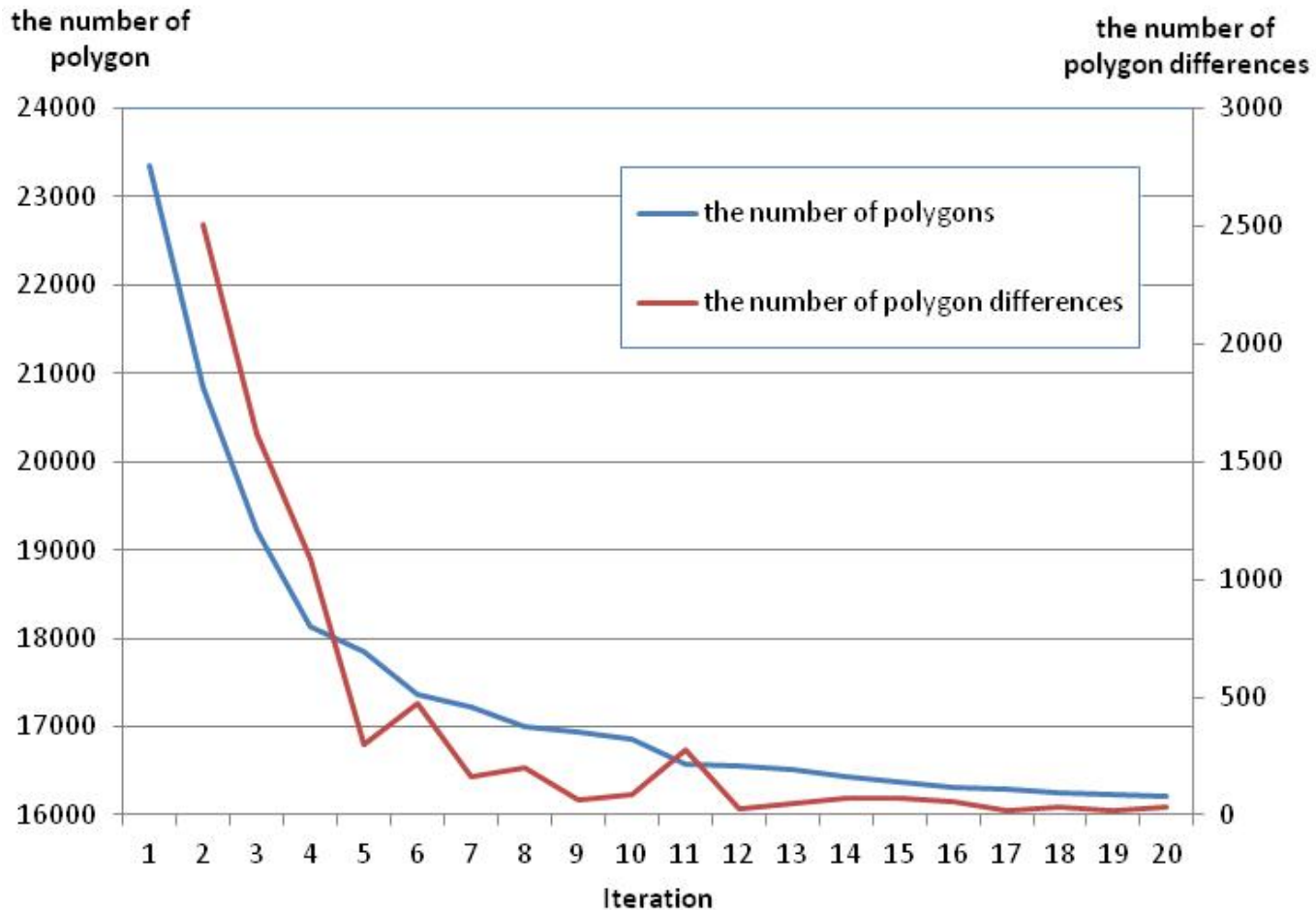
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Places defined by crime events: Criminogenic places

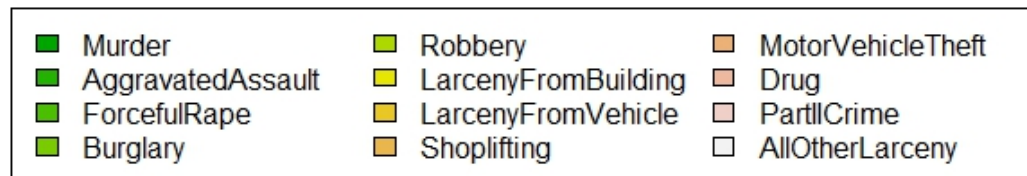
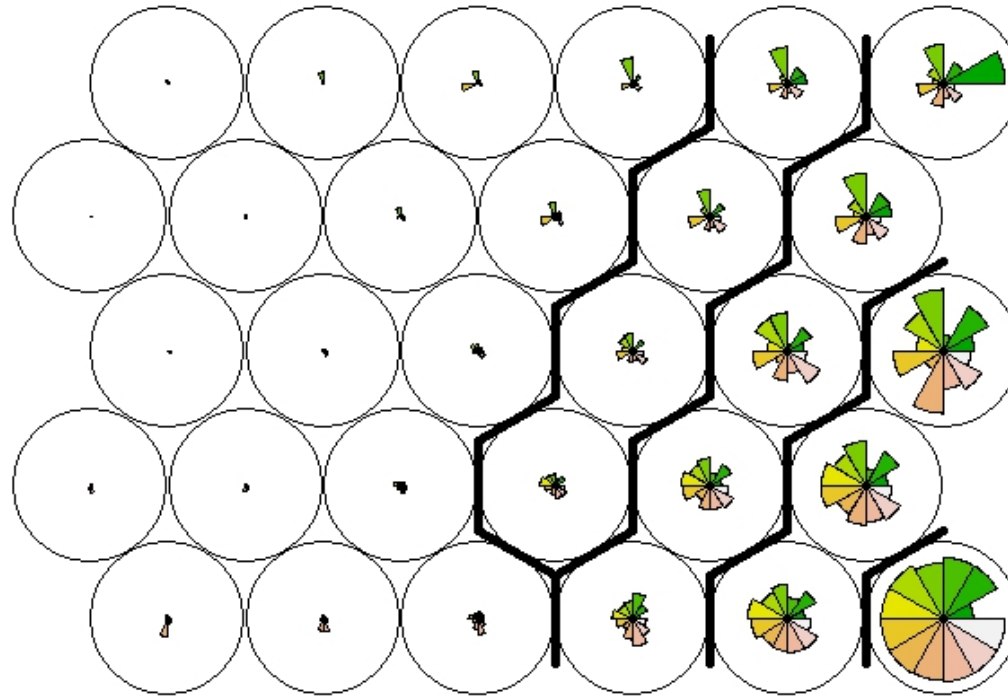


