Racial Disparities in Police Language Use

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CS124

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Our Question

Do officers treat White community members with a greater degree of respect than they afford to Blacks?
Police-Community Interaction

- Media focus on explosive incidents
- Research focus on outcomes

but:
- one quarter of adults have contact with the police during the course of a year
  - majority occurring in traffic stops
Respect is Important

- A person who is treated with respect
  - ... has more trust in the individual officer’s fairness (Tyler & Ho, 2001)
  - ... and the procedural fairness of the institution (Tyler & Sunshine, 2003)
  - ... and is more willing to support or cooperate with the police (Tyler, 1990; Mazerolle et al., 2013)
Previous work on procedural fairness

- Relies on:
  - citizens’ recollection of past interactions (Epp et al, 2014)
  - researcher observation of officer behavior (Mastrofski et al, 2009; Dai, Frank, & Sun, 2011; Jonathan-Zamir, Mastrofski, & Moyal, 2015; Mastrofski et al, 2016)

- These are invaluable but indirect
  - … and presence of researcher may influence police behavior (Mastrofski & Parks, 1990)
This work: Body camera footage

- Oakland PD has been wearing body cameras since 2010
- Usually used only as evidence
- ... but, a window into everyday behavior!
Our proposal: Footage as Data

- We look at all traffic stops of black and white community members in April 2014

- 981 stops by 245 officers
  - Drivers: 682 black, 299 white
  - 183 hours of footage
Transcribed dataset

- Professional transcribers
  - Underwent background checks by OPD
  - Watched videos
  - Transcribed words
  - Diarized (who is talking to whom)

- Resulting data set:
  - 36,738 officer utterances, 350k+ words
Sample transcription

0:00:00 0:00:09 OFFICER [to dispatch]: Unknown occupant and it's going to be for registration. It should be code four.
0:00:20 0:00:20 OFFICER: Hi.
0:00:20 0:00:20 FEMALE: Hi.
0:00:21 0:00:23 OFFICER: I pulled you over because your registration is expired by almost a year.
0:00:25 0:00:28 FEMALE: Okay, I have the paperwork for it, a moving permit?
0:00:28 0:00:28 OFFICER: I'm sorry?
0:00:29 0:00:30 FEMALE: I have the paperwork for it.
0:00:30 0:00:31 OFFICER: Okay.
Study 1

Perceptions of Officer Treatment from Language
Study 1: Goals

- Can human raters judge respect from officers’ language?
- Are there differences in officer respect towards Black versus White community members?
Utterance Rating Task

- Participant Coders (N=70) blind to citizen race labeled 414 unique officer utterances
  - 10 coders per utterance
  - 4-point Likert scales (high rater agreement $\alpha$s=.73-.91)

Respectful, Polite, Friendly, Formal, and Impartial
Utterance Rating Task

Read the following interaction with a police officer: The citizen just said:

It's in my glove compartment.

And then the officer says:
Let me take a look at it. How about insurance?

How *impolite* or *polite* was the officer?

- [ ] Very Impolite
- [ ] Somewhat Impolite
- [ ] Somewhat Polite
- [ ] Very Polite
Utterance Rating Task

![Chart showing mean ratings for different attributes by community member race.
- Formality
- Friendliness
- Impartiality
- Politeness
- Respectfulness

Community Member Race: black, white]
The Latent Space of Respect

- The questions we asked are all very correlated

- How do we discover the underlying construct?

- Principal Component Analysis
  - Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components
The Latent Space of Respect

Two PCs explain 93% of the variance:

<table>
<thead>
<tr>
<th></th>
<th>Respect</th>
<th>Formality</th>
</tr>
</thead>
<tbody>
<tr>
<td>variance explained:</td>
<td>71%</td>
<td>22%</td>
</tr>
<tr>
<td>Formal</td>
<td>0.27</td>
<td>0.91</td>
</tr>
<tr>
<td>Friendly</td>
<td>0.47</td>
<td>-0.39</td>
</tr>
<tr>
<td>Polite</td>
<td>0.49</td>
<td>-0.04</td>
</tr>
<tr>
<td>Respectful</td>
<td>0.47</td>
<td>0.03</td>
</tr>
<tr>
<td>Impartial</td>
<td>0.50</td>
<td>-0.11</td>
</tr>
</tbody>
</table>
The Latent Space of Respect

- Race on these dimensions:
Next Steps: Scaling up

- We ran this whole experiment and only labeled 414 officer utterances!
  - What about the remaining 35k+?
  - ... and that’s only 1 month, and only traffic stops

- Could we automate this process to be able to look at large amounts of text data?
  - ... and control for many contextual variables
Study 2

Modeling Respect with Computational Linguistics
Study 2: Goals

- Use linguistic theories of respect and social distance to develop linguistic features that can be detected in transcripts

- Use the human labeled data as supervised training data to learn weights on these interpretable features
Linguistic Models of Respect


● “Positive and Negative Politeness”

