Language from Police Body Camera Footage Shows Racial Disparities In Officer Respect
Voigt et al.

CS 224C Presentation:
Rhea Kapur, Chijioke Mgbahurike, Anna Saraiva
An Untapped Resource

- Despite the proliferation of body-worn cameras in law enforcement
An Untapped Resource

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- Lack of analyzation by law enforcement
An Untapped Resource

- Despite the proliferation of body-worn cameras in law enforcement
- Lack of analyzation by law enforcement
- Concentration on high profile engagements
How do everyday interactions between police and community members differ in respect to black vs white community members?
Data

- Transcribed body camera footage
- Routine vehicle stops (N = 981)
- White (N=299) Black (N=682)
- Oakland Police Department
- April 2014
Novelty

- Datasource
Novelty

- Datasource
- Systematic analysis
Novelty

- Datasource
- Systematic analysis
  - 3 tiered study
  - 
  - 
Novelty

- Datasource
- Systematic analysis
  - 3 tiered study
  - Tied to theories in sociolinguistics
Can humans reliably judge officers’ respect from language
Does judged respect differ against white vs black comm. members
They Can! And They Do!

- 414 unique randomly sampled officer utterances:
  - 4 point likert scale:
    - Respectful
    - Polite
    - Friendly
    - Formal
    - Impartial
They Can! And They Do!*  

- Annotator Consistency  
  - Cronbach’s $\alpha = 0.73 - 0.91$  
  - Group utterances in batches  
  - Same 10+ annotators rate same batch  
  - Linear mixed effects model
<table>
<thead>
<tr>
<th>Fixed Parts</th>
<th>Respectful</th>
<th>Polite</th>
<th>Impartial</th>
<th>Friendly</th>
<th>Formal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>CI</td>
<td>p</td>
<td>b</td>
<td>CI</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.94</td>
<td>2.83 - 3.04</td>
<td>&lt;.001</td>
<td>2.95</td>
<td>2.85 - 3.06</td>
</tr>
<tr>
<td>Driver Age</td>
<td>0.03</td>
<td>-0.02 - 0.08</td>
<td>.22</td>
<td>0.01</td>
<td>-0.04 - 0.07</td>
</tr>
<tr>
<td>Driver Gender (F)</td>
<td>0.04</td>
<td>-0.07 - 0.16</td>
<td>.42</td>
<td>0.05</td>
<td>-0.07 - 0.16</td>
</tr>
<tr>
<td>Driver Race (B)</td>
<td>-0.22</td>
<td>-0.33 - 0.10</td>
<td>&lt;.001</td>
<td>-0.22</td>
<td>-0.34 - 0.11</td>
</tr>
</tbody>
</table>

| Random Parts     |           |        |           |           |        |        |           |           |        |           |           |        |           |           |
|                  | σ²         |        |           |           |        |        |           |           |        |           |           |        |           |           |
|                  | 0.17       |        | 0.19       | 0.21       |        | 0.22       | 0.25       |        | 0.05       | 0.04       | 0.07       | 0.05       | 0.06       |        |
|                  | τ₀₀,Stop   |        | 0.05       | 0.04       |        | 0.07       | 0.05       |        | 0.22       | 0.19       | 0.24       | 0.17       | 0.18       |        |
|                  | N_Stop     |        | 251       | 251       |        | 251       | 251       |        | 251       | 251       | 251       | 251       | 251       |        |
|                  | ICC_Stop   |        | 0.22       | 0.19       |        | 0.24       | 0.17       |        | 0.17       | 0.17       | 0.17       | 0.17       | 0.17       |        |
| Observations     | 414        |        | 414       | 414       |        | 414       | 414       |        | 414       | 414       | 414       | 414       | 414       |        |
| R² / Ω₀²         | .52 / .39 |        | .48 / .35 | .56 / .42 |        | .47 / .33 | .47 / .34 |        |           |           |           |           |           |        |

Table 5: Linear mixed-effects models results for judgements in Study 1.
### PCA: Please Confirm Assumptions

<table>
<thead>
<tr>
<th></th>
<th>PC1: Respect</th>
<th>PC2: Formality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Formal</td>
<td>0.272</td>
<td>0.913</td>
</tr>
<tr>
<td>Friendly</td>
<td>0.464</td>
<td>-0.388</td>
</tr>
<tr>
<td>Impartial</td>
<td>0.502</td>
<td>-0.113</td>
</tr>
<tr>
<td>Polite</td>
<td>0.487</td>
<td>-0.047</td>
</tr>
<tr>
<td>Respectful</td>
<td>0.471</td>
<td>0.026</td>
</tr>
<tr>
<td>% of Variance Explained</td>
<td>71.3%</td>
<td>21.9%</td>
</tr>
</tbody>
</table>