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Iterations stabilize the delineation of places

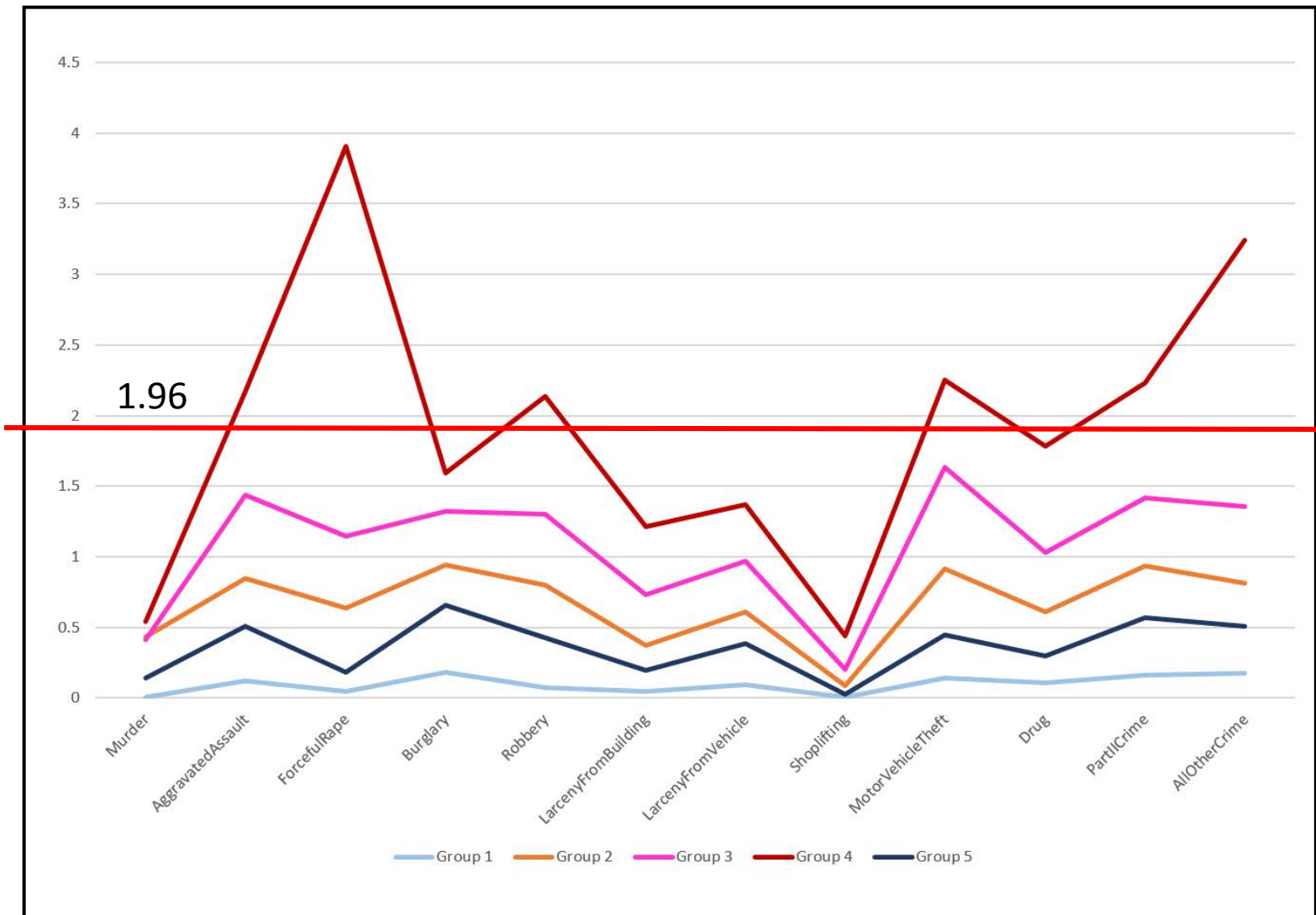


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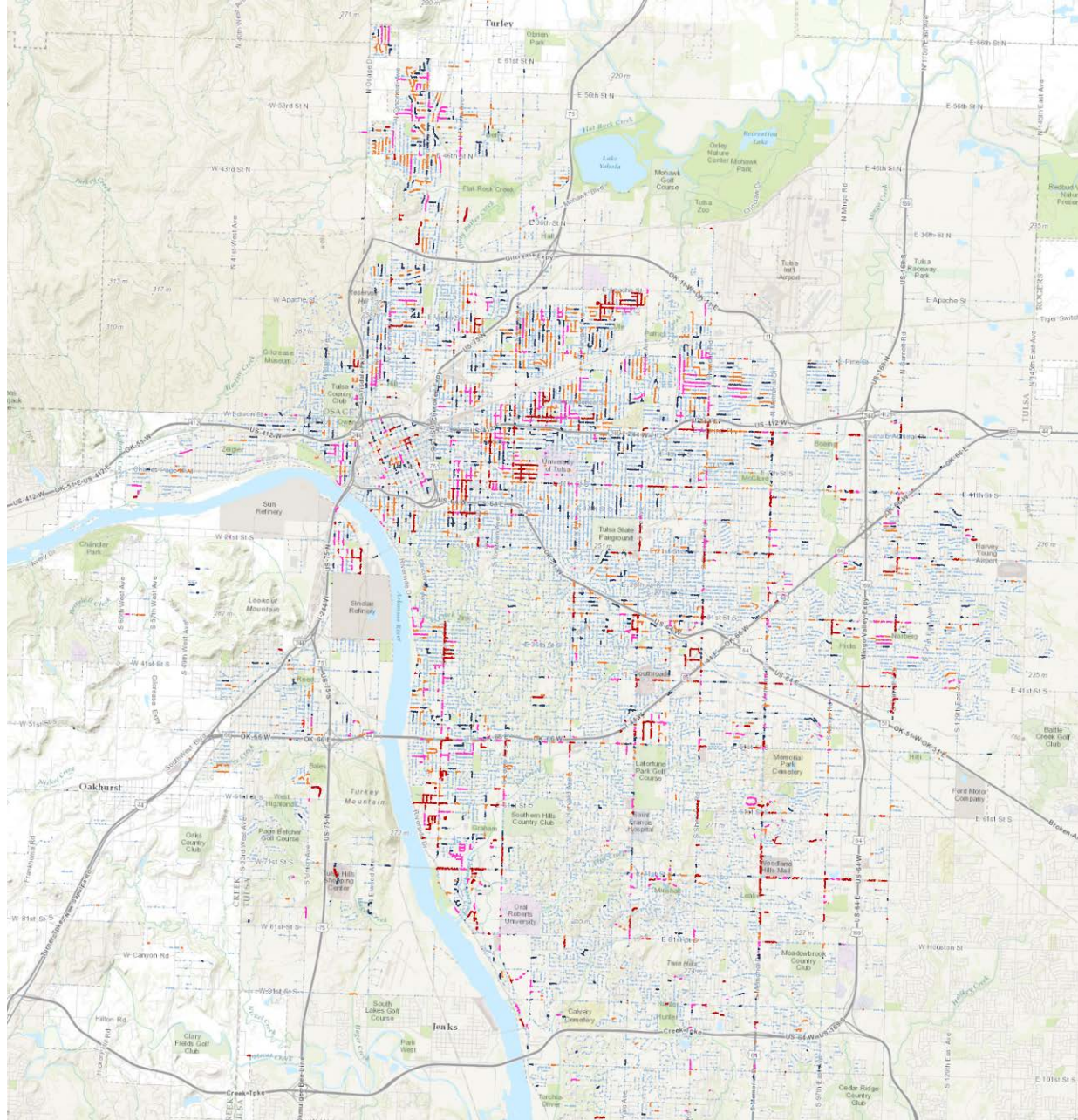


