# Tweetment Effects on the Tweeted: An Experiment to Reduce Twitter Harassment

Kevin Munger

NYU

December 1, 2016 Prepared for Yale Human Nature Lab

• Find harassers on Twitter

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- Randomize assignment 2x2
  - In-group v Out-group (race of bot)
  - ► High Status v Low Status (number of followers)

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- See how long the treatment persists

# Why does it happen?

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- Girard's theory of mimetic desire

### State of the art

- Experiments in the lab
  - ► Convenience samples
  - ► Short time frame
  - ▶ In the lab

# State of the art My Approach

- Experiments in the lab Experiment in the "field"
  - ► Convenience samples Sample of real, consistent harassers
  - Short time frame Continuous and unbounded time frame
  - ▶ In the lab In the same context as the harassment

### Find harassers

• Needs to be fast, and accurate

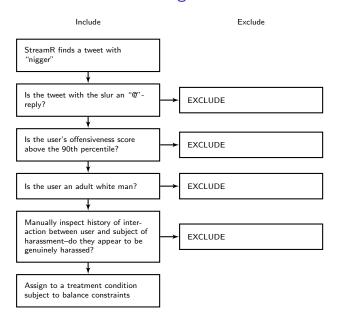
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#### Find harassers

- Needs to be fast, and accurate
- Don't care about recall
- In the presence of strongly offensive language, a dictionary of slurs is best (Chen et al, 2012)

## Detection "Algorithm"



# Apply Treatment





Hey man, just remember that there are real people who are hurt when you harass them with that kind of language

### Treatment uptake



All hypotheses have been pre-registered through EGAP.

#### **Hypothesis**

The ranking of the magnitudes of the decrease in harassment will be: In-group/High status  $> \frac{In-group/Low\ status}{Out-group/High\ status} > Out-group/Low\ status$ .

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Table: Experimental Design and Hypothesized Effect Sizes

	In-group	Out-group		
Low followers	Medium effect	Small effect		
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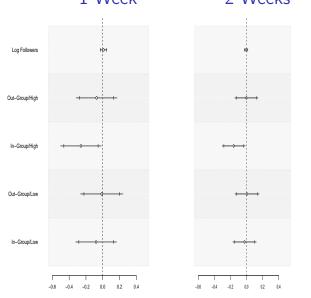
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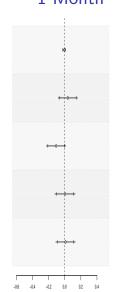
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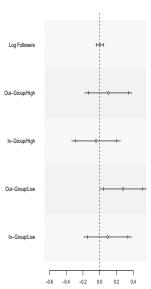
The decrease in offensive language will be smaller in subjects who provide less information in their profile.

# Change in Racist Language: Full Sample (242) 1 Week 2 Weeks 1 Month

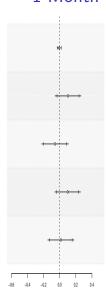




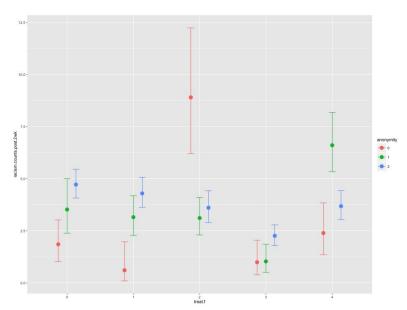
# Change in Racist Language: Non-Anonymous Sample (84) 1 Week 2 Weeks 1 Month







# Science Moves Quickly



#### In Real World Terms

My intervention caused the 50 subjects in the most effective condition to tweet the word "nigger" an estimated 186 fewer times in the month after treatment.

# **Ongoing Project**

Political civility

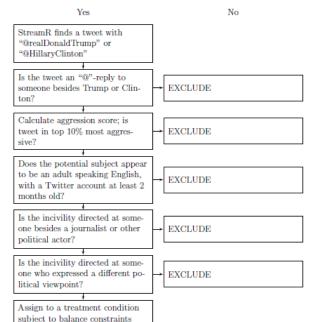
# **Ongoing Project**

- Political civility
- Incivility demobilizes and polarizes

#### A Visual Overview



#### Detection



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- Trump-critical subjects get a tweet from a Democrat or Hillary bot
- Test effectiveness of three types of messages
- Ideologically scale subjects (Barberá, 2015) and look for heterogeneous effects

• Different rhetoric to appeal to different moral frameworks

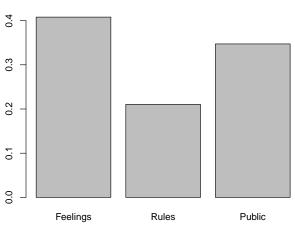
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  - ▶ Placebo message: "Remember that everything you post here is public. Everyone can see that you tweeted this."

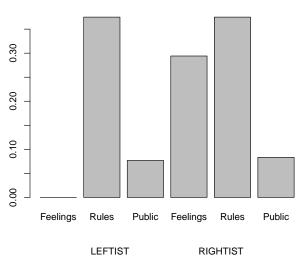
# Preliminary Results

#### Response Rates by Treatment (N=224)



# **Preliminary Results**

#### Percentage of Conciliatory Response (N=72)



## An Optimistic Note



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## An Optimistic Note







Follow

# Thanks for your comments, and for listening!

- km2713@nyu.edu
- @kmmunger (no harassment, please)

#### Attrition rates

	Control	Α	В	С	D
Baseline # of subjects	40	49	44	50	48
# with $> 1$ Post-treatment tweets	40	46	42	47	47
# with $>$ 25 Post-treatment tweets	40	34	33	35	43
Attrition %, < 25 tweets	10%	18%	16%	18%	4%

The number of subjects who tweeted more than 1 or 25 times after the application of the treatment.