#anorexia, #anarexia, #anarexyia: Characterizing Online Community Practices with Orthographic Variation

Ian Stewart, Stevie Chancellor, Munmun De Choudhury and Jacob Eisenstein SocialNLP 2017

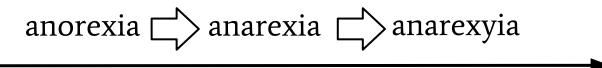


Language variation online

- Online language is subject to profound variation and rapid change over time. (Androutsopoulos 2011)
- An individual's adoption of language change in a particular online community is related to their community **membership.** (Sebba 2009)

Orthographic change

- Prior studies in online language have focused mainly on **lexical** change. (Danescu-Niculescu-Mizil et al. 2013)
- Change at the level of **orthography** is also important but less well understood. (Herring 2012)



Research questions

RQ1: Who adopts new orthographic variants?

RQ2: Does a variant's **depth** influence its likelihood of **adoption** by these community members?

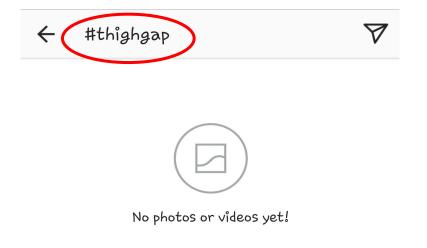
RQ3: Does a variant's **depth** influence its **social reception**?

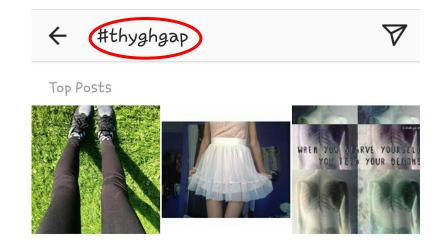
Warning: eating disorders

Pro-ED Instagram

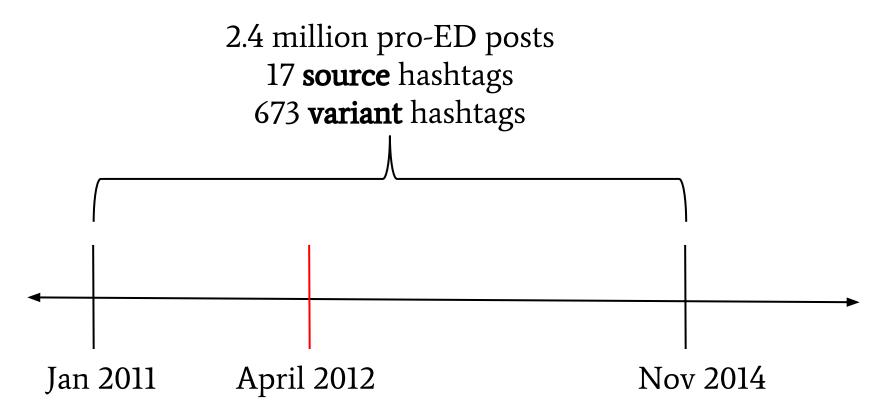
- Community that "share[s] content, advice and provide[s] social support for **disordered or unusual eating choices.**" (Chancellor et al. 2016)
- Community of practice: "aggregate of people who come together around mutual engagement in an endeavor." (Eckert & McConnell-Ginet 1992)

Content ban

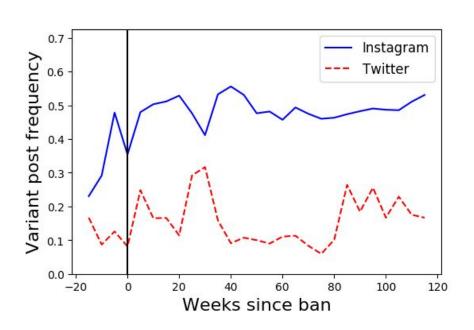


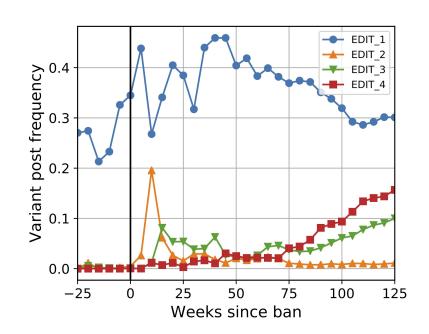


Pro-ED posts (Chancellor et al. 2016)