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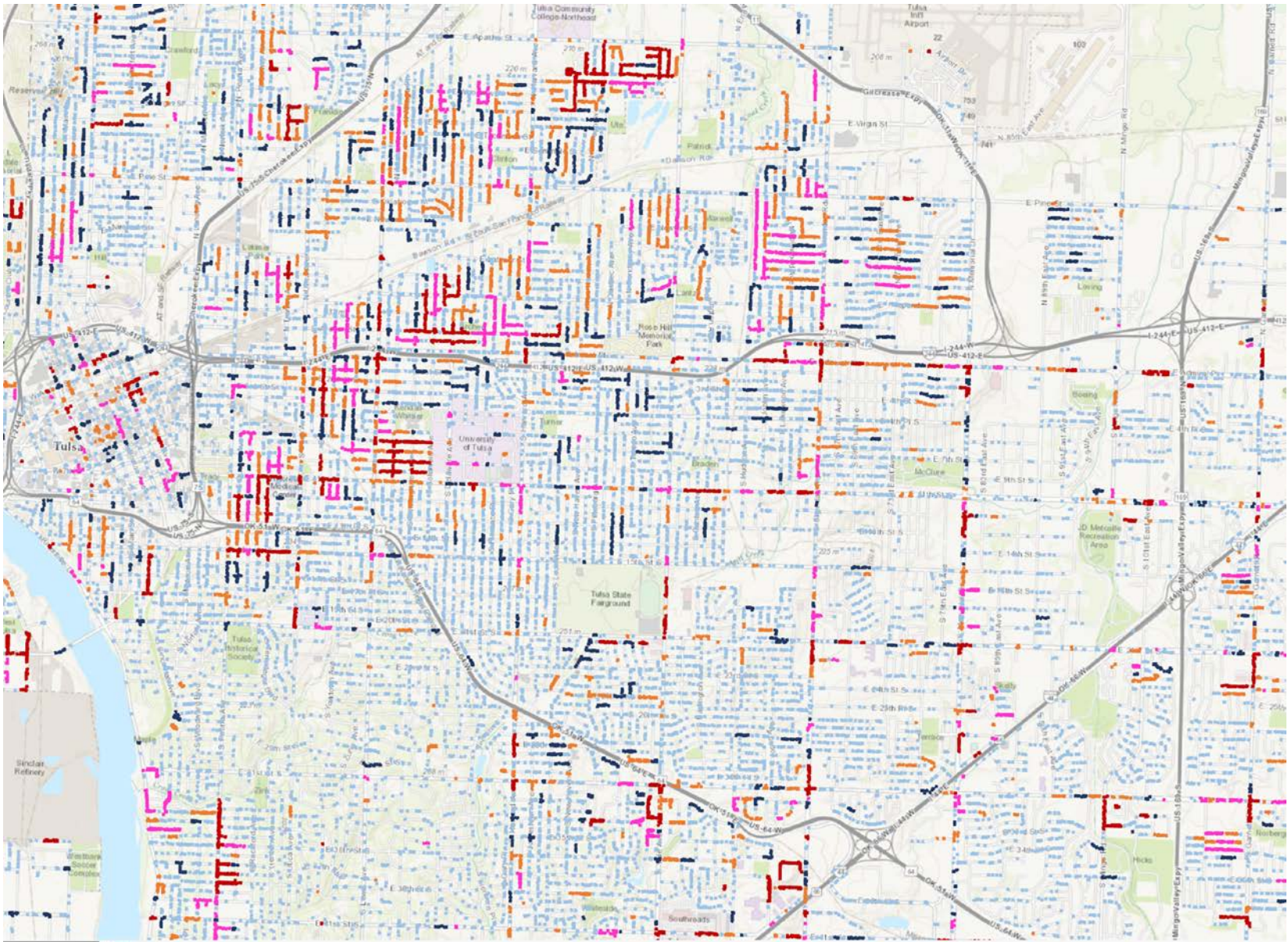
Relative Distributions of Crime Types (mean Z-scores in each type)