**Community Member Race**

- black
- white
Can we model it?
Top 1000 most common first names from the 1990 US Census, where first letter is capitalized in transcript

Lexicon: "sir", "ma'am", "mam", "mister", "mr\*", "ms\*", "madam", "miss", "gentleman", "lady"

Lexicon: "for me"

Lexicon: "for you"

Lexicon: "let you", "allow you", "you can", "you may", "you could"

Lexicon: "thank", "thanks", "appreciate"

Lexicon: "goodbye", "bye", "see you later"

Regular expression capturing cases like "keep your hands on the wheel" and "leave your hands where I can see them": "hands? \([*,?!,;:]+\)?(wheel|see)"

All words in the "Tentat" LIWC lexicon

All words in the "Imprompt" LIWC lexicon


Regular expression capturing cases like "I'm Officer [name] from the OPD" and "How's it going?": "\(( (my name).*officer | officer.*(oakland|opd))\)\{(hi|hello|hey|good afternoon|good morning|good evening|how are you doing|how's it going)\}"

Top 5000 most common last names from the 1990 US Census, where first letter is capitalized in transcript

All words in the "Negate" LIWC lexicon

For the "Negativ" category in the Harvard General Inquirer, matching on word lemmas

All words in the "Positiv" category in the Harvard General Inquirer, matching on word lemmas

[name], can I see that driver's license again? It's showing suspended. Is that's you?

-1.07

Disfluency

Negative Word

Disfluency
A Reliable Model...

Root Mean Squared Error:

- Respect - Model: 0.840, Human: 0.842
- Formality - Model: 0.882, Human: 0.764
- 414 sampled utterance
What doesn't matter?
Showed No Difference
Officer Race Showed No Difference
Showed No Difference

Officer Race Geographic Info
Showed No Difference

Officer Race Geographic Info Number of Officers
Showed No Difference

Officer Race

Geographic Info

Number of Officers

Race & Formality
Showed No Difference
To recap...
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- Scalable and sensitive technique for body-cam interactions
- Consistent judgement from police-community interactions
- Respect & Formality Axis
- Positive & negative strategies for politeness
- Racial disparities in respect for Black community members
Peer Reviewer
Review & Expand

Strengths:

- Use of human participants as well as language models
- Test “thin slices” approach before implementing it in scale
- Analysis of evolution of disparities as interaction time passed
Review & Expand

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● Analysis of evolution of disparities as interaction time passed

Weaknesses:

● The problem with analyzing stops: search vs hit rates (similar problems with Fryer (2019))
● Camera footage doesn’t give the full picture
● Controlling for potentially endogenous variables
● Very limited external validity, focusing on one city in one month
Search Rate vs Hit Rate
Racial bias is present if

\[
\frac{(4)}{(3) + (4)} > \frac{(2)}{(1) + (2)}
\]

But denominators themselves might be endogenous and subject to bias.
Review & Expand

Questions:

- Were there checks for accuracy of transcriptions?
- Besides Respect and Formality, what were the differential rates in specific phrases, such as “hands on wheel”?
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Future Research:

- Transcription done at scale
- Expand to other cities and time periods
- Additional behavior derived from camera footage
NYPD
Industry Practitioner
Developing an Internal Officer Feedback System at the NYPD

- Let’s quantify officer respectfulness within our city and police department
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- Use this information in personalized officer training and review sessions
NYPD Academic Researcher
Extended Meta-Study Using Internal System Data

- Are general takeaways from Voigt et al. (ex. that interactions are less respectful when blacks are pulled over vs. whites) replicated in our specific police department, in the city of New York?
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- If we look at officer characteristics as well (race, age, gender, etc.) are there any patterns re. respectfulness?
Social Impact Assessor
Implications of the Paper

Concrete:

- Police-community interactions can be quantitatively assessed and categorized
- Robust benchmarks for police accountability
- Tools for police training

Abstract:

- What other sociolinguistic effect could be analyzed?
- Applicability to parallel industries, i.e. healthcare, education
- Feasible real world impact