

# Which police officers escalate force?

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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



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# 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)



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# Match officers on the same scene

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

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- Conditional logistic regression
- Officers frequently accumulating negative marks in their file 3x more likely to shoot

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- 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
- Data needs demand moving beyond shootings to other force types

## Type of force depends on officer and environment

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



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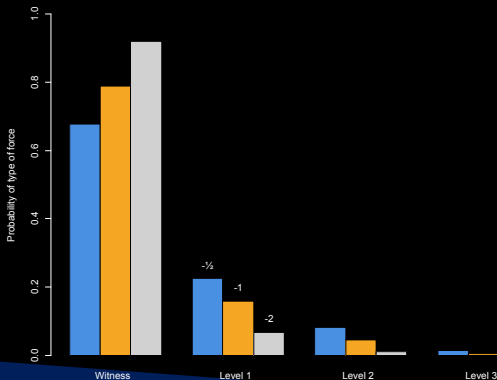
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- Like a multinomial regression model with an officer fixed effect and nuisance environmental effect
- With an order constraint on  $\mathbf{s}$ , identical to Anderson (1984) ordinal stereotype model
  - Other ordinal models do not simplify when conditioning on outcomes



# Ordinal stereotype imposes a distribution on force types

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



# Data collection and model estimation is hard

$$P(Y_i = y|\mathbf{z}) = \frac{\exp(\theta_y + s_y(h(\mathbf{z}) + \lambda_i))}{\sum_{k=0}^3 \exp(\theta_k + s_k(h(\mathbf{z}) + \lambda_i))}$$

Difficult to

- randomly sample officers in time and space
- document  $\mathbf{z}$
- choose  $h(\mathbf{z})$

## Change to a conditional likelihood question

Consider a use of force incident

- with three officers on scene
- 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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Probability does not depend on the environment. No need to measure  $\mathbf{z}$  or worry about  $h(\mathbf{z})$



# Advantages of conditional likelihood

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
- Depends on a conditional independence  $(Y_i, Y_j \perp\!\!\!\perp \mathbf{z}, \lambda)$





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The only times and places with information for the conditional likelihood are those with multiple officers on the scene of a use-of-force incident



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# Computational challenges

For a general incident with  $m$  officers

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Efficient computation of Poisson-Multinomial denominator

- $m = 2$ , easily computed
- $3 \leq m \leq 7$ , no-repeat Heap (1967) recursive algorithm,  $O(m!)$  time
- $m \geq 8$ , discrete Fourier transform Lin et al (2023),  $O(m^4)$  time
- Efficient denominator calculation plus parallelization by incident makes MCMC possible

$\lambda$  is identifiable up to an additive constant

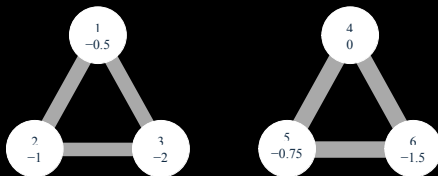
$$L_\ell(\mathbf{s}, \lambda + \mathbf{1}c) = \frac{\exp\left(\sum_{i=1}^{m_\ell} s_{y_i}(\lambda_i + c)\right)}{\sum_{\mathbf{y}^* \in \mathcal{K}_\ell} \exp\left(\sum_{i=1}^{m_\ell} s_{y_i^*}(\lambda_i + c)\right)} = L_\ell(\mathbf{s}, \lambda)$$

