Which police officers escalate force?

Greg Ridgeway

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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)

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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Analyses did not pinpoint specific officers, results not actionable

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

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

- 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 free from $h_y(\mathbf{z})$

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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 $h_y(\mathbf{z})$

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Five steps to arrive at the unique f

1. Only candidate sufficient statistic that could eliminate $h_y(\mathbf{z})$ in a conditional likelihood is $\mathbf{k}$, the counts of each force type used

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

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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

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Anderson's ordinal stereotype model

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

$$= \frac{\exp(h_y(\mathbf{z}) + s_y\lambda_i)}{\sum_{j=0}^{J}\exp(h_j(\mathbf{z}) + s_j\lambda_i)}$$

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

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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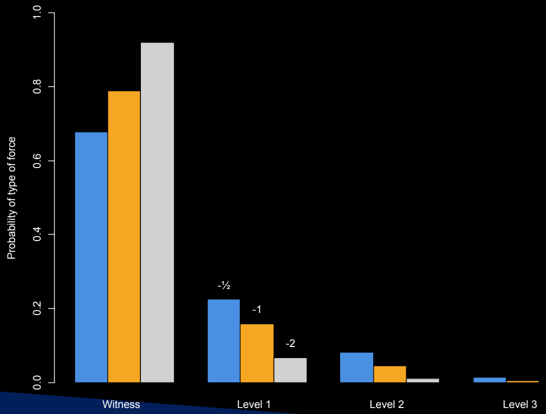
Ordinal stereotype imposes a distribution on force types

- $h_y(\mathbf{z})$ 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)

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

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

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

Computational challenges

Complete conditional likelihood is

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

Efficient computation of Poisson-Multinomial denominator

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

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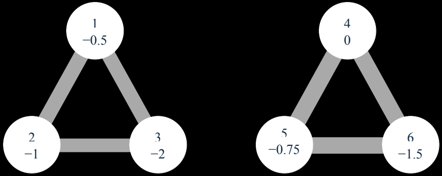
- Disconnected use-of-force networks introduce additional identifiability problems



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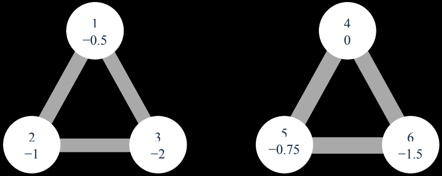
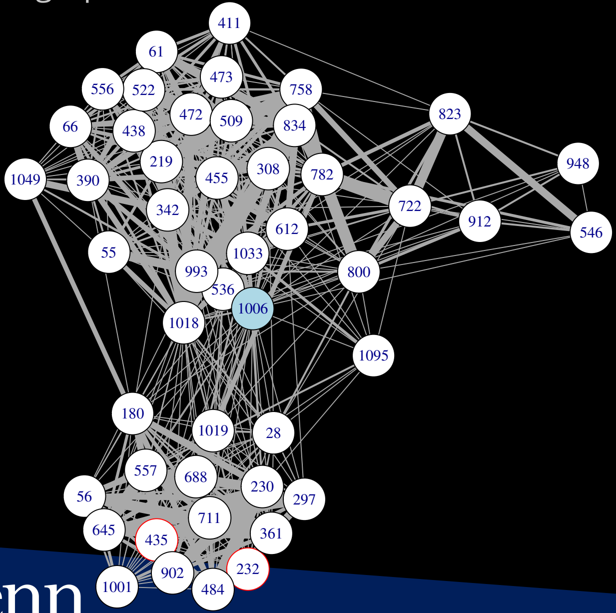


- Only officers within the same network are comparable
- Additional complexity when comparing with officers weakly connected

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



Defining peers based on conditional variance

- Use Metropolis-Hastings to draw from posterior distribution of λ
  - no identifying constraints
  - prior on λ to maintain numerical stability

Defining peers based on conditional variance

- Use Metropolis-Hastings to draw from posterior distribution of λ
  - no identifying constraints
  - prior on λ to maintain numerical stability
- Define Officer i to be in Officer 1006's local network if

$$\begin{aligned} \sigma^2_{i|1006} &= \mathrm{Var}(\lambda_i|\lambda_{1006}) \\ &\approx \mathrm{Var}(\lambda_i)(1-\rho^2_{i|1006}) < t \end{aligned}$$

- 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

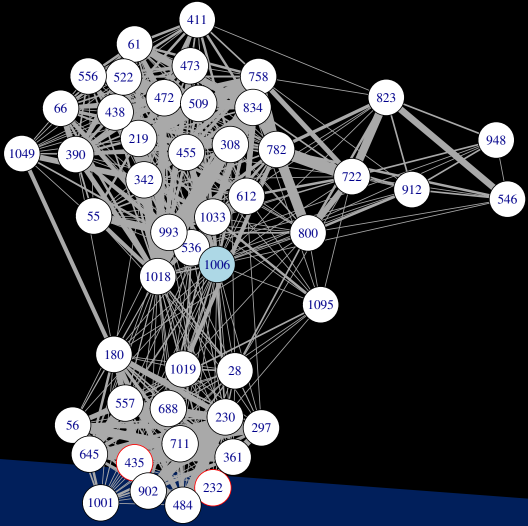
Defining peers based on conditional variance