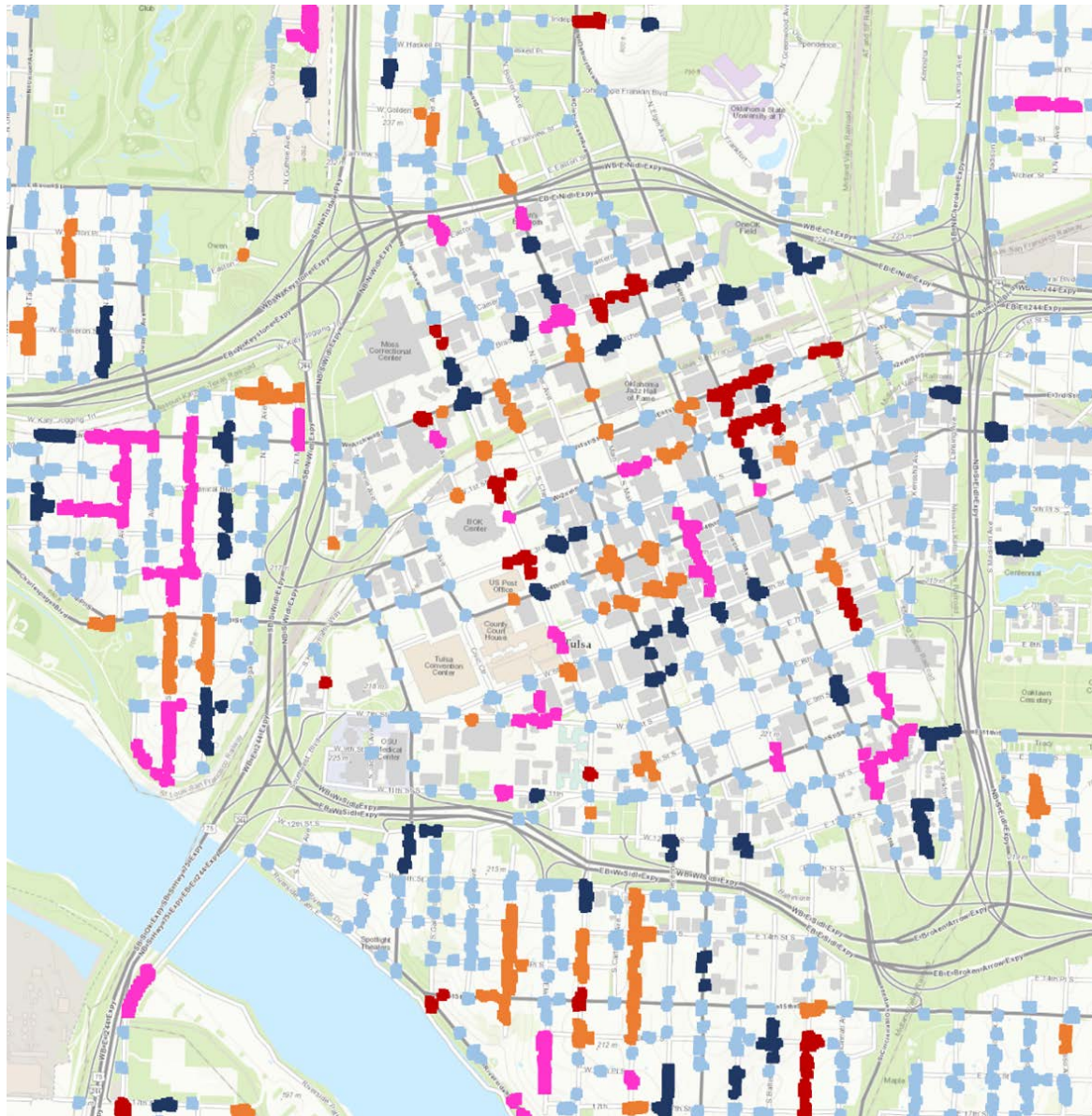
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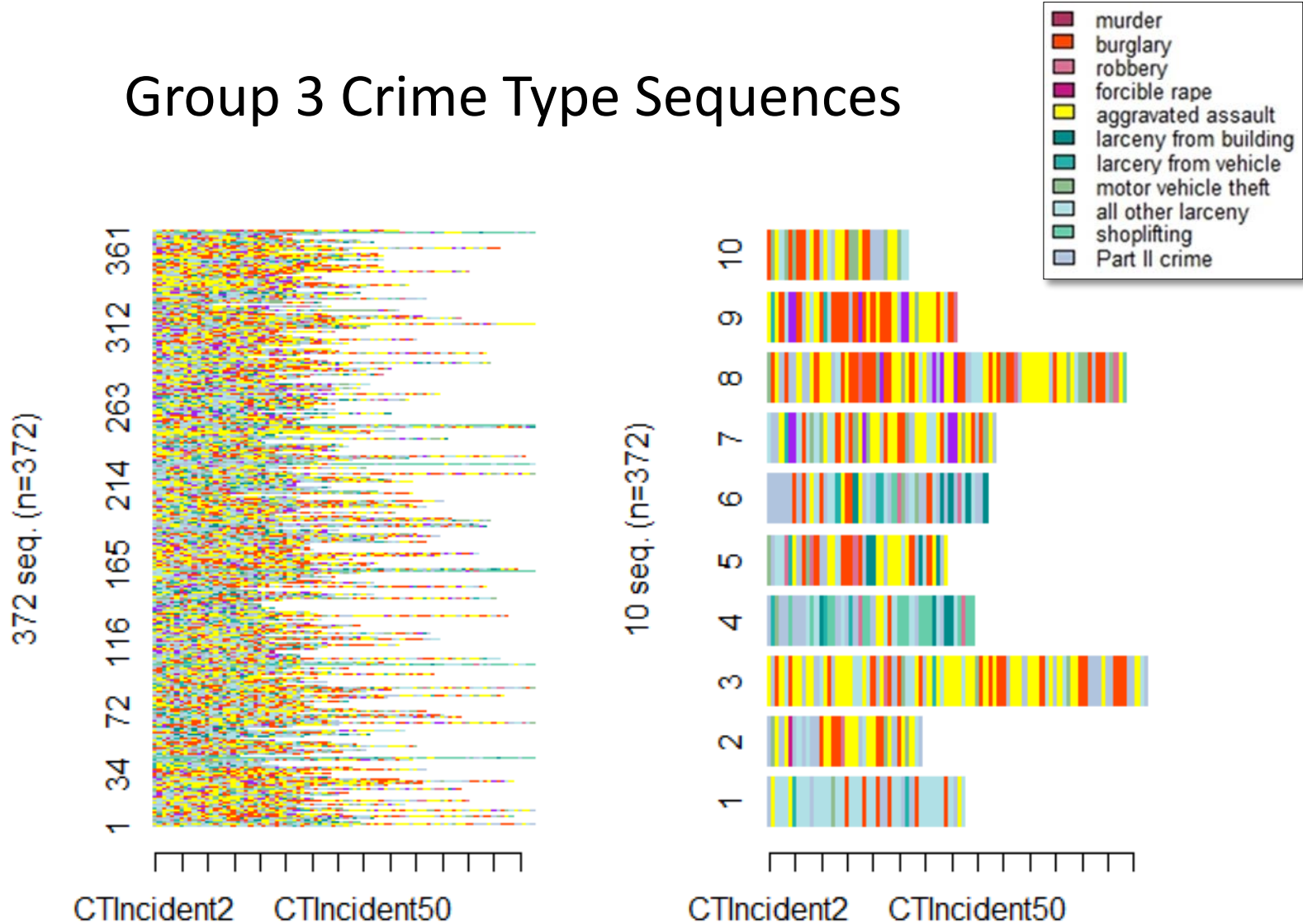
Group	# of Segments	% Segments	Lengths (m)	% Lengths
0	8,208	23.6%	2,743,577	68%
1 (lowest)	17,472	50.3%	862382	21.4%
2 (3 rd lowest)	3,021	8.7%	137491	3.4%
3 (2 nd highest)	1,797	5.2%	89788	2.2%
4 (highest)	1,681	4.8%	83173	2%
5 (2 nd lowest)	2,584	7.4%	121029	3%
Total	34,763	100%	4,037,440	100%

~25%

~10%

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Group 3 Crime Type Sequences



All places

First 10 common sequence patterns

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Probability to crime types in Group 3