- Differences between two officers'  $\lambda$  can be identifiable

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



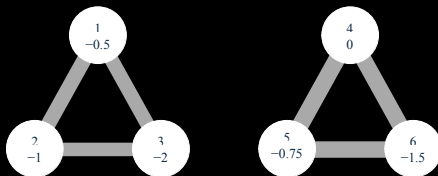
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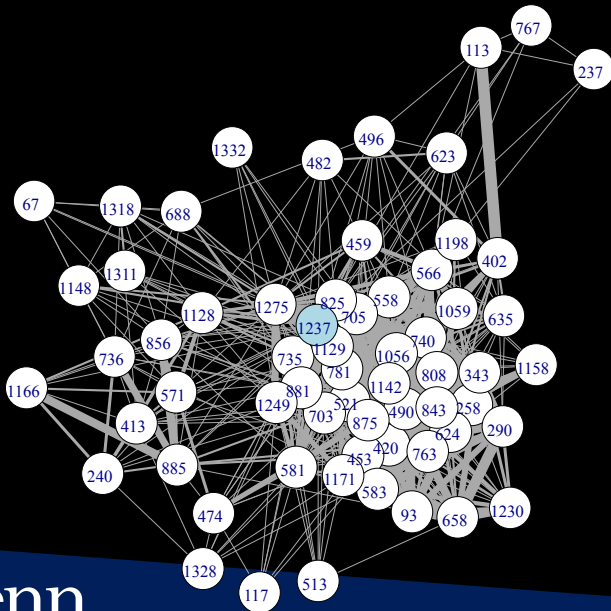
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- Only officers within the same network are comparable
- Additional complexity when comparing with officers weakly connected



# Local use-of-force network for Officer 1237



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## Defining local network

Officer  $i$  is in Officer 1237's local network if

$$\sigma_{i|1237}^2 = \text{Var}(\lambda_i | \lambda_{1237}) \approx \text{Var}(\lambda_i) - \frac{\text{Cov}(\lambda_i, \lambda_{1237})^2}{\text{Var}(\lambda_{1237})} < t$$



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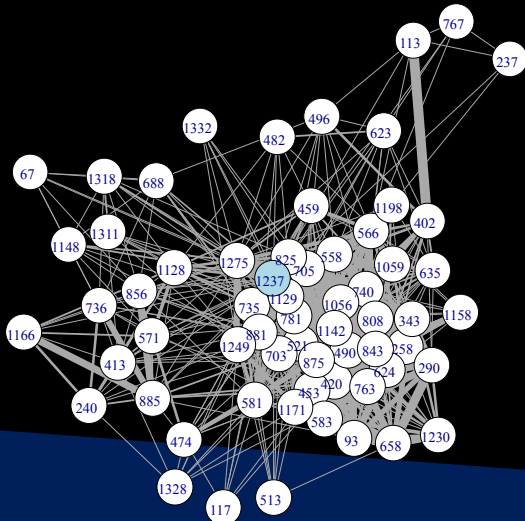
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$\sigma_{i|1237}^2 < 0.7$  for Officers  
1275, 705, 703, 1129, and 825

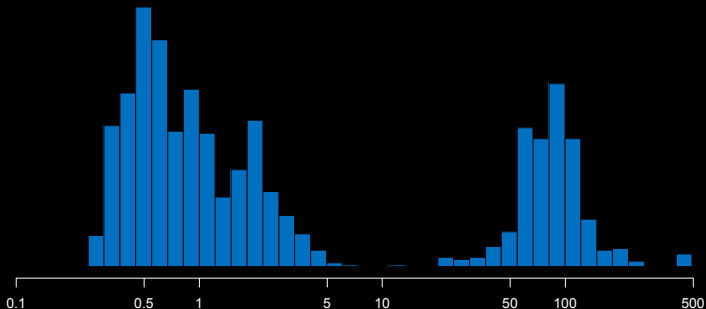
$\sigma_{i|1237}^2 > 70$  for Officers 67,  
1311, and 117



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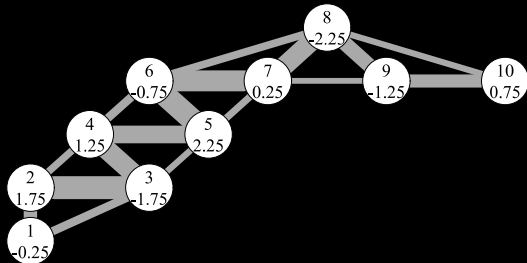
$\text{Var}(\lambda_i | \lambda_{1237})$  reveals well-connected officers