Officer i's peer group defined as

$$\mathcal{O}_i = \{i^* \mid \mathbf{Var}(\lambda_{i^*} \mid \lambda_i, \mathbf{data}) < t\}$$

$\sigma^2_{i|1006} < 0.3$ for Officers 536, 993, 1018, 1033

$\sigma^2_{i|1006} > 0.6$ for Officers 232 and 435



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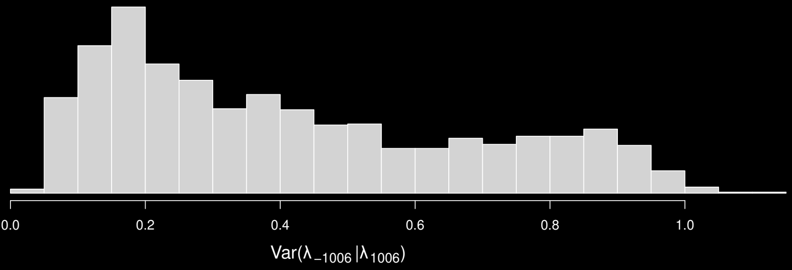
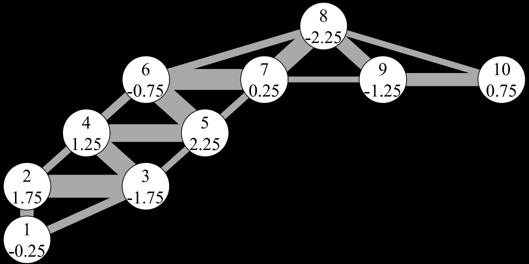
$\mathrm{Var}(\lambda_i \mid \lambda_{1006})$ reveals well-connected officers



- $\lambda_{1006} - \lambda_i$ 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 conditional variance

A ten-officer example (24 incidents/officer)



		posterior	
Parameter	true	mean	SD
$\lambda_1 - \lambda_2$	-2.00	-1.73	0.79
$\lambda_1 - \lambda_3$	1.50	1.74	0.81

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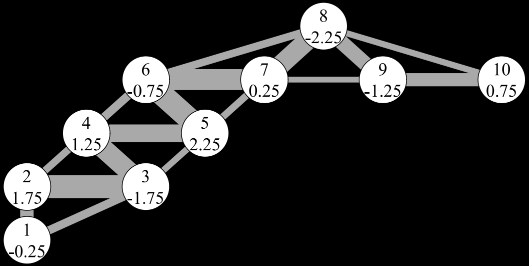

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$\lambda_1 - \lambda_4$	-1.50	-0.86	0.79
$\lambda_1 - \lambda_5$	-2.50	-1.29	0.90
$\lambda_1 - \lambda_6$	0.50	0.76	0.82
$\lambda_1 - \lambda_7$	-0.50	-0.40	0.90
$\lambda_1 - \lambda_8$	2.00	1.53	0.86
$\lambda_1 - \lambda_9$	1.00	0.91	0.88
$\lambda_1 - \lambda_{10}$	-1.00	0.16	0.92
s_2	1.50	2.25	0.67
s_3	2.00	2.56	0.68

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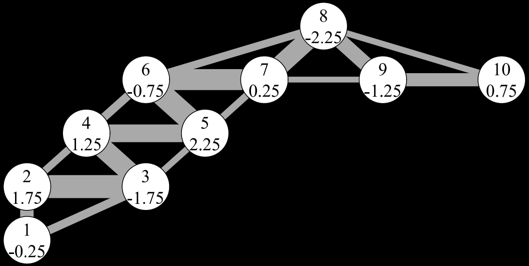
A ten-officer example (250 incidents/officer)



		posterior	
Parameter	true	mean	SD
$\lambda_1 - \lambda_2$	-2.00	-1.53	0.26
$\lambda_1 - \lambda_3$	1.50	1.23	0.24
$\lambda_1 - \lambda_4$	-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

Analysis of Seattle PD data

Data include

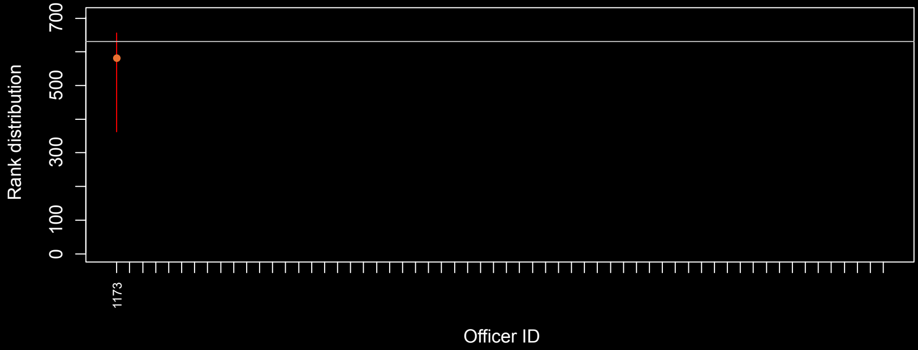
- 4,821 force incidents
- 1,503 unique officers
- 8,209 uses of force
- 28,807 officers witnessing force

