

Which police officers escalate force?

Greg Ridgeway

Rebecca W. Bushnell Professor of Criminology
Professor of Statistics and Data Science
University of Pennsylvania

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Some officers seem inclined to escalate



- Laquan McDonald shooting, October 20, 2014
- CPD Officer Van Dyke fired 16 rounds
- Officer Walsh fired no rounds, holstering his firearm



Untangling officer risk from environment risk

Officers who use more force differ from other officers in obvious ways

- In the field
- In particular environments
- Conducting higher risk operations

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“the overrepresentation of minority officers among police shooters [is] closely associated with racially varying pattern of assignment, socialization, and residence” - Fyfe (1981)

Match officers on the same scene

Find *features of officers* predictive of **being a shooter** (Ridgeway 2016)

- Data from 175 NYPD shooting incidents (239 shooters, 155 non-shooters)
- Conditional logistic regression
- Officers frequently accumulating negative marks in their file 3x more likely to shoot

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Find *features* predictive of **rounds fired** (Ridgeway, Cave, Grieco, Loeffler 2021)

- Data from 317 shootings from 46 large agencies (849 officers, 5026 rounds)
- Truncated conditional Poisson regression
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Analyses did not pinpoint **specific officers**, results not actionable

- Identify *specific officers* rather than features of officers
- Sample size requirements demand moving beyond shootings

Type of force depends on officer and environment

- $Y = y$ indicates type of force, $y \in \{0, 1, 2, 3\}$
- Each officer has λ , latent propensity to escalate force
- Environment \mathbf{z} (e.g., time, place, lighting, suspect, policies and laws)

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$$P(Y_i = y|\mathbf{z}) = f(h_y(\mathbf{z}) + s_y\lambda_i)$$

- Challenges
 - \mathbf{z} complex and hard to measure
 - $h_y(\mathbf{z})$ also highly complex
 - No data collected when $y = 0$
 - No obvious choice for f



Three conditions determine unique f for inference about λ
free from $h_y(\mathbf{z})$

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1. $P(Y_i = y|\mathbf{z}) = f(h_y(\mathbf{z}) + s_y\lambda_i)$
2. Increases in λ correspond to increases in relative risk of more serious force. If $y_2 > y_1$ and $\epsilon > 0$ then

$$\frac{P(Y = y_2|\mathbf{z}, \lambda + \epsilon)}{P(Y = y_1|\mathbf{z}, \lambda + \epsilon)} > \frac{P(Y = y_2|\mathbf{z}, \lambda)}{P(Y = y_1|\mathbf{z}, \lambda)}$$

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3. Use conditional likelihood for officers matched on the same scene to eliminate dependence on $h_y(\mathbf{z})$

$$P(Y_1, \dots, Y_m | \mathbf{h}, \lambda, \mathbf{s}) = P(Y_1, \dots, Y_m | \mathbf{k}(\mathbf{Y}), \mathbf{h}, \lambda, \mathbf{s}) P(\mathbf{k}(\mathbf{Y}) | \mathbf{h}, \lambda, \mathbf{s})$$

- Optimizing any of these three probabilities produces *consistent* estimates
- If \mathbf{k} is a sufficient statistic for \mathbf{h} , \mathbf{h} drops out of the likelihood conditional on \mathbf{k}

Five steps to arrive at the unique f

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2. Conditional likelihood for one incident with m officers is

$$CL(\mathbf{h}, \mathbf{s}, \lambda \mid \mathbf{k}) = \frac{\prod_{i=1}^m f(y_i, h_{y_i}(\mathbf{z}) + s_{y_i} \lambda_i)}{\sum_{\mathbf{y}^* \in \mathcal{K}} \prod_{i=1}^m f(y_i^*, h_{y_i^*}(\mathbf{z}) + s_{y_i^*} \lambda_i)}$$



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4. Only (non-trivial) solution is f , g , and G are exponential
5. Only exponential model satisfying relative risk constraint is Anderson's ordinal stereotype model