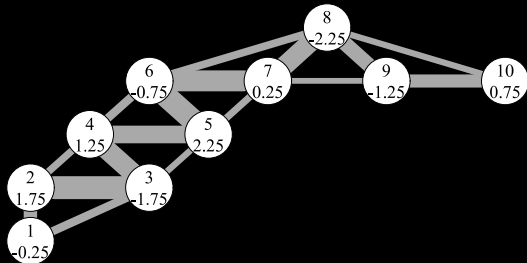
- $\lambda_{1237} - \lambda_i$  is estimable with precision only if Officer 1237's and Officer  $i$ 's networks are well-connected
- Officers in disconnected subgraphs or with few shared incidents will have a large conditional variance



# A ten-officer example



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Parameter	true	posterior	
		mean	SD
$\lambda_1 - \lambda_2$	-2.00	-2.09	0.34
$\lambda_1 - \lambda_3$	1.50	1.85	0.31
$\lambda_1 - \lambda_4$	-1.50	-1.74	0.43
$\lambda_1 - \lambda_5$	-2.50	-3.08	0.58
$\lambda_1 - \lambda_6$	0.50	0.47	0.51
$\lambda_1 - \lambda_7$	-0.50	-0.44	0.52
$\lambda_1 - \lambda_8$	2.00	2.33	0.57
$\lambda_1 - \lambda_9$	1.00	1.04	0.57
$\lambda_1 - \lambda_{10}$	-1.00	-0.91	0.62
$s_2$	1.50	1.44	0.08
$s_3$	2.00	1.88	0.12



# Analysis of full Seattle PD data

- 3,701 force incidents
- 1,386 unique officers
- 5,909 uses of force
- 15,666 officers witnessing force



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## Officer 1237 likely a high force escalator

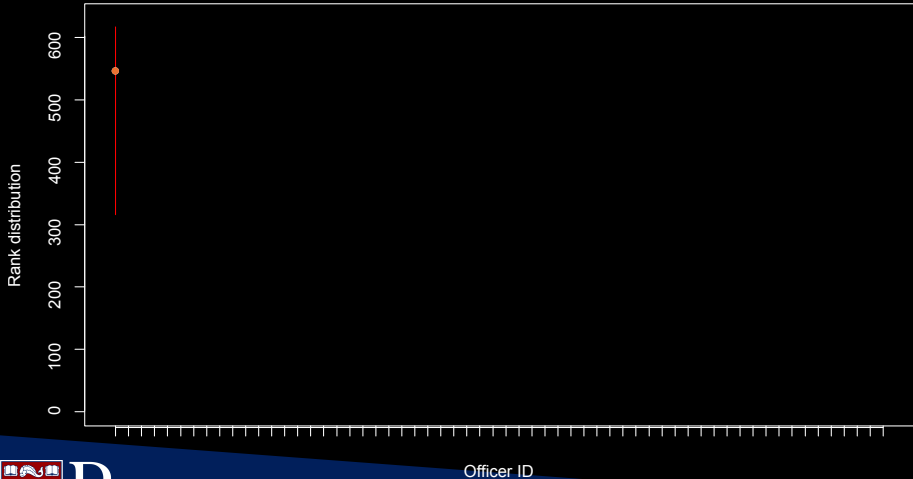
- Posterior rank distribution of  $\lambda$ s for Officer 1237's local network
- 626 officers in Officer 1237's local network