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 λs for Officer 1006's local network
- 663 officers in Officer 1006's local network



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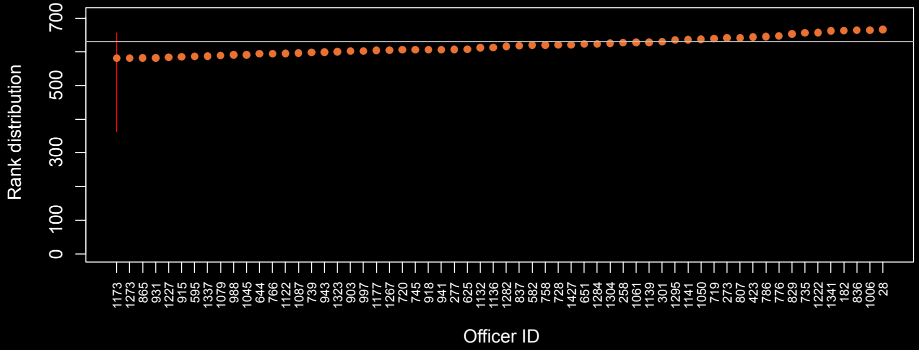

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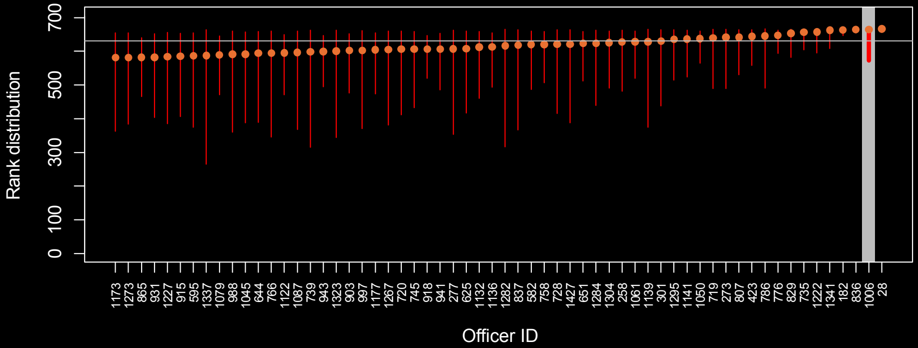

Flag officers with high force escalation

ID	Peers	Incidents	Count by force level				Prob. rank
			Witness	1	2	3	top 5%
#1006	663	9	1	8	0	0	0.92

- Peers is the number of officers with $\mathrm{Var}(\lambda_i \mid \lambda_{1006}, \mathbf{data}) < 0.3$
- Incidents is number of incidents involving Officer 1006
- Posterior probability is 0.92 that Officer 1006 is in the highest 5% of 663 peers
- Officer 1006 has not used serious forms of force, but is unusually hands on

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Flag officers with high force escalation

ID	Peers	Incidents	Count of force level				Prob. rank	$\hat{\lambda}$	95% interval
			Witness	1	2	3	top 5%		
#1006	663	9	1	8	0	0	0.92	2.02	(0.83, 3.23)

- $\hat{\lambda}$ is centered on the peer group average λ for identifiability
- $\hat{\lambda} = 2$ implies that compared to the average peer
  - RR of Level 1 instead of Level 0 is 7x greater
  - RR of Level 2 instead of Level 1 is 11% greater
  - RR of Level 3 instead of Level 2 is 17% greater

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ID	Peers	Incidents	Count of force level				Prob. rank	$\hat{\lambda}$	95% interval
			Witness	1	2	3	top 5%		
#836	661	75	33	39	2	1	1.00	1.99	(1.51, 2.48)
#28	661	37	12	24	1	0	1.00	2.24	(1.57, 2.93)
#182	661	79	25	43	11	0	1.00	1.88	(1.38, 2.40)
#1341	661	29	8	12	9	0	0.94	1.82	(1.01, 2.61)
#1006	663	9	1	8	0	0	0.92	2.02	(0.83, 3.23)
#735	661	49	22	17	9	1	0.90	1.58	(0.99, 2.17)
#1222	661	40	16	21	3	0	0.88	1.59	(0.93, 2.22)
#1450	662	7	0	6	1	0	0.87	1.99	(0.66, 3.34)
#829	661	52	24	15	12	1	0.82	1.49	(0.87, 2.12)

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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