Anderson's ordinal stereotype model

$$P(Y_i = y|\mathbf{x}) = \frac{\exp(\alpha_y + s_y\beta'\mathbf{x})}{\sum_{j=0}^J \exp(\alpha_j + s_j\beta'\mathbf{x})} \quad (\text{standard OSM})$$

$$P(Y_i = y|\mathbf{h}, \lambda, \mathbf{s}) = \frac{\exp(h_y(\mathbf{z}) + s_y\lambda_i)}{\sum_{j=0}^J \exp(h_j(\mathbf{z}) + s_j\lambda_i)} \quad (\text{UoF model})$$

where $s_0 = 0, s_1 = 1 \leq s_2 \leq \dots \leq s_J$

λ measures increase in relative risk

$$\frac{P(Y = y_2 | \lambda = \lambda_1)}{P(Y = y_1 | \lambda = \lambda_1)} = \frac{P(Y = y_2 | \lambda = \lambda_0)}{P(Y = y_1 | \lambda = \lambda_0)} e^{(s_{y_2} - s_{y_1})(\lambda_1 - \lambda_0)}$$

- e^λ is the multiplicative change in the risk of Level 1 force relative to Level 0 associated with escalation λ , relative to a reference officer with $\lambda = 0$



$\frac{1}{s_{y_2} - s_{y_1}}$ measures “distance” between force levels

In order for the relative risk of using force type y_2 instead of force type y_1 to increase by a factor of C , λ would need to increase by

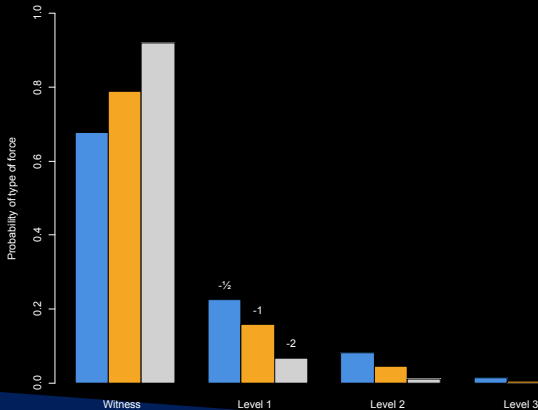
$$\frac{1}{s_{y_2} - s_{y_1}} \log C$$



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Ordinal stereotype imposes a distribution on force types

- $h_y(\mathbf{z})$ set to match Seattle's force rate for force type y
- $\mathbf{s} = \{0, 1, \frac{3}{2}, 2\}$
- $\lambda_1 = -\frac{1}{2}, \lambda_2 = -1, \lambda_3 = -2$



Conditional likelihood for an example incident

Consider a use-of-force incident

- three officers on scene ($m = 3$)
- one officer does nothing (Level 0)
- one officer physically restrains (Level 1)
- one officer strikes baton to the head (Level 3)

What's the probability $Y_1 = 0$, $Y_2 = 1$, and $Y_3 = 3$?

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$$\begin{aligned} P(Y_1 = 0, Y_2 = 1, Y_3 = 3 \mid \mathbf{k} = \{1, 1, 0, 1\}, \mathbf{s}, \lambda, h(\mathbf{z})) \\ = \frac{e^{s_0\lambda_1 + s_1\lambda_2 + s_3\lambda_3}}{e^{s_0\lambda_1 + s_1\lambda_2 + s_3\lambda_3} + \dots + e^{s_3\lambda_1 + s_1\lambda_2 + s_0\lambda_3}} \end{aligned}$$

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Does not depend on the environment
No need to measure \mathbf{z} or worry about $h(\mathbf{z})$

Solves all issues... with some wrinkles

For a general incident with m officers

$$P(\mathbf{Y} = \mathbf{y} | \mathbf{s}, \lambda, \mathbf{k}) = \frac{\exp\left(\sum_{i=1}^m s_{y_i} \lambda_i\right)}{\sum_{\mathbf{y}^* \in \mathcal{K}} \exp\left(\sum_{i=1}^m s_{y_i^*} \lambda_i\right)}$$

- No need for environmental/situational measures
- Moments when all officers have $y = 0$ have no information
- Moments involving a single officer have no information

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However...