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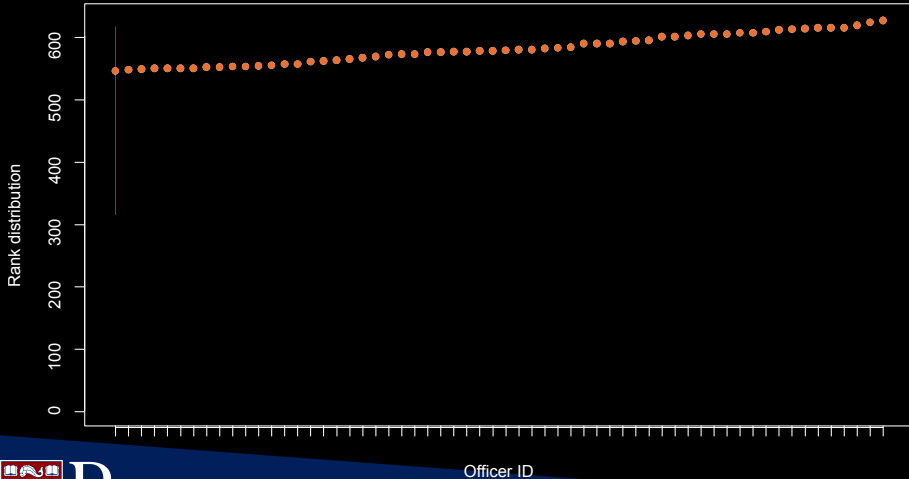
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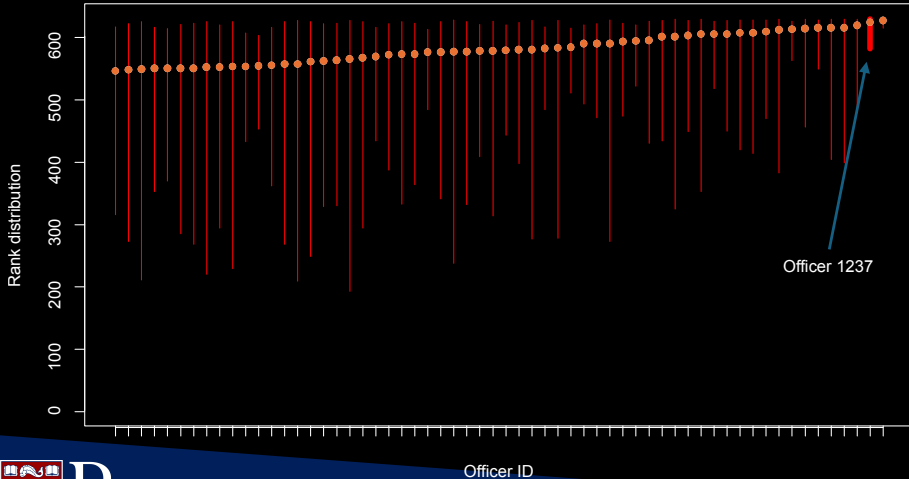
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## Flag officers with high force escalation

Officer ID	Peers	Count of force type used				Prob. rank top 5%
		Witness	Level 1	Level 2	Level 3	
#1237	626	5	11	7	0	0.94



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Officer ID	Peers	Count of force type used				Prob. rank top 5%
		Witness	Level 1	Level 2	Level 3	
#0412	515	0	10	7	0	1.00
#0018	638	6	22	1	0	1.00
#0434	514	0	6	2	0	1.00
#0911	515	0	7	0	0	1.00
#0251	514	0	7	1	1	0.99
#0479	514	0	10	1	0	0.99
#0478	514	0	4	2	0	0.97
#0746	555	2	0	5	0	0.97
#1237	626	5	11	7	0	0.94



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- Conditional likelihood solves the long-standing problem of confounding by assignment
- Demonstrates the value in documenting witness officers, now mandated in some consent decrees such as in Chicago
- Interesting combination of policing, statistics, mathematics, and computer science
  - Poisson-Multinomial, Schur complement, discrete Fourier transform, Heap's algorithm, Markov Chain Monte Carlo, parallel computing

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