How group identity and human-computer interaction shape online communication

David García

with M. Strohmaier, C. Wagner, E. Graells-Garrido, F. Menczer
Chair of Systems Design at ETH Zurich

- Data Driven Modeling & Computational Social Science

- Retrieval and Analysis of Digital traces

  - Networks: Social networks, communication, reputation, resilience
  - Text: Public messages, product reviews, sentiment analysis
  - Dynamics: Time series analysis, complex systems, collective emotions
Computational Social Science

Quantitative testing theories from the social sciences at unprecedented breadth and depth and scale
(Lazer et. al. Science, 2009)

- Quantitative, empirical vs previous qualitative and theoretical work
- Not data-driven descriptive studies: *research between disciplines*
- Towards computational models to understand human behavior

*Related but not the same as Big Data, Data Science, Web Science, Digital Sociology, Human-Computer Interaction, Behavioral Science...*
Digital, Computerized, and Generative

The *Computational* in Computational Social Science means:

<table>
<thead>
<tr>
<th>Digital</th>
</tr>
</thead>
<tbody>
<tr>
<td>Based on large datasets of human behavior, either produced by the Web and social media, or on digital databases of culture and History</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Computerized</th>
</tr>
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<tr>
<td>The quantitative analysis of data in an automated, tractable, repeatable, and extensible fashion</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
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<td>Application of data and results to design of agent-based models that explain observed social phenomena and motivate interventions</td>
</tr>
</tbody>
</table>
Digital traces of cultural distance: Eurovision

Digital traces of cultural distance: Eurovision

The Bechdel test of social media

Godwin's law in the World Cup 2014

As the German national team scores goals in a soccer match, the probability of a comparison involving Nazis or Hitler approaches 1

Nazi mentions

Tweets that contain the word "nazi", "nazis", or "Hitler"

data source: Topsy.com

Creating by David Garcia dgarcia.eu
Godwin's law in the World Cup 2014

As the German national team scores goals in a soccer match, the probability of a comparison involving Nazis or Hitler approaches 1

LAST SLIDE BASED ON TWITTER DATA
Outline

1. The Linguistic Intergroup Bias
   - Group identity in language
   - Wikipedia study
   - The gig economy study

2. The QWERTY effect
   - Keyboards in communication
   - Decoding Study
   - Encoding Study
Group identity in communication

The Linguistic Intergroup Bias (Maass et. al. 1989)

People encode and communicate desirable in-group and undesirable out-group behaviors more abstractly than undesirable in-group and desirable out-group behaviors.
Group identity in communication

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Group identity in communication

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- Barcelona newspaper: 
  "Messi committed a foul in the match"
- Madrid newspaper: 
  "Messi: the violent and aggressive player"
- National newspaper: 
  "Riots after R. Madrid - F.C. Barcelona"
The digital traces of LIB

Analysis of LIB (Otterbacher, 2015)

1 identification of sentiment through the subjectivity clues lexicon

http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

Word subjectivity annotations
- 2718 positive
- 4912 negative
- 570 neutral
- 21 both

2 detection of abstract language through POS tagging
- adjectives are abstract
- verbs can be abstract or concrete
Linguistic Intergroup Bias in Wikipedia

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LIB in Wikipedia?

- With respect to gender: The vast majority Wikipedia editors are male
- LIB for biographies depending on gender?
- Should not exist: Wikipedia neutrality/pluralism regulations
- Should not exist: Readers of articles are undetermined

Data Summary

- Wikipedia biographies from DBpedia 2014
- Selection of biographies with at least 250 words
- Gender from (Bamman and Smith, 2014) annotations
- ~ 50K biographies
Detecting abstract language

Tendency to express positive traits in an abstract manner:

**Positive abstract ratio**

\[ r_+ = \frac{\# \text{ positive adjectives}}{\# \text{ positive terms}} \]

Tendency to express negative traits in an abstract manner:

**Negative abstract ratio**

\[ r_- = \frac{\# \text{ negative adjectives}}{\# \text{ negative terms}} \]
LIB in Wikipedia