	[-> NA]	[-> AA]	[-> AOL]	[-> BG]	[-> DG]	[-> FR]	[-> LB]	[-> LV]	[-> MVT]	[-> MD]	[-> P2C]	[-> RB]	[-> SL]	
[NA ->]	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
[AA ->]	0.02	0.34	0.14	0.16	0.04	0.01	0.02	0.03	0.07	0.00	0.14	0.03	0.01	1.01
[AOL ->]	0.02	0.21	0.26	0.13	0.03	0.01	0.03	0.04	0.08	0.00	0.14	0.03	0.03	1.01
[BG ->]	0.03	0.24	0.14	0.26	0.03	0.00	0.01	0.03	0.08	0.00	0.14	0.03	0.01	1.00
[DG ->]	0.02	0.22	0.13	0.13	0.13	0.00	0.04	0.02	0.09	0.00	0.16	0.03	0.03	1.00
[FR ->]	0.02	0.28	0.16	0.15	0.06	0.00	0.02	0.06	0.06	0.00	0.14	0.03	0.02	1.00
[LB ->]	0.03	0.20	0.21	0.06	0.03	0.00	0.12	0.03	0.07	0.00	0.15	0.04	0.05	0.99
[LV ->]	0.02	0.21	0.20	0.15	0.04	0.00	0.02	0.09	0.07	0.00	0.15	0.02	0.02	0.99
[MVT ->]	0.02	0.24	0.15	0.17	0.04	0.00	0.01	0.04	0.14	0.00	0.13	0.03	0.02	0.99
[MD ->]	0.00	0.15	0.15	0.08	0.00	0.00	0.00	0.08	0.08	0.00	0.31	0.15	0.00	1.00
[P2C ->]	0.02	0.21	0.14	0.14	0.04	0.00	0.02	0.03	0.07	0.00	0.22	0.04	0.05	0.98
[RB ->]	0.02	0.22	0.16	0.13	0.07	0.00	0.02	0.02	0.09	0.00	0.17	0.08	0.04	1.02
[SL ->]	0.01	0.06	0.10	0.02	0.03	0.00	0.04	0.01	0.03	0.00	0.16	0.03	0.52	1.01
	1.23	2.58	1.94	1.58	0.54	0.02	0.35	0.48	0.93	0.00	2.01	0.54	0.80	13.00
	0.09	0.20	0.15	0.12	0.04	0.00	0.03	0.04	0.07	0.00	0.15	0.04	0.06	

NA
 AA aggravated assault
 AOL all other larceny
 BG burglary
 DG drug
 FR forcible rape
 LB larceny from building
 LV larceny from vehicle
 MVT motor vehicle theft
 MD murder
 P2C Part II crime
 RB robbery

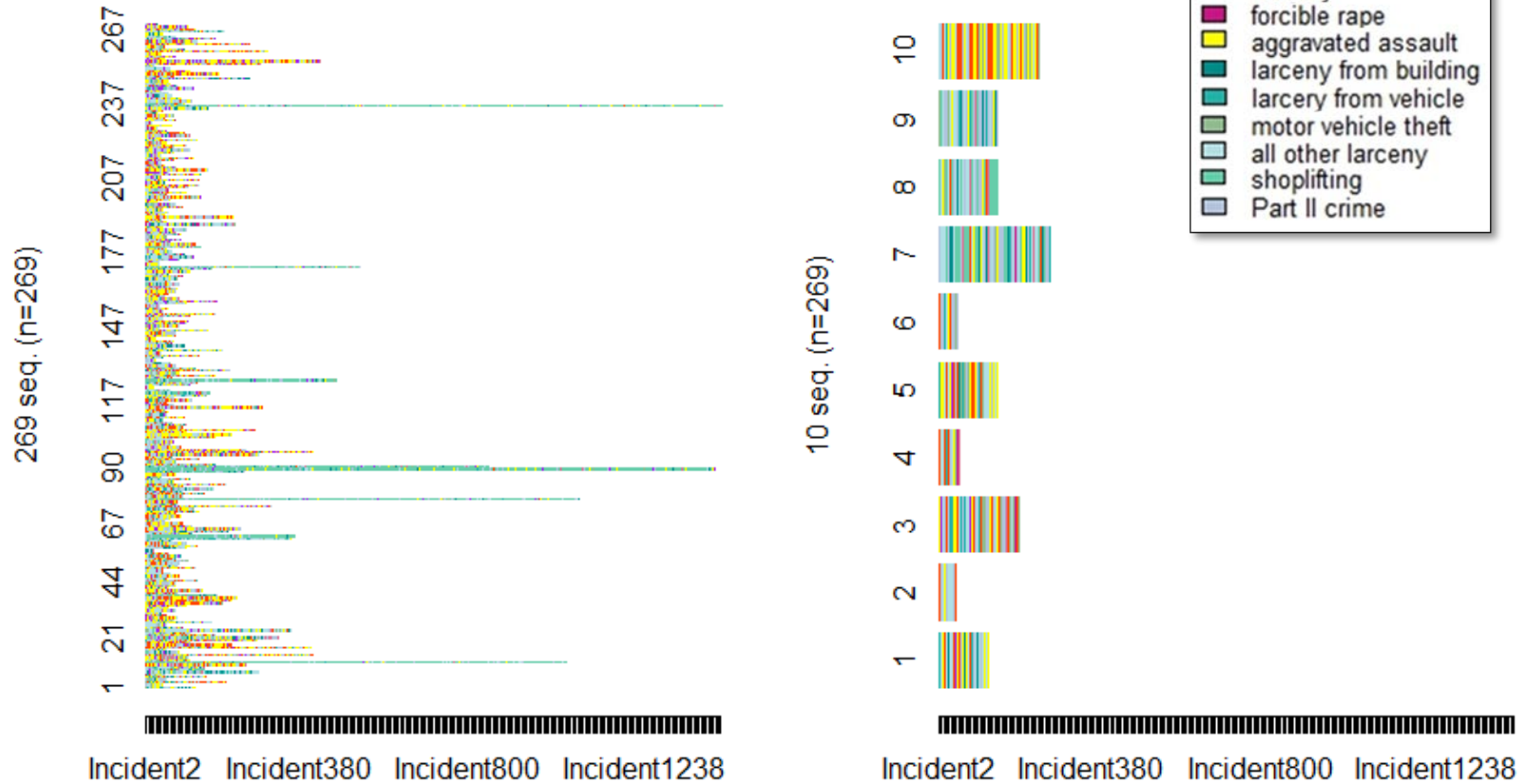
Relatively high transition probability

Relatively high fidelity of crime types at places

31% of P2C preceded by Murders.