- Assumes conditional independence ($Y_i, Y_j \perp\!\!\!\perp \mathbf{z}, \lambda$)
- Denominator is computationally challenging
- λ generally not identifiable

Computational challenges

Complete conditional likelihood is

$$CL(\mathbf{s}, \lambda) = \prod_{\ell=1}^n \frac{\exp\left(\sum_{i=1}^{m_{\ell}} s_{y_{i\ell}} \lambda_{\text{id}(i,\ell)}\right)}{\sum_{\mathbf{y}^* \in \mathcal{K}_{\ell}} \exp\left(\sum_{i=1}^{m_{\ell}} s_{y_i^*} \lambda_{\text{id}(i,\ell)}\right)}$$

Efficient computation of Poisson-Multinomial denominator

- $m_{\ell} = 2$, easily computed
- Attempt 1: no-repeat Heap (1967) recursive algorithm, $O(m!)$
- Attempt 2: DFT Lin et al (2023), $O(m^J)$
- Attempt 3: Dynamic program, $O(m^{1.35})$
- Parallelize across use-of-force incidents



λ is identifiable up to an additive constant

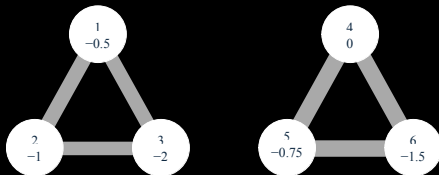
$$L_\ell(\mathbf{s}, \lambda + \mathbf{1}c) = \frac{\exp\left(\sum_{i=1}^{m_\ell} s_{y_i}(\lambda_i + c)\right)}{\sum_{\mathbf{y}^* \in \mathcal{K}_\ell} \exp\left(\sum_{i=1}^{m_\ell} s_{y_i^*}(\lambda_i + c)\right)} = L_\ell(\mathbf{s}, \lambda)$$

- Differences between two officers' λ can be identifiable

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- Disconnected use-of-force networks introduce additional identifiability problems



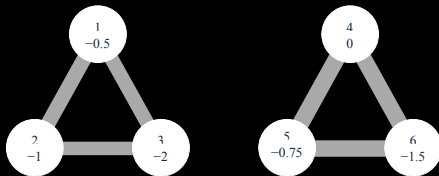
- Only officers within the same network are comparable



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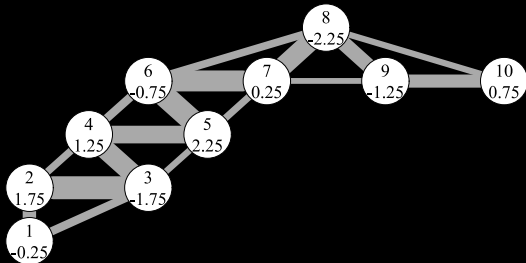
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- Only officers within the same network are comparable
- Additional complexity when comparing with officers weakly connected



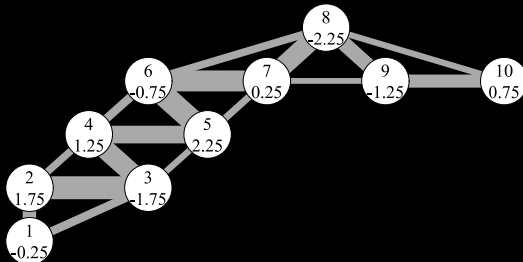
A ten-officer example (simulated)



Parameter	posterior		
	true	mean	SD
$\lambda_1 - \lambda_2$	-2.00	-1.53	0.26
$\lambda_1 - \lambda_3$	1.50	1.23	0.24



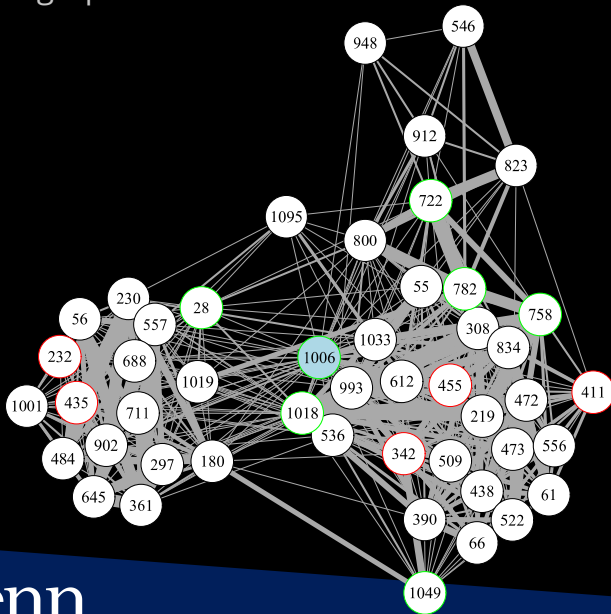
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$\lambda_1 - \lambda_4$	-1.50	-1.48	0.36
$\lambda_1 - \lambda_5$	-2.50	-2.14	0.44
$\lambda_1 - \lambda_6$	0.50	0.59	0.41
$\lambda_1 - \lambda_7$	-0.50	-0.63	0.43
$\lambda_1 - \lambda_8$	2.00	2.16	0.47
$\lambda_1 - \lambda_9$	1.00	1.16	0.48
$\lambda_1 - \lambda_{10}$	-1.00	-0.66	0.55
s_2	1.50	1.53	0.11
s_3	2.00	2.08	0.16