<table>
<thead>
<tr>
<th></th>
<th>% in men</th>
<th>% in women</th>
<th>$\chi^2$</th>
<th>w</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract positive</td>
<td>27.96</td>
<td>25.53</td>
<td>933.7***</td>
<td>0.04</td>
<td>8.69</td>
</tr>
<tr>
<td>Abstract negative</td>
<td>13.47</td>
<td>13.69</td>
<td>6.26**</td>
<td>0.005</td>
<td>-1.62</td>
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Comparison of the ratios of abstract terms among positive and negative terms for men and women. Slightly more abstract terms are used for positive aspects in men’s biographies, while slightly more abstract terms are used for negative aspects in women’s biographies. ***: $p<0.001$, **: $p<0.01$. 
LIB in Wikipedia

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![Graph showing the comparison of predicted values between male and female in different birth years.](image1)

![Graph showing the comparison of predicted values between male and female in different birth years.](image2)
Women through the glass ceiling: gender asymmetries in Wikipedia

Claudia Wagner\(^1,2\)\(^*\), Eduardo Graells-Garrido\(^3\), David García\(^4\) and Filippo Menczer\(^5\)

https://github.com/dgarcia-eu/LIB_Tutorial
1 The Linguistic Intergroup Bias
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2 The QWERTY effect
   - Keyboards in communication
   - Decoding Study
   - Encoding Study
/lib in the gig economy?

The gig economy

A gig economy is an environment in which temporary positions are common and organizations contract with independent workers for short-term engagements. (techtarget.com)

- Job stability depends on customer reviews and ratings
- Minimal moderation of feedback
- Could there be LIB in the reviews given by gig economy customers?

collaborators: A. Hannak, C. Wagner, M. Strohmaier, C. Wilson, A. Mislove
Data on the gig economy

Task Rabbit dataset
- ~ 3K users (53% male)
- ~ 54K reviews

Fiverr dataset
- ~ 9K workers (63% male)
- ~ 136K reviews
Sentiment-bearing word abstraction

Word-level model

Given that a positive word is uttered in a review for a worker of certain race and gender, what is the probability that such word is an adjective?

- Logistic regression model over words with gender, race, and their interaction as explanatory variables
- Controls: average rating of the worker, amount of gigs of the worker, experience, etc
- Effect visualization of probabilities depending on combinations of race and gender
LIB in Task Rabbit and Fiverr

Task Rabbit Positive

Task Rabbit Negative

Fiverr Positive

Fiverr Negative
LIB in Task Rabbit and Fiverr

Task Rabbit Positive

P(adj|pos) 0.40 0.42 0.44
WM BM AM WF BF AF

Task Rabbit Negative

P(adj|neg) 0.22 0.26 0.30
WM BM AM WF BF AF

Fiverr Positive

P(adj|pos) 0.25 0.27 0.29
WM BM AM WF BF AF

Fiverr Negative

P(adj|neg) 0.15 0.20 0.25
WM BM AM WF BF AF
Discussions and caveats

1. Different results for Task Rabbit and Fiverr
   - Effect of gender and race ratios?

2. No information on identity of the writers of texts
   - LIB or general discrimination?

3. Signals of style
   - It is not what is said, it is how it is said

4. Wikipedia effects
   - Does time weaken the LIB?
   - Can we observe the LIB across Wikipedia languages?

5. More advanced models?
   - Including topics
   - Recovering LIB from representations
   - Predictive formulations
The QWERTY effect

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What were the body organs that you used the last time that you communicated with someone?
What were the body organs that you used the last time that you communicated with someone?
The Right Side Ratio

$$RSR = \frac{R}{R + L}$$
The Right Side Ratio

\[ RSR = \frac{R}{R + L} \]
The Right Side Ratio

\[ RSR = \frac{R}{R + L} \]
The QWERTY Effect: How typing shapes the meanings of words.