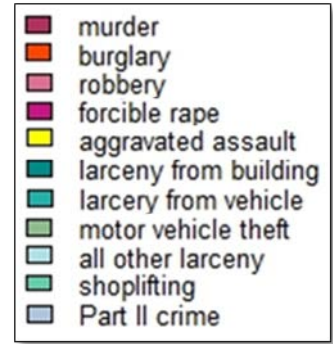
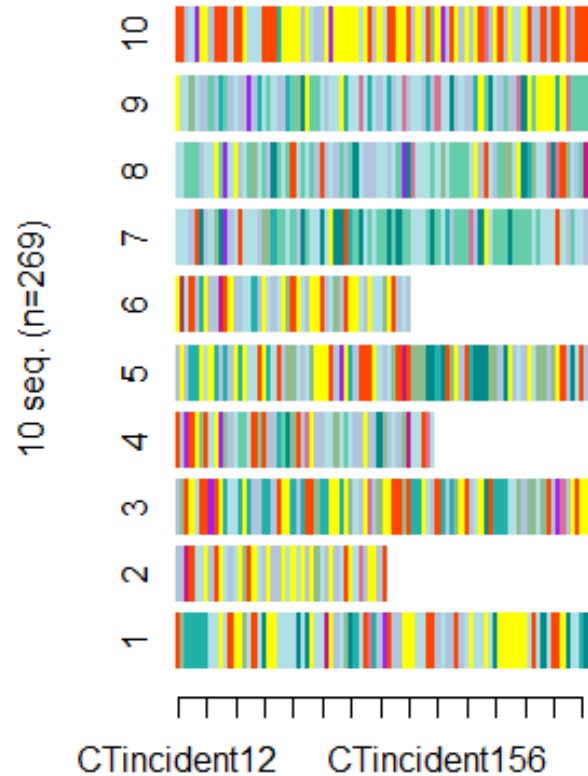
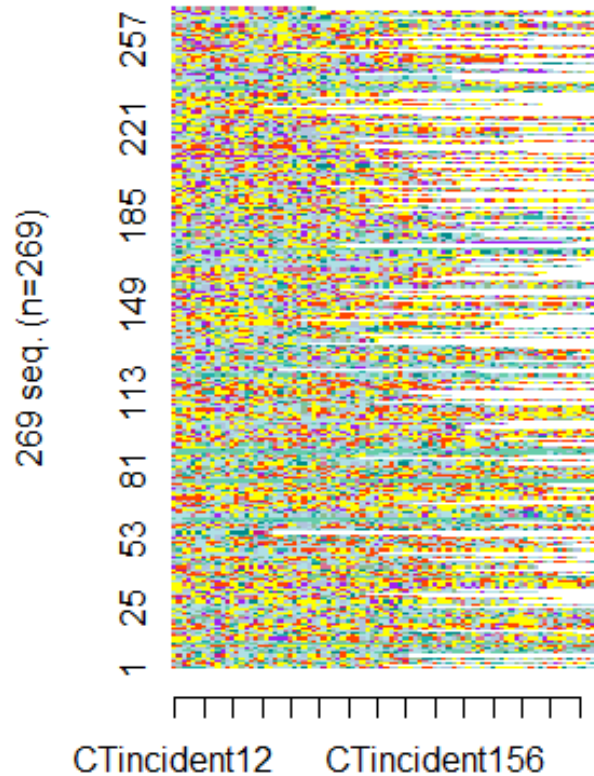
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Group 4 Crime Type Sequences



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Group 4 Crime Type Sequences: first 80 crime events



All places

First 10 sequence patterns

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Probability to crime types in Group 4

