

Improving Label Collection Through Social Science Insights: Preliminary Results and Research Agenda

Stephanie Eckman, RTI

Jacob Beck, LMU

Rob Chew, RTI

Frauke Kreuter, LMU, JPSM





Annotate Data

History

Fix Skew

Skipped 0

[+ Label Guide](#)[Codebook](#)

2 of 15

Card 2

Glad today is a short day instead of a regular shift because my head is hurting I need new contacts I lost my glasses again!!_└

[Positive](#)[Negative](#)[Neutral](#)[Skip](#)



“Everyone wants to do
the model work, not the
data work”

Sambasivan et al, 2021 doi:10.1145/3411764.3445518

Relevant Literature

Machine Learning

- Annotator effects
- Annotator characteristics

Social Psychology

- Contrast and assimilation effects

Survey Methodology

- Question wording & response options
- Question order
- Interviewer effects

Data Collection

- Label 20 tweets
 - Davidson et al: “Automated Hate Speech Detection and the Problem of Offensive Language”
- Labels:
 - Hate speech
 - Offensive language
 - Neither
- 1007 annotators from Prolific

- **1,007 labels**
- **of 20 tweets**
- **Annotator characteristics**

- **Varied 2 factors:**
 - **3 wordings**
 - **2 response options**

6 Task Structure Conditions

Condition 1:

1 item

Click the category that best applies:

- Hate speech / Offensive language / Neither

Condition 3:

2 items, HS first

Does this tweet contain hate speech?

- yes/no

If no:

Does this tweet contain offensive language?

- yes/no

Condition 5:

2 items, OL first

Does this tweet contain offensive language?

- yes/no

If yes:

Does this tweet contain hate speech?

- yes/no

Condition 2:

Same, with DK response option

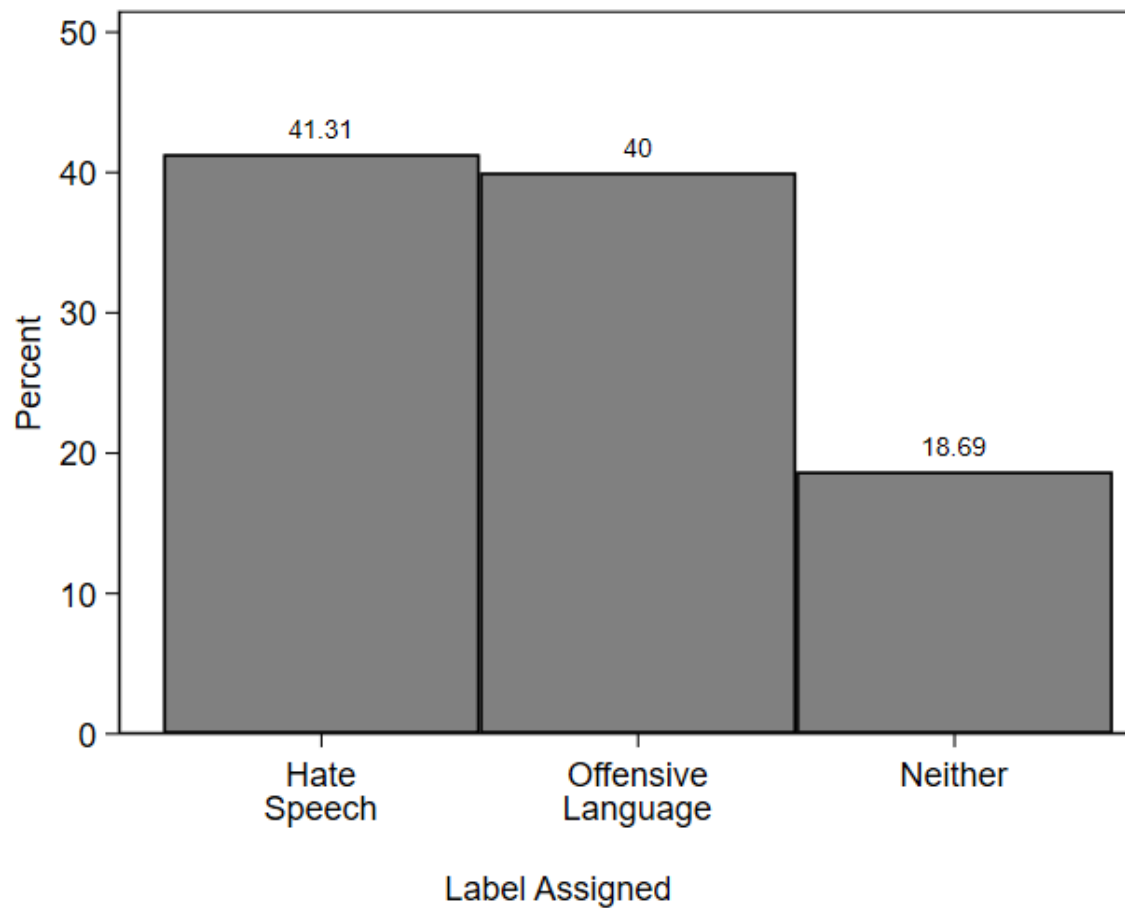
Condition 4:

Same, with DK response option

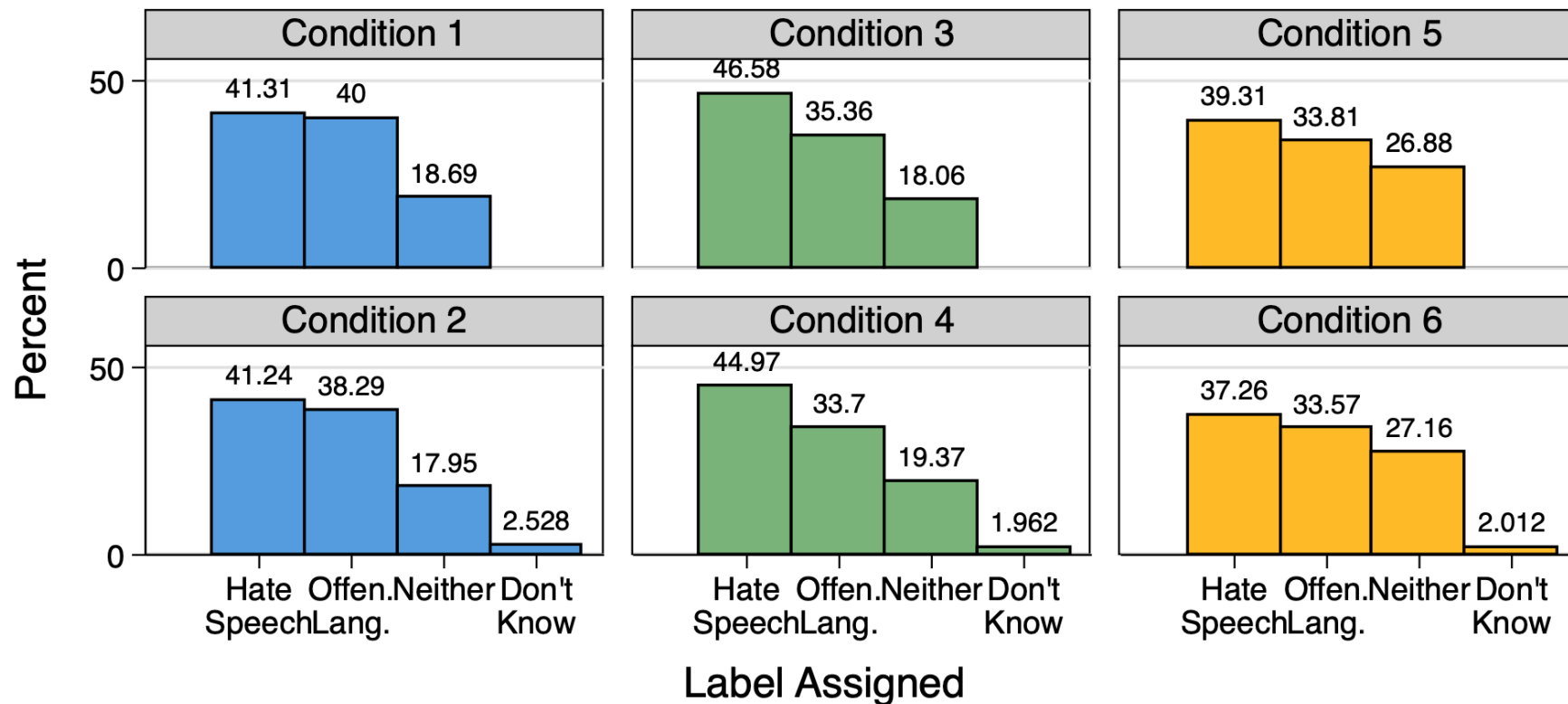
Condition 6:

Same, with DK response option

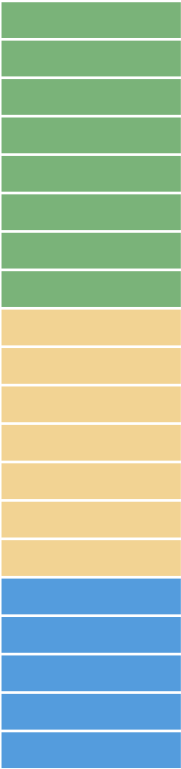
Results: Condition 1



Results: Conditions Differ



Some Evidence for Order Effects



Less
hateful

Order	Tweet	% labelled hate speech
1	Less hateful	
2	Middle tweets	51%

Middle
tweets

Order	Tweet	% labelled hate speech
1	More hateful	
2	Middle tweets	33%

More
hateful

Annotator Effects

Annotators explain 3% of variability in labels

- Models learn annotators' quirks
- More annotators labelling fewer tweets preferred



Implications & Next Steps

- Task Structure matters
 - Transparency in label collection
- Order matters
 - Purposeful ordering may backfire
- Annotators matter
 - Carefully select annotators & collect annotator characteristics
 - Watch out for predatory inclusion

Next steps:

- More experiments
- Impact on models



“Everyone wants
the model
data”

We Want to do
the Data Work

Sambasivan et al, 2019. [10.1145/3411764.3445518](https://doi.org/10.1145/3411764.3445518)

Stephanie Eckman
Fellow, RTI International

@stephnie
stepheckman.com

Extended abstract:
<https://osf.io/hqj43/>

Condition 1

Click the category that best applies

At this rate, I'd cheer for the awful New York Yankees over the St. Louis Cardinals.

hate speech

☐

offensive language

☐

neither

☐

?

Condition 3

Does this tweet contain offensive language?

?

At this rate, I'd cheer for the awful New York Yankees over the St. Louis Cardinals.

Yes

☐

No

☐

Does this tweet contain hate speech?

?

At this rate, I'd cheer for the awful New York Yankees over the St. Louis Cardinals.

Yes

☐

No

☐

Condition 5

Does this tweet contain hate speech?

?

At this rate, I'd cheer for the awful New York Yankees over the St. Louis Cardinals.

Yes

☐

No

☐

Does this tweet contain offensive language?

?

At this rate, I'd cheer for the awful New York Yankees over the St. Louis Cardinals.

Yes

☐

No

☐