Radius 1 subgraph of Officer 1006's use-of-force network



Defining peers based on conditional variance

- Use Hamiltonian Monte Carlo to draw from posterior distribution of λ
 - no identifying constraints
 - prior on $\lambda \sim N(0, \sigma^2)$ to maintain numerical stability

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 - no identifying constraints
 - prior on $\lambda \sim N(0, \sigma^2)$ to maintain numerical stability
- Define Officer i to be in Officer 1006's peer group if

$$\text{Var}(\lambda_{1006} - \lambda_i | \text{data}) < 2\sigma^2 t$$

where $2\sigma^2$ is the prior variance of the difference, $t \approx \frac{1}{4}$

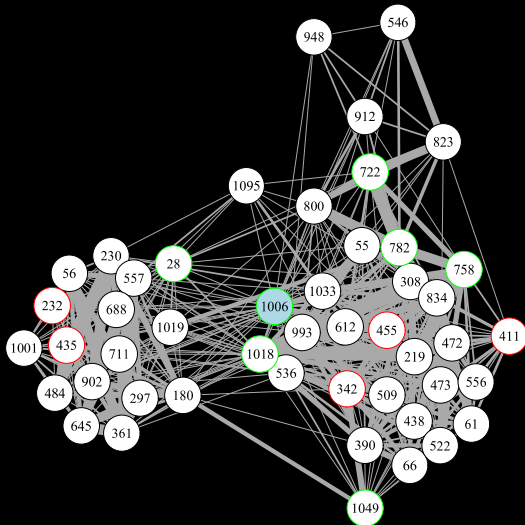
- t small, comparisons involve small groups of officers, losing ability to assess department outliers
- t large, detect outliers among a large set of officers, but less precision

Defining peers based on conditional variance

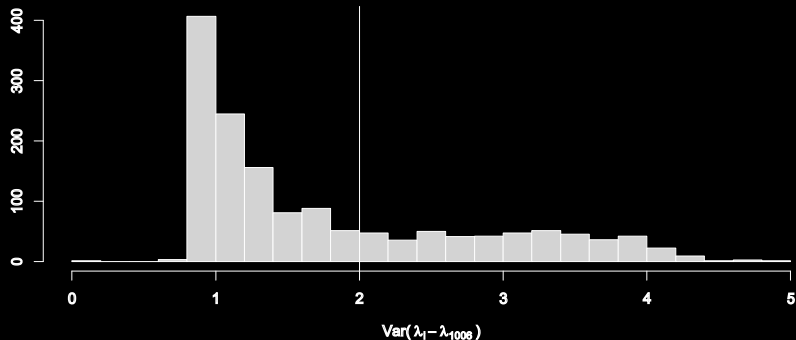
$\text{Var}(\lambda_i - \lambda_{1006}) < 0.9$ for officers in green

$\text{Var}(\lambda_i - \lambda_{1006}) > 2.5$ for officers in red

Disconnected subgraphs can have $\text{Var}(\lambda_i - \lambda_{1006}) > 7.0$



$\text{Var}(\lambda_i - \lambda_{1006})$ reveals well-connected officers



- $\lambda_i - \lambda_{1006}$ is estimable with precision only if Officer 1006's and Officer i 's networks are well-connected
- Officers in disconnected subgraphs or with few shared incidents will have a large $\text{Var}(\lambda_i - \lambda_{1006})$



Analysis of Seattle PD data

Data include

- 4,821 force incidents
- 1,503 unique officers
- 8,209 uses of force
- 28,807 officers witnessing force