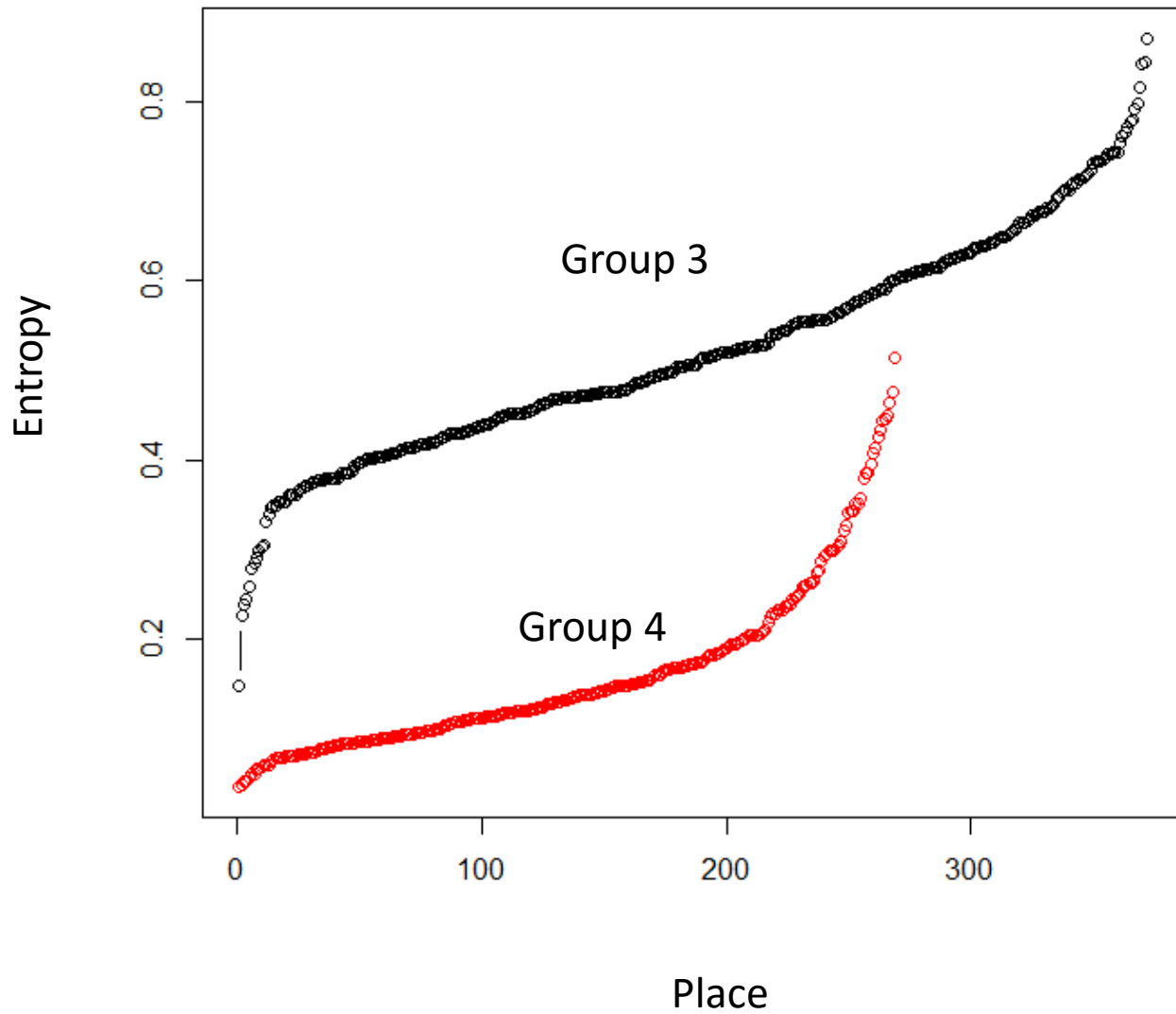
	[-> NA]	[-> AA]	[-> AOL]	[-> BG]	[-> DG]	[-> FR]	[-> LB]	[-> LV]	[-> MVT]	[-> MD]	[-> P2C]	[-> RB]	[-> SL]	
[NA ->]	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
[AA ->]	0.01	0.33	0.14	0.13	0.05	0.01	0.02	0.02	0.06	0.00	0.14	0.04	0.04	0.99
[AOL ->]	0.01	0.17	0.29	0.09	0.04	0.01	0.04	0.04	0.06	0.00	0.14	0.04	0.09	1.02
[BG ->]	0.01	0.25	0.13	0.24	0.04	0.02	0.01	0.03	0.06	0.00	0.15	0.04	0.02	1.00
[DG ->]	0.00	0.23	0.14	0.09	0.16	0.01	0.02	0.02	0.05	0.00	0.18	0.04	0.05	0.99
[FR ->]	0.01	0.29	0.13	0.13	0.05	0.05	0.03	0.02	0.06	0.00	0.15	0.05	0.02	0.99
[LB ->]	0.01	0.14	0.23	0.04	0.03	0.01	0.12	0.03	0.05	0.00	0.13	0.03	0.17	0.99
[LV ->]	0.00	0.17	0.21	0.09	0.02	0.01	0.02	0.11	0.05	0.00	0.15	0.04	0.11	0.98
[MVT ->]	0.01	0.22	0.16	0.13	0.04	0.01	0.03	0.03	0.10	0.00	0.17	0.04	0.05	0.99
[MD ->]	0.00	0.28	0.15	0.12	0.08	0.00	0.00	0.00	0.08	0.08	0.22	0.00	0.00	1.01
[P2C ->]	0.01	0.20	0.15	0.11	0.05	0.01	0.03	0.03	0.06	0.00	0.20	0.04	0.11	1.00
[RB ->]	0.01	0.22	0.16	0.11	0.05	0.01	0.03	0.03	0.07	0.00	0.16	0.08	0.08	1.01
[SL ->]	0.00	0.04	0.08	0.01	0.01	0.00	0.03	0.01	0.01	0.00	0.08	0.02	0.70	0.99
	1.08	2.54	1.97	1.29	0.62	0.15	0.38	0.37	0.71	0.08	1.87	0.46	1.44	13.00
	0.08	0.20	0.15	0.10	0.05	0.01	0.03	0.03	0.05	0.01	0.14	0.04	0.11	

NA aggravated assault
 AA aggravated assault
 AOL all other larceny
 BG burglary
 DG drug
 FR forcible rape
 LB larceny from building
 LV larceny from vehicle
 MVT motor vehicle theft
 MD murder
 P2C Part II crime
 RB robbery

Relatively high transition probability

Relatively high fidelity of crime types at places

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Thoughts

- space: absolute, container, Euclidean
- place: complex, organic, dynamic, experiential, experiential, and understandable
 - To Pete Fisher
 - Places are socially and dynamically produced
 - Uncertainty
 - Fuzziness
- Place for spatial big data
 - vertical integration of activities and events at places
 - from events to identify places
 - from places to predict event transitions