Kyle Jasmin · Daniel Casasanto

The QWERTY effect hypothesis

On average, words typed with more letters from the right side of the keyboard are more positive in meaning than words typed with more letters from the left.
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The QWERTY effect hypothesis

On average, words typed with more letters from the right side of the keyboard are more positive in meaning than words typed with more letters from the left.

Previous evidence

- Evidence in word ratings for English, Spanish, Dutch, and German
- Stronger for post-QWERTY neologisms and present for pseudowords
The research gap

1. Previous evidence from small scale subjective ratings experiments
   - Limitations: design issues, rater disagreement, external validity
   - Observational evidence on baby names is inconclusive
   - Can we observe the QWERTY effect on the Web?

2. Can we observe the QWERTY effect in encoding as well?

Decoding: interpreting the meaning of words (reading)
Encoding: translating meaning into words (writing)
Previous evidence only on decoding
Decoding Study

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Decoding study design

Valence $V$: positivity of crowdsourced evaluation (average rating, percentage of likes...)

Right-Side Ratio $RSR$: of the title or name of what is evaluated

We additionally measure contextual and linguistic controls (word length, frequency, popularity)
## Decoding study datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>N elements</th>
<th>$\langle V \rangle$</th>
<th>scale</th>
<th>$\langle RSR \rangle$</th>
<th>source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>4,257,624</td>
<td>3.86</td>
<td>1-5</td>
<td>0.4176</td>
<td>(McAuley, 2015)</td>
</tr>
<tr>
<td>Yelp</td>
<td>56,103</td>
<td>3.66</td>
<td>1-5</td>
<td>0.4056</td>
<td>Yelp Challenge</td>
</tr>
<tr>
<td>Epinions</td>
<td>223,880</td>
<td>3.89</td>
<td>1-5</td>
<td>0.4174</td>
<td>(Tanase, 2013)</td>
</tr>
<tr>
<td>Dooyoo</td>
<td>112,698</td>
<td>3.89</td>
<td>1-5</td>
<td>0.4184</td>
<td>(Tanase, 2013)</td>
</tr>
<tr>
<td>IMDB</td>
<td>327,608</td>
<td>6.30</td>
<td>1-10</td>
<td>0.425</td>
<td>OMDB</td>
</tr>
<tr>
<td>Rotten Tomatoes</td>
<td>80,756</td>
<td>3.04</td>
<td>1-5</td>
<td>0.4233</td>
<td>OMDB</td>
</tr>
<tr>
<td>MovieLens</td>
<td>29,505</td>
<td>3.11</td>
<td>1-5</td>
<td>0.4245</td>
<td>(Harper, 2015)</td>
</tr>
<tr>
<td>BookCrossing</td>
<td>149,804</td>
<td>7.42</td>
<td>1-10</td>
<td>0.4164</td>
<td>(Ziegler, 2005)</td>
</tr>
<tr>
<td>Youtube</td>
<td>3,292,153</td>
<td>0.94</td>
<td>0/1</td>
<td>0.4294</td>
<td>(Abisheva, 2014)</td>
</tr>
<tr>
<td>Redtube</td>
<td>351,677</td>
<td>0.70</td>
<td>0/1</td>
<td>0.4225</td>
<td>new</td>
</tr>
<tr>
<td>Pornhub</td>
<td>333,967</td>
<td>0.83</td>
<td>0/1</td>
<td>0.4264</td>
<td>new</td>
</tr>
</tbody>
</table>
Statistical analysis methods

1 Linear effect analysis:

\[ V = a + b \times RSR + \epsilon \]

- Hypothesis: Right-side coefficient \( b > 0 \)
- 5 Methods: OLS, MM-robust, bootstrapping, permutation, Spearman

2 Residualized regression to control for possible confounding factors

\[ V = \sum_i c_i \times X_i + V_r \quad V_r = a' + b' \times RSR + \epsilon' \]

- 2.1 Residualized OLS test
- 2.2 When data very large: stratified regression on each control variable
YouTube Video Likes

