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Understanding & Correcting Selection Bias in the Sentiments derived from Flemish tweets

Statistics Flanders
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1. Problem setting

- Surveys = costly, time-consuming, and subject to bias
- Social media = more representative of true opinion[1]

- **Twitter**: Academic Research API
  - Query tweets
  - No demographic attributes available

[1] Biffignandi et al., 2018

1.1 Twitter is a biased source of information

- Demographics of Twitter population differ from those of general population
  - 74.7% men[1]
  - Young people[2]

  ⇒ **Selection bias**

- Demographic attributes of Twitter users aren't available
  → Use machine learning to infer them

<u>Problem</u>: How to measure this bias and correct it?

1 https://www.xavierdegraux.be/sociale-netwerken-belgie-statistieken-2021
2 Vandendriessche et al., 2020

1.2 Research questions

- How can demographic labels be assigned efficiently and with minimal supervision to a sample of Twitter users?
- How does the population distribution of Flemish Twitter users differ from census data in terms of gender, age, and location?
- Which methods are best suited to correct the selection bias present in Twitter users datasets?

2. Approach

Target variables:

- Gender *{Male, Female}*
- Age category *{-18, 19-29, 30-39, 40+}*
- Location *{Antwerp, Limburg, Flemish Brabant, East Flanders, West Flanders, Brussels-Wallonia, Foreign countries}*

Inferring demographic attributes of Twitter users → Correcting the selection bias

2.1 Dataset

- Few public datasets (mainly English)

- 1,2M tweets and 28k user profiles
  - *Timeframe*: 2019-2020
  - *Language*: Dutch
  - *Geolocation*: Belgium

- **Hand-labeling**: costly, time-consuming, and not scalable
  - *Test set*: 2% labeled by 14 student annotators
  - *Training set*: alternative solution needed

    ⇒ **Weak supervision**

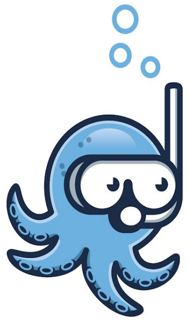
3. Demographic Inference

Keyword searches

Regular expressions

Third-party models

Machine Learning models



Gender, Age & Location

3.1 Heuristics & knowledge bases

Keyword searches & regular expressions

Age

- Keyword list *'twenties', 'grandpa'*
- Regular expressions

Gender

- Keyword list *'he/him', 'sister'*
- Dictionary of first names

Location

- Zip codes
- Town names (& W-Eu countries + capitals)

3.2 Third-party models (gender)

VGG-Face[1]: face detection + gender prediction

CLIP[2]: token assignment to image

- Woman 0.01
- Man 0.90
- Object 0.09

- Woman 0.01
- Man 0.24
- Object 0.75

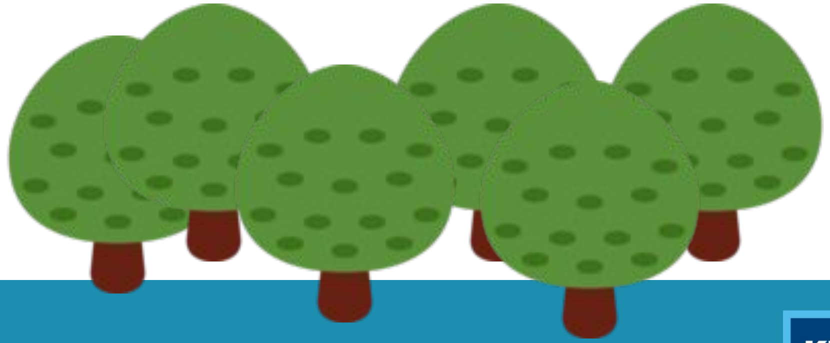
3.3 Machine Learning Classifiers

Features:

- Common terms in profile descriptions and tweets
- Topics discussed
- Celebrities followed (politicians, artists, football clubs, …)
- .nl/.be + account metadata

Models:

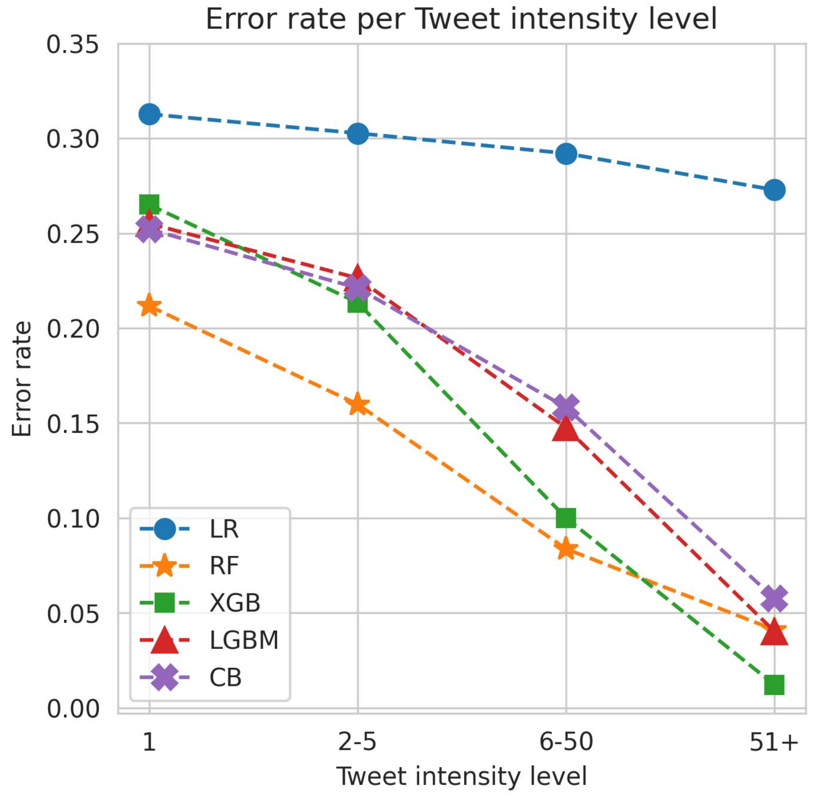
- Logistic regression: multi-class & ordinal
- Tree ensembles: RF, XGB, LGBM, and CB



4. Results

- Accuracy of the predictions:
  - Gender (2 categories): 92 %
  - Age (4 categories): 55%
  - Location (7 categories): 75%

- Better results on users with many tweets



4.1 Top features per predicted category

Female:

- Emojis: ✨🦋💕❤️🚺🌻👩🤍
- Description: fashion, lezen

Male:

- Description: cloud, software, developer, gamer, guy, echtgenoot/husband
- Follows: @ElevenSportsBEn/f, @KVCWesterlo

40+:

- Tweets about politics + mentioning
- Tweet content: @torfsrik, @groen, @kristofcalvo, @vlbelang, @phroose, @cdenv, @spa, @jdeceulaer, @bartdewever

4.1 Top features per predicted category

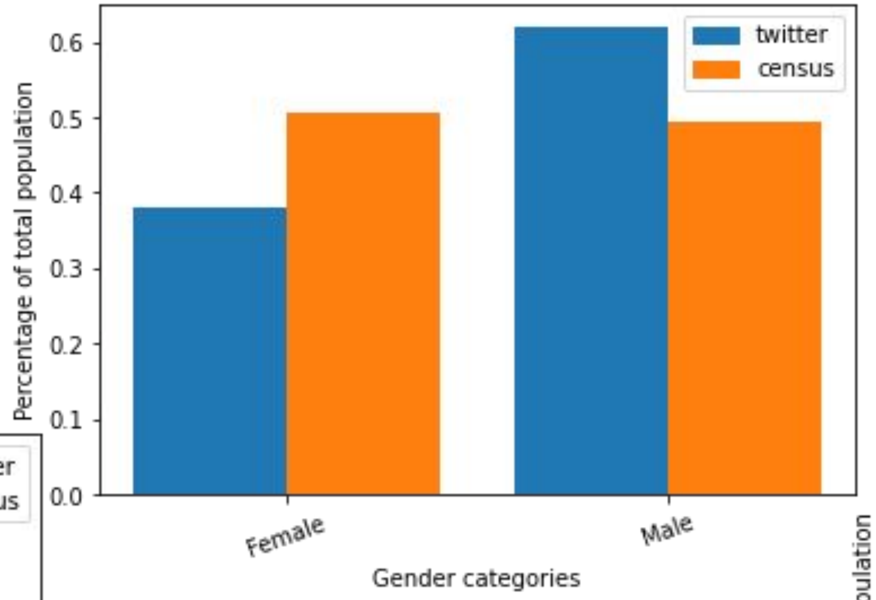
Foreign:

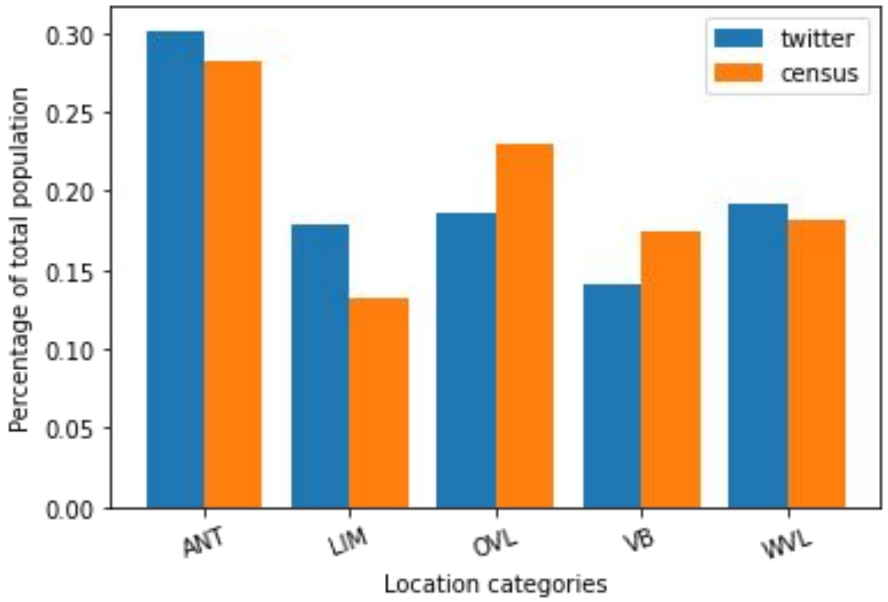
- .nl hyperlink in profile
- Follow Dutch celebrities/sports clubs

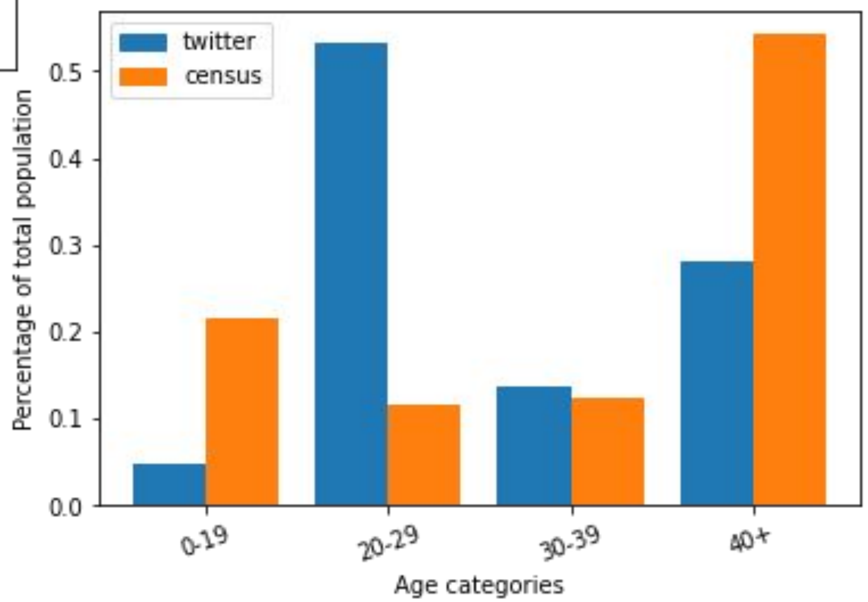
Other location categories:

- Antwerpen: @Stad_Antwerpen
- West-Flanders: @ClubBrugge
- East-Flanders: @UGent, @KAAGent
- Flemish-Brabant: @KULeuven, @PolitieLeuven
- Limburg: @KRCGenkOfficial

4.2 Compared to census







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4.3 Limits

- No guarantee to get sufficient labels for all categories
  - Over-representation of users in their twenties
  - Hurts the performance

- We considered users with geolocated tweets only (41% of all users)[1]