Variants grow more frequent, "deeper"



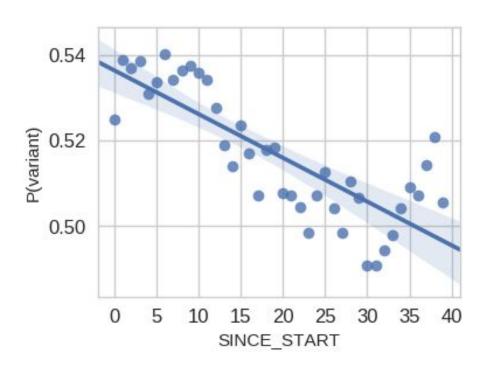


Who drives this change?

Differentiating community members

- Membership attributes:
 - Age
 - Lifespan

• **Newcomers** and **committed** (long-lifespan) community members.



- Regression results
 - Predicting appearance of any variant in a post.

- Regression results
 - Age: $\beta = -0.00456***$, effect size = **-0.348**
 - Lifespan: $\beta = 0.00294***$, effect size = **0.654**

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*** = p < 0.001
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• Conclusion: variants adopted more often by **newcomers** and **committed** members.

Research questions

RQ1: Which community members adopt more variants?

RQ2: Does a variant's depth influence its likelihood of adoption by these community members?

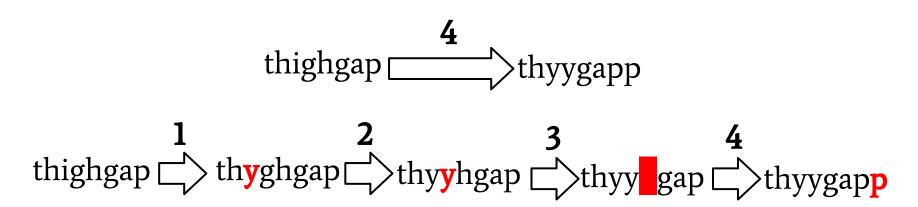
RQ3: Does a variant's depth influence the post's social reception?

Compute depth: edit distance

- Operations needed to transform source → variant hashtag
 - Used in dialectology (Nerbonne, Heeringa & Kleiweg 1999)

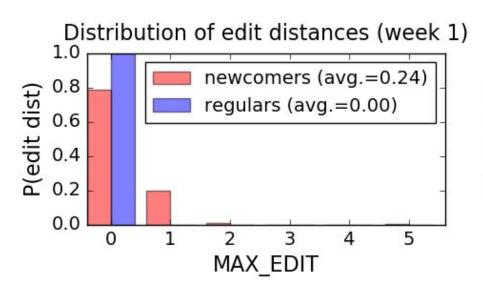
Compute depth: edit distance

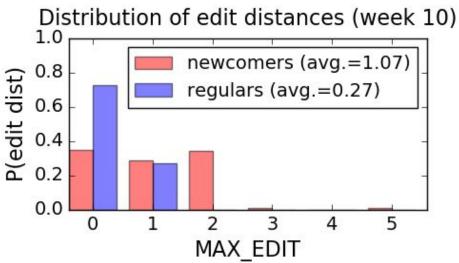
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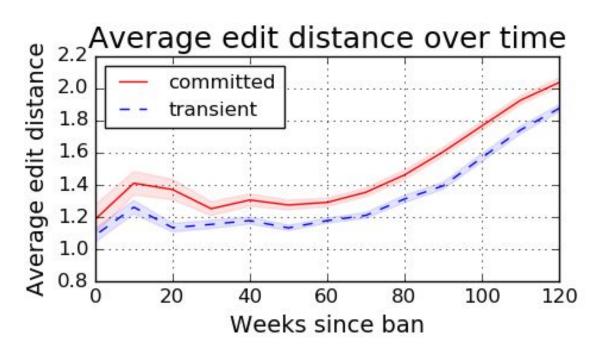
• Deeper variants are adopted by **newcomers** and **committed** members.