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</tbody>
</table>

controls: name len, avg word f, avg letter f, nwords, views, comms, date, $N_r$

![Graph showing Likes Ratio vs Video Name RSR](image1)

<table>
<thead>
<tr>
<th>Method</th>
<th>$\hat{b}$</th>
<th>Resid. $\hat{b}$</th>
<th>Bootstrap</th>
<th>Permutation</th>
<th>Spearman</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.0171</td>
<td>0.935</td>
<td>$p &lt; 0.05$</td>
<td>$p &lt; 0.05$</td>
<td>$p &lt; 0.05$</td>
</tr>
<tr>
<td>MM</td>
<td>0.0007</td>
<td>0.945</td>
<td>$p &lt; 0.05$</td>
<td>$p &lt; 0.05$</td>
<td>$p &lt; 0.05$</td>
</tr>
</tbody>
</table>
### Amazon Product Ratings

<table>
<thead>
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<th>Scale</th>
<th>(\langle RSR \rangle)</th>
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<td>4,257,624</td>
<td>3.86</td>
<td>1-5</td>
<td>0.4176</td>
</tr>
</tbody>
</table>

controls: name len, avg word freq, avg letter freq, nwdocs sales rank, price, \(N_r\)

#### Average Rating vs. Product Name RSR

![Average Rating vs. Product Name RSR](image)

#### Density of OLS, MM, Resid. \(\hat{b}\)

<table>
<thead>
<tr>
<th>OLS (\hat{b})</th>
<th>MM (\hat{b})</th>
<th>Resid. (\hat{b})</th>
<th>Bootstrap</th>
<th>Permutation</th>
<th>Spearman</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1984</td>
<td>0.1384</td>
<td>0.0348</td>
<td>(p &lt; 0.05)</td>
<td>(p &lt; 0.05)</td>
<td>(p &lt; 0.05)</td>
</tr>
</tbody>
</table>
### Book Crossing Book Ratings

<table>
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<tr>
<td>BookCrossing (Ziegler et al, 2005)</td>
<td>149,804</td>
<td>7.42</td>
<td>1-10</td>
<td>0.4164</td>
</tr>
</tbody>
</table>

controls: name len, avg word freq, avg letter freq, nwords, $N_r$

![Graph showing average rating and density distribution](image)

<table>
<thead>
<tr>
<th>Method</th>
<th>$\hat{b}$</th>
<th>$\hat{b}_{MM}$</th>
<th>Resid. $\hat{b}$</th>
<th>Bootstrap</th>
<th>Permutation</th>
<th>Spearman</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>0.0414</td>
<td>0.0516</td>
<td>-0.0408</td>
<td>$p &gt; 0.1$</td>
<td>$p &gt; 0.1$</td>
<td>$p &gt; 0.1$</td>
</tr>
</tbody>
</table>
Decoding results summary

- Renormalized estimate of the right side coefficient $\hat{b}$
- Estimate is positive and significant for 9 out of 11 datasets
- Youtube videos with more right letters in the title get more likes
- Products with more right letters in the name have higher ratings
- Movies with more right letters in the title get better ratings
Regression analysis over subsets selected by control variable

**YouTube:** Effect still present for changing controls
Understanding the effect of context: Amazon

Regression analysis over subsets selected by control variable

- Amazon: Effect disappears for high sales and infrequent language
Encoding Study

1 The Linguistic Intergroup Bias
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Encoding study design and methods

1. \( V = a_I + b_I \times \text{Length} \)
2. \( V = a_{RL} + b_R \times R + b_L \times L + b_{RL} \times R \times L \)

- MM-robust \( \Delta R^2_{adj} \)
- bootstrapping and permutation t.
- Hypotheses: \( b_R > 0 \) and \( b_L < 0 \)

Datasets:

<table>
<thead>
<tr>
<th>Website</th>
<th>N reviews</th>
<th>( \langle r \rangle )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon</td>
<td>971,026</td>
<td>4.0582</td>
</tr>
<tr>
<td>Yelp</td>
<td>1,554,163</td>
<td>3.7412</td>
</tr>
<tr>
<td>Dooyoo</td>
<td>523,997</td>
<td>4.0258</td>
</tr>
<tr>
<td>Epinions</td>
<td>101,595</td>
<td>3.9768</td>
</tr>
</tbody>
</table>

stellar rating ➤ V

qwer yuio ta ds jkl fz xvw
qe nm rre nm afdsf as vz
cjhjhx vfdwkkq erfdashl
vdzcv zhnndfre wqe woy
ioihok freaz vz
Review text ➤ R, L
Yelp Business Reviews

<table>
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<th>⟨r⟩</th>
<th>scale</th>
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<thead>
<tr>
<th>Length model</th>
<th>RL model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_l), (b_l)</td>
<td>(a_{RL}), (b_R), (b_L), (b_{RL})</td>
</tr>
<tr>
<td>4.172784, -0.000458</td>
<td>4.263156, 0.000625, -0.001733</td>
</tr>
</tbody>
</table>
## Encoding study results

### Length Model:

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<tr>
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<th>$b_l$</th>
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<td>-0.000123</td>
</tr>
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<td>Dooyoo</td>
<td>4.255313</td>
<td>0.000014</td>
</tr>
<tr>
<td>Epinions</td>
<td>4.274520</td>
<td>0.000007</td>
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</table>

### RL Model:

<table>
<thead>
<tr>
<th>Dataset</th>
<th>$a_{RL}$</th>
<th>$b_R$</th>
<th>$b_L$</th>
<th>$b_{RL}$</th>
<th>$\Delta R^2_{adj}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yelp</td>
<td>4.263156</td>
<td>0.000625</td>
<td>-0.001733</td>
<td>$10^{-7}$</td>
<td>8.2%</td>
</tr>
<tr>
<td>Amazon</td>
<td>4.110348</td>
<td>0.00086</td>
<td>-0.000940</td>
<td>$10^{-8}$</td>
<td>40.4%</td>
</tr>
<tr>
<td>Dooyoo</td>
<td>4.256541</td>
<td>0.000169</td>
<td>-0.000101</td>
<td>0.00</td>
<td>14.5%</td>
</tr>
<tr>
<td>Epinions</td>
<td>4.278481</td>
<td>0.000048</td>
<td>-0.000027</td>
<td>0.00</td>
<td>-5.1%</td>
</tr>
</tbody>
</table>
Discussion: Interpretations

1- The theory
Using the keyboard influences word meanings
1- The theory

Using the keyboard influences word meanings

2- The design

Was the QWERTY design influenced by meanings?
### Discussion: Interpretations

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<table>
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<th>2- The design</th>
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<tr>
<th>3- The confound</th>
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Discussion: Interpretations

1- The theory
Using the keyboard influences word meanings

2- The design
Was the QWERTY design influenced by meanings?

3- The confound
Is this an effect of phonetic/linguistic properties?

4- The unexpected
Is there an army of one-handed spambots?
Discussion: Caveats

1. Beware $N = \text{all}$
   - Representativeness warning: Big data but narrow media
   - No selection of data: Additional clusters and correlations

2. We only saw the traces of the QWERTY effect
   - Lack of control opposed to experimental studies
   - Missing questions: Other languages, effect of handedness...

3. We only test the QWERTY effect hypothesis
   - No evidence that we can predict meaning from the RSR
   - No evidence that we can change evaluations through the RSR

4. Small effects might not be so small
   - Interpreting effect sizes in language is not trivial
Conclusion

- We found evidence of the QWERTY effect when encoding and decoding text from the Web in a wide variety of media.
- We found some limiting factors and counterexamples.
- Data and codes: https://github.com/dgarcia-eu/QWERTY_WWW
Conclusion

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Just a recommendation

If you doubt between two names: Choose the right one!
Thanks for listening!

More in: dgarcia.eu and Twitter: @dgarcia_eu