● Mitigating face-threatening acts
  ○ Positive face
    ■ hearer’s self-image
  ○ Negative face
    ■ hearer’s freedom of action
Linguistic Models of Respect

- Linguistic theories of politeness focus on requests
  - Ordering you to do something is face-threatening

- Negative Politeness:
  - Minimize (maximize) my request
  - put on record that it’s an imposition on you (vs. ignore the impact on you)

- Positive Politeness:
  - Emphasize your value (vs. deemphasize your value)
  - Emphasize (vs. deemphasize) my good relationship with you
Features for Negative Politeness

- Apologizing
  - “sorry”, “oops”, “my fault”, “excuse me”
- Gratitude
  - “thank.*”, “appreciate”
- Imposition minimizers
  - “it’s ok”, “don’t worry”, “no big deal”, “you’re good”
- Hedges (LIWC “Tentative words”)
  - “maybe”, “a little”, “kind of”, “sort of”
- Give Agency
  - “let you”, “allow you”, “you may”, “you can”
- Negative impoliteness: Control their actions
  - “hands on the wheel”
Features for Positive Politeness

- **Formal versus informal titles**
  - “sir”, “ma’am”, “Mr.”... versus “bro”, “man”, “dude”

- **Last names, first names**
  - [Frequent names from US Census]

- **Introductions**
  - “Hello”, “My name is”, “I’m Officer X”

- **Mentioning safety**
  - “safe.*”

- **Positive words**
  - “good”, “great”, “awesome”, “perfect”
Apologies
“( sorry | oops | woops | excuse me | forgive me | apologies | my bad | apologize | my fault )”

Time Minimizing
“(a|one|a few) (minute|min|second|sec|moment)s? | this[^,?!]+quick | right back ”
Methodology

- **Hand-engineered features**
  - Lexicons
  - Regular expressions
  - Dependency-based rules
  - More complex functions (“bald commands” etc)

- **Statistical Model: simple linear regression**
  - log-transformed counts of features per utterance
  - stepwise removal of uninformative features
## Results

- **Respect** model is able to perform roughly like an average annotator

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Adjusted $R^2$</td>
<td>0.258</td>
</tr>
<tr>
<td>Model RMSE</td>
<td>0.840</td>
</tr>
<tr>
<td>Average annotator RMSE</td>
<td>0.842</td>
</tr>
<tr>
<td>(range from 0.497 - 1.677)</td>
<td></td>
</tr>
</tbody>
</table>

- **Formality** model is worse but still reasonable

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Adjusted $R^2$</td>
<td>0.190</td>
</tr>
<tr>
<td>Model RMSE</td>
<td>0.882</td>
</tr>
<tr>
<td>Average annotator RMSE</td>
<td>0.764</td>
</tr>
<tr>
<td>(range from 0.517 - 1.703)</td>
<td></td>
</tr>
</tbody>
</table>
Feature Weights

Respect Model Coefficients

Apologizing
For You
Gratitude
Reassurance
Last Names
Formal Titles
For Me
Safety
Give Agency
Filled Pauses (Um/Uh)
Adverbial Just
Positive Words
Hedges
Introductions

Log Odds Ratio by Race

More common in...
Black Stops
White Stops

† is p < 0.1, * is p < 0.05, ** is p < 0.01, *** is p < 0.001
Feature Weights

Respect Model Coefficients

Log Odds Ratio by Race

† is p < 0.1, * is p < 0.05, ** is p < 0.01, *** is p < 0.001
<table>
<thead>
<tr>
<th>FIRST NAME</th>
<th>ASK FOR AGENCY</th>
<th>QUESTIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>[name], can I see that driver's license again?</td>
<td>It- it's showing suspended. Is that- that's you?</td>
<td></td>
</tr>
<tr>
<td>DISFLUENCY</td>
<td>NEGATIVE WORD</td>
<td>DISFLUENCY</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>INFORMAL TITLE</th>
<th>ASK FOR AGENCY</th>
<th>ADVERBIAL &quot;JUST&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>All right, my man. Do me a favor. Just keep your hands on the steering wheel real quick.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot;HANDS ON THE WHEEL&quot;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Example</td>
<td>Respect Score</td>
<td></td>
</tr>
<tr>
<td>---------</td>
<td>---------------</td>
<td></td>
</tr>
<tr>
<td><strong>APOLOGY</strong></td>
<td><strong>INTRODUCTION</strong></td>
<td><strong>LAST NAME</strong></td>
</tr>
<tr>
<td>Sorry to stop you. My name’s Officer [name] with the Police Department.</td>
<td></td>
<td>0.84</td>
</tr>
<tr>
<td><strong>FORMAL TITLE</strong></td>
<td><strong>SAFETY PLEASE</strong></td>
<td></td>
</tr>
<tr>
<td>There you go, ma’am. Drive safe, please.</td>
<td></td>
<td>1.21</td>
</tr>
<tr>
<td><strong>ADVERBIAL &quot;JUST&quot;</strong></td>
<td><strong>FILLED PAUSE</strong></td>
<td><strong>REASSURANCE</strong></td>
</tr>
<tr>
<td>It just says that, uh, you’ve fixed it. No problem. Thank you very much, sir.</td>
<td></td>
<td>2.07</td>
</tr>
</tbody>
</table>
Study 3