Newcomers > regulars





Committed > transient



- Regression
 - Predicting appearance of **shallow** (distance 1) and **deep** (distance 4) variant.

- **More extreme effects** for deeper variants.
- Distance 1
 - \circ Age: $\beta = -0.00177***$, effect size = **-0.097**
- Distance 4
 - Age: $\beta = -0.00450***$, effect size = **-0.416**

• Conclusion: **deeper variants** are more often adopted by newcomers and committed members.

Social reception: likes and comments.

- Regression results
 - Control for hashtags used, presence of any variant, and fixed-effect for each member.

COMMENTS

LIKES

Edit distance: -3.72E-3

Edit distance: 0.0130***

*** = p < 0.001, otherwise p > 0.05

• Conclusion: greater orthographic depth implies **more likes**.

Implications

- Why do newcomers use more variants and deeper variation?
 - (1) Newcomers are **over-compensating** for perceived orthographic conventions.
 - (2) "Newcomers" are banned accounts whose behavior is worsening after returning from ban (Cheng, Danescu-Niculescu-Mizil, Leskovec 2014).
 - (3) Newcomers are generating new variants to **distinguish** from current community members ("flag-planting").

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 - (3) Newcomers are generating new variants to distinguish from current community members ("flag-planting").
- Deeper variants → stronger effects.
 - Effect is **incremental**, not just binary.
 - Orthographic variation reveals hidden community dynamics.

References

- Androutsopoulos, J. (2011). Language change and digital media: a review of conceptions and evidence. *Standard Languages and Language Standards in a Changing Europe*, 145–159.
- Chancellor, S., Pater, J. A., Clear, T., Gilbert, E., & De Choudhury, M. (2016). #thyghgapp: Instagram Content Moderation and Lexical Variation in Pro-Eating Disorder Communities. 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing, 1201–1213.
- Cheng, J., Danescu-Niculescu-Mizil, C., & Leskovec, J. (2014). How Community Feedback Shapes User Behavior. In *ICWSM* (pp. 41--50).
- Danescu-Niculescu-Mizil, C., West, R., Jurafsky, D., & Potts, C. (2013). No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities. *Proceedings of the 22nd International Conference on World Wide Web*, 307–317.
- Eckert, P., & McConnell-Ginet, S. (1992). Think Practically and Look Locally: Language and Gender as Community-Based Practice. *Annual Review of Anthropology*, *21*(1992), 461–490.
- Herring, S. C. (2012). Grammar and electronic communication. *The Encyclopedia of Applied Linguistics*, 1–9.
- Nerbonne, J., Heeringa, W. and Kleiweg, P. (1999). "Edit distance and dialect proximity". In *Time Warps, String Edits and Macromolecules: The Theory and Practice of Sequence Comparison*, 2nd edition, Edited by: Sankoff, D. and Kruskal, J. v—xv.
- Sebba, M. (2009). Sociolinguistic approaches to writing systems research. Writing Systems Research, 1(1), 35–49.

Acknowledgments

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Questions?



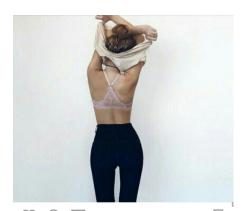
istewart6@gatech.edu



@alethioguy

Backup slides

Pro-ED Instagram



● 7 likes

Todays total : 906 calories 😝 today was horrible 💝 😝 #Ana #anorexia #staystrong #fat #ugly #disgusting #nothappy #sad #strong #ed #eatingdisorder #girl #cutting #losingweight #weight #wishweight #clean #horribleday #horrible #selfharm

Great



Feeling a little better..if i want to

reach my goal i have to be patient and work harder. I

hope you are doing the same :) #cardio #excercise

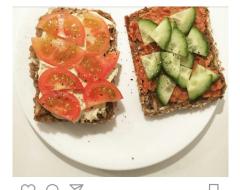
#loseweight #workout #skinny #thin #thighggap

#thighgap

• 6 likes

#collarbones





/ U V

11 likes

#dinner today was some whole grain spelt bread with sunflower seeds (yummy) topped with humous, tomatoes, dried tomato spread and some cucumber... I also had some leftover sauerkraut ##d #anorexia #bulimia #vegan #dinner #veganrecovery #thisorhospital #edfamily #anawho #2fab4ana #recover #edfighter #edwarriors #edwarrior #edsoldier #edfree #eatingdisorderrecovery