[1] Sloan and Morgan, 2015

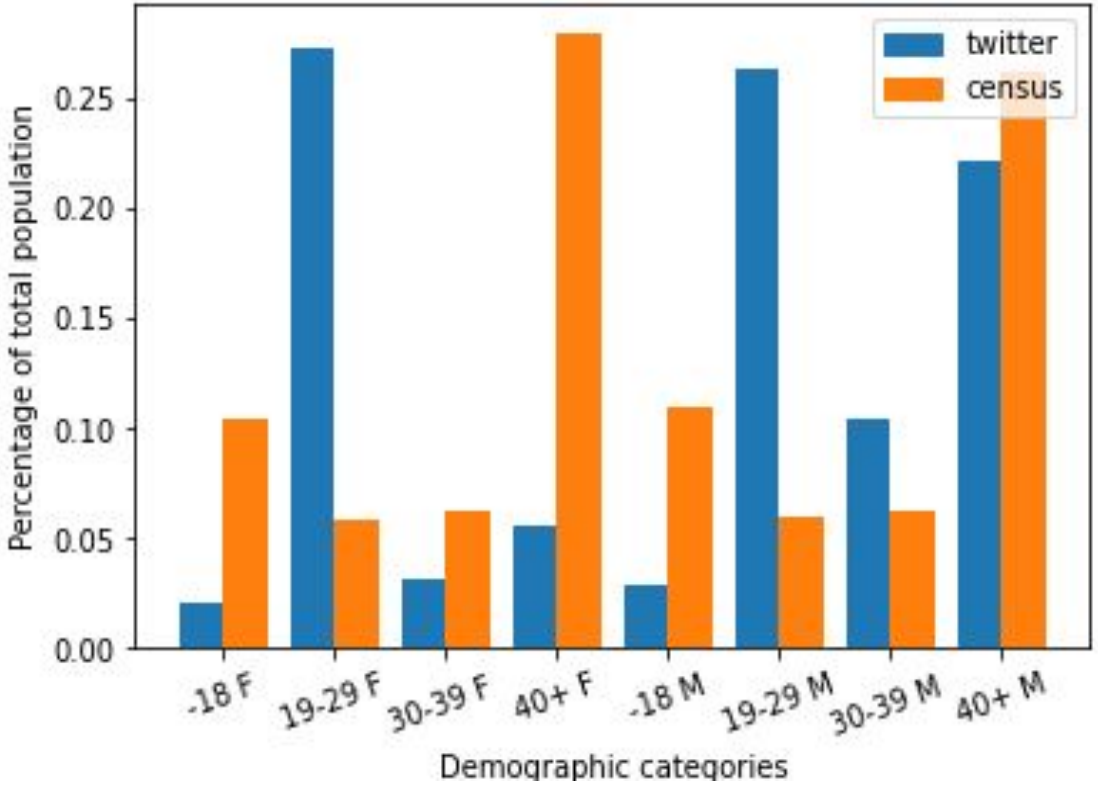
4.4 Future research

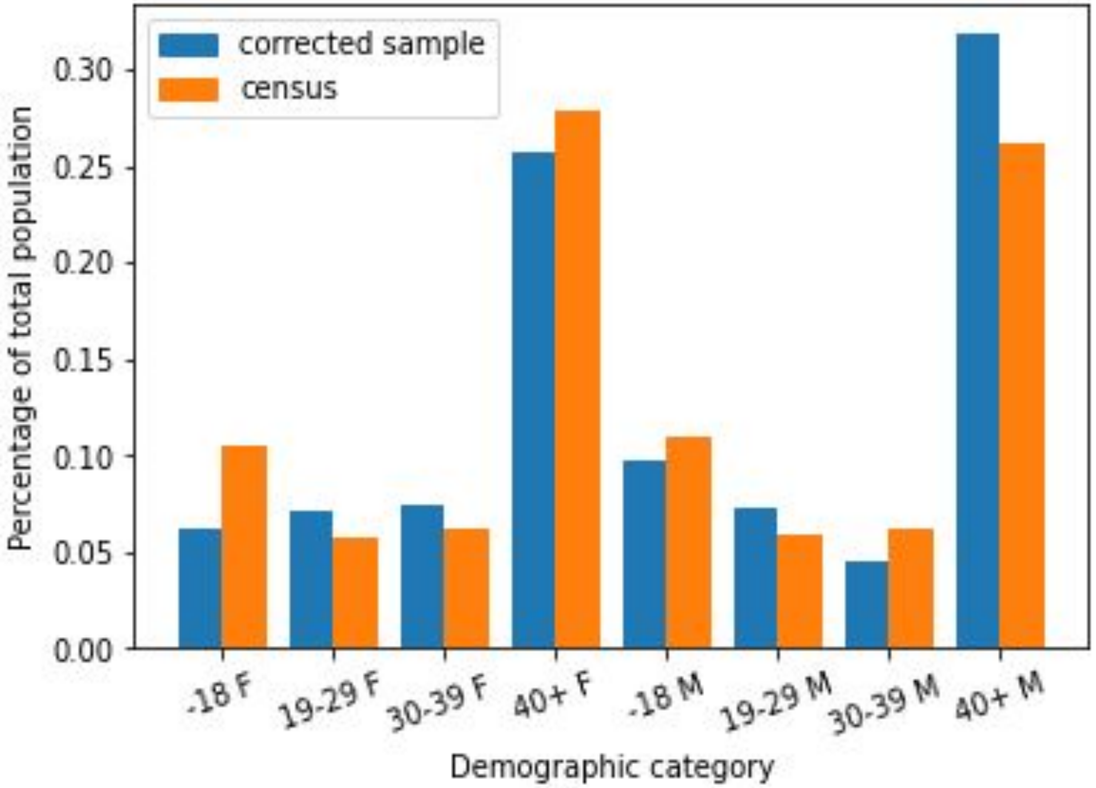
- Leveraging new attributes
  - Education level: High school, Bachelor, Master, …
  - Income level
  - More fine-grained age and location categories