Racial Disparity Across the Entire Dataset
Study 3: Goals

- Do the results from Study 1 hold across an entire month of traffic stops?
- ... even controlling for contextual factors?
## Study 3: Results

<table>
<thead>
<tr>
<th></th>
<th>Respect</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>CI</td>
<td>$p$</td>
<td>$\beta$</td>
<td>CI</td>
<td>$p$</td>
</tr>
<tr>
<td>Arrest Occurred</td>
<td>-0.00</td>
<td>-0.03 - 0.03</td>
<td>.933</td>
<td>0.01</td>
<td>-0.02 - 0.04</td>
<td>.528</td>
</tr>
<tr>
<td>Citation Issued</td>
<td>0.04</td>
<td>0.02 - 0.06</td>
<td>$&lt;.001$</td>
<td>0.01</td>
<td>-0.01 - 0.03</td>
<td>.209</td>
</tr>
<tr>
<td>Search Conducted</td>
<td>-0.08</td>
<td>-0.11 - 0.05</td>
<td>$&lt;.001$</td>
<td>-0.00</td>
<td>-0.03 - 0.02</td>
<td>.848</td>
</tr>
<tr>
<td>Age</td>
<td>0.07</td>
<td>0.05 - 0.09</td>
<td>$&lt;.001$</td>
<td>0.05</td>
<td>0.03 - 0.07</td>
<td>$&lt;.001$</td>
</tr>
<tr>
<td>Gender (F)</td>
<td>0.02</td>
<td>-0.00 - 0.04</td>
<td>.062</td>
<td>0.02</td>
<td>0.00 - 0.04</td>
<td>.025</td>
</tr>
<tr>
<td>Race (W)</td>
<td>0.05</td>
<td>0.03 - 0.08</td>
<td>$&lt;.001$</td>
<td>-0.01</td>
<td>-0.04 - 0.01</td>
<td>.236</td>
</tr>
<tr>
<td>Officer Race (B)</td>
<td>0.00</td>
<td>-0.03 - 0.04</td>
<td>.884</td>
<td>0.00</td>
<td>-0.03 - 0.03</td>
<td>.987</td>
</tr>
<tr>
<td>Officer Race (O)</td>
<td>-0.00</td>
<td>-0.04 - 0.03</td>
<td>.809</td>
<td>-0.00</td>
<td>-0.03 - 0.02</td>
<td>.783</td>
</tr>
<tr>
<td>Officer Race (B) : Race (W)</td>
<td>-0.01</td>
<td>-0.03 - 0.02</td>
<td>.583</td>
<td>0.01</td>
<td>-0.01 - 0.03</td>
<td>.188</td>
</tr>
<tr>
<td>Officer Race (O) : Race (W)</td>
<td>-0.01</td>
<td>-0.03 - 0.02</td>
<td>.486</td>
<td>-0.00</td>
<td>-0.02 - 0.02</td>
<td>.928</td>
</tr>
</tbody>
</table>
Interpretation

White community members are 57% more likely to hear an officer say one of the top 10% most respectful utterances in our dataset.

Black community members are 61% more likely to hear an officer say one of the top 10% least respectful utterances in our dataset.
Controls

- Holds even considering:
  - Only “everyday” interactions (no arrest, no search)
  - Crime rate in the area
  - Density of businesses in the area
  - Whether driver race was known before the stop
  - Officer years of experience
Controls - Severity

- We asked officers to rate the stops for their severity
  - 1 - very minor (expired registration)
  - 4 - very severe (speeding)

- Black drivers are stopped for less severe offenses
- ... but no impact on respect
Controls - Officer Race

- Surprisingly, not a factor! (including homophily)
Across the Interaction

- Respect rises throughout the interaction
- … but rises faster for whites
Across the Interaction

- No race effect for Formality
- Officers less formal over the interaction
Conclusions from the first paper

- Confirms community reports: interactions with black community members are more fraught

- Provides concrete strategies for officers

- Cooperation with Oakland to integrate results into procedural justice training
  - ... and we can measure impact
Implications for Escalation

- Looked at LIWC Anger/Swear words used by Community Member
- When officers are more respectful, are drivers less angry?
Moving Forward

- **Tone of Voice:**
  - Preliminary results suggest a similar trend

- **Community member language:**
  - Escalation
  - Compliance, politeness

- **Other Departments**
Conclusion

• NLP can help us understand abstract concepts like “Respect” and quantify them

• The techniques you learned in this class are powerful and applicable to the real world!

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Thank you!

Questions welcome!
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