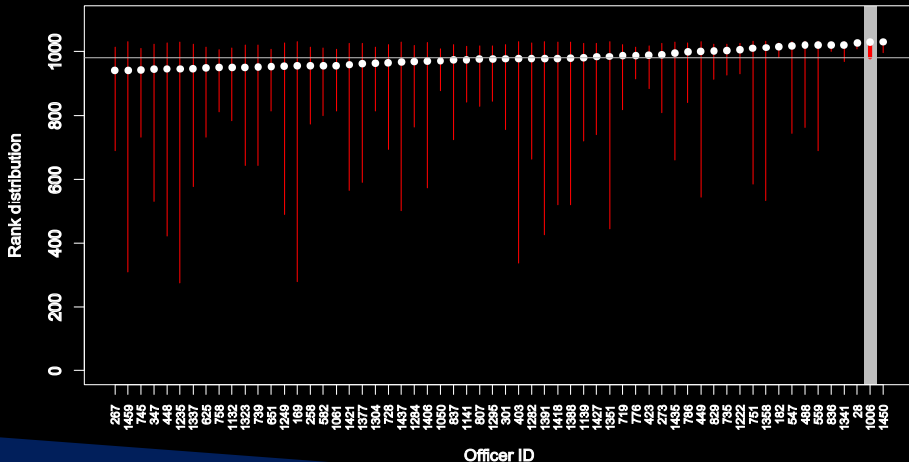
Did not include

- 808 incidents with a single officer
- 455 incidents in which all used same force level
- Incidents with more than 19 officers (<8% of incidents, some had 100+)



Officer 1006 likely a high force escalator

- Posterior rank distribution of λ s for Officer 1006's local network
- 1031 officers in Officer 1006's local network



Flag officers with high force escalation

ID	Peers	Incidents	Count by force level				Prob. rank top 5%
			Witness	1	2	3	
#1006	1031	9	1	8	0	0	0.98

- Peers is the number of officers with $\text{Var}(\lambda_i - \lambda_{1006} \mid \mathbf{data}) < 2.0$
- Incidents is number of incidents involving Officer 1006
- Posterior probability is 0.98 that Officer 1006 is in the highest 5% of 1031 peers
- Officer 1006 has not used serious forms of force, but is unusually hands on



Flag officers with high force escalation

ID	Peers	Incidents	Count of force level			Prob. rank top 5%	$\hat{\lambda}$	
			Witness	1	2			3
#1006	1031	9	1	8	0	0	0.98	3.32 (1.73, 5.17)

- $\hat{\lambda}$ is centered on the peer group average λ for identifiability
- $\hat{\lambda} = 3.3$ implies that compared to the average peer
 - RR of Level 1 instead of Level 0 is 27x greater
 - RR of Level 2 instead of Level 1 is 3% greater
 - RR of Level 3 instead of Level 2 is 29% greater

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ID	Peers	Incidents	Count of force level				Prob. rank top 5%	$\hat{\lambda}$
			Witness	1	2	3		
#28	1170	37	12	24	1	0	1.00	3.00 (2.28, 3.75)
#836	1184	75	33	39	2	1	1.00	2.63 (2.11, 3.14)
#1450	889	7	0	6	1	0	0.99	3.73 (1.77, 6.00)
#1006	1031	9	1	8	0	0	0.98	3.32 (1.73, 5.17)
#182	1182	79	25	43	11	0	0.97	2.44 (1.90, 2.99)
#1341	1153	29	8	12	9	0	0.96	2.65 (1.75, 3.56)
#1222	1170	40	16	21	3	0	0.83	2.23 (1.54, 2.94)
#488	1028	21	2	12	7	0	0.81	2.45 (0.77, 4.20)
#559	1002	15	2	12	1	0	0.80	2.44 (0.55, 4.29)

Flag officers who might fail to intervene

ID	Peers	Incidents	Count of force level			Prob. rank bottom 5%	$\hat{\lambda}$	
			Witness	1	2			3
#399	812	37	37	0	0	0	0.97	-3.72 (-6.21, -1.75)
#247	846	53	53	0	0	0	0.97	-3.68 (-6.24, -1.82)
#287	860	61	60	1	0	0	0.97	-3.67 (-6.15, -1.85)
#629	830	24	24	0	0	0	0.97	-3.71 (-6.22, -1.76)
#175	688	18	18	0	0	0	0.97	-3.82 (-6.50, -1.59)
#457	867	65	64	1	0	0	0.98	-3.78 (-6.18, -1.93)
#636	829	39	39	0	0	0	0.99	-3.98 (-6.46, -2.00)



Conclusions

- Solves a long-standing problem of confounding by assignment
- Can be integrated into police early intervention systems
- Demonstrates the value of documenting witness officers, now mandated in some consent decrees such as in Chicago
- My favorite kind of problem: integration of policing, statistics, mathematics, and computer science

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Placebo test