- More advanced labeling models to improve coverage and accuracy

5. Correction methods

Resampling[1]





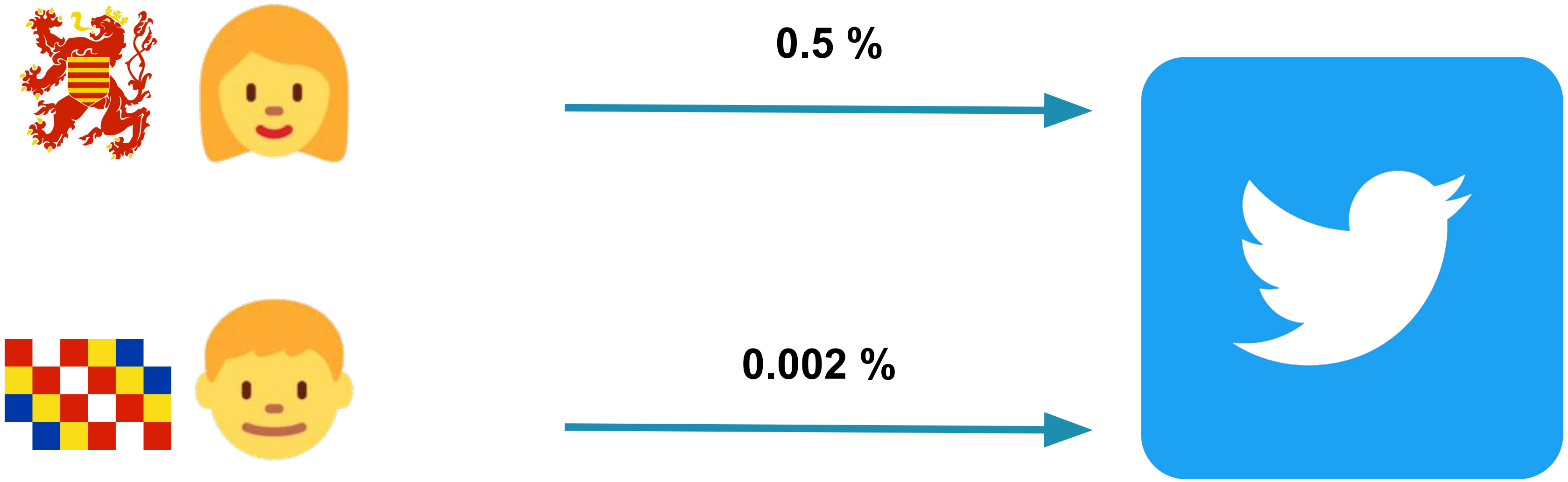
[1] Wang et al., 2020

5. Correction methods

Reweighting[1]

Computes probability that a demographic group joins Twitter

Assign weights based on inclusion probabilities



[1] Wang et al., 2019

6. Conclusion

- Demographic inference is successful for gender and location
- Age prediction is more challenging
- Resampling methods allow to remove the selection bias
- More experiments are needed for reweighting methods

Link to code https://github.com/jtonglet/Twitter-Selection-Bias/

Remarks & suggestions?

Thank you for your attention!

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