Pro-ED Instagram

```
Feeling a little better..if i want to reach my goal i have to be patient and work harder. I hope you are doing the same :) #cardio #excercise #loseweight #workout #skinny #thir #thighggap #collarbones

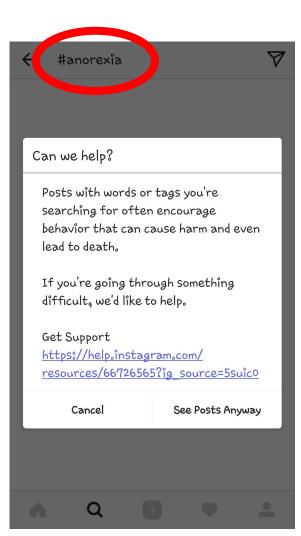
#thighgap
```

Pro-ED Instagram

Feeling a little better..if i want to reach my goal i have to be patient and work harder. I hope you are doing the same:) #cardio #excercise #loseweight #workout #skinny #thir #thighggap #collarbones #thighgap

(space between thighs)

Ban effect



All source hashtags

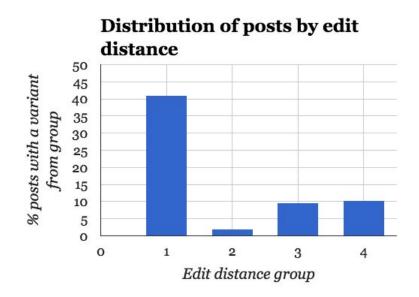
- ana
- anorexia
- anorexianervosa
- bonespo
- bulimia
- eatingdisorder
- mia
- proana
- proanorexia

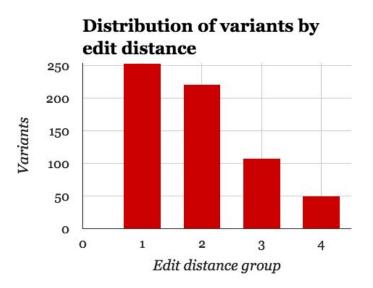
- probulimia
- promia
- secretsociety123
- skinny
- thighgap
- thin
- thinspiration
- thinspo

Distribution of variants

Edit distance	Top 3 variants	Source hashtags	Variants	% posts with at least one variant from group
1	anarexia, bulimic, eatingdisorders	17	253	41.1%
2	anarexyia, thinspooo, thynspoo	15	221	2.07%
3	secretsociety123, thinspoooo, thygap	15	108	9.60%
4	secret_society123, secretsociety_123, thinspooooo	10	50	10.4%

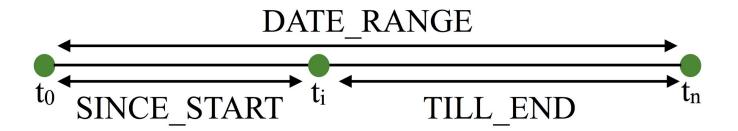
Distribution of variants



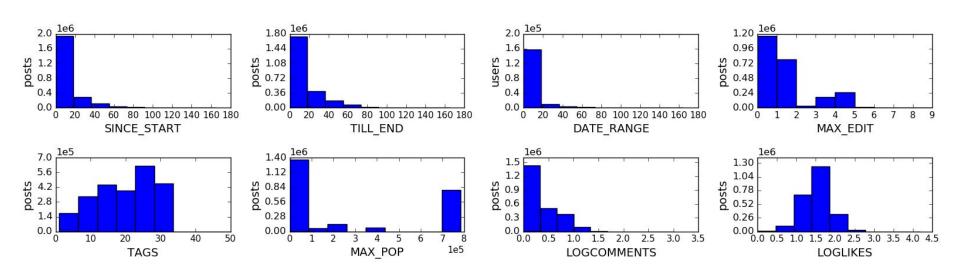


Differentiating community members

- Per post:
 - SINCE_START, TILL_END
- Per member:
 - DATE_RANGE



Variable distributions



Regression: predictors

	RQ1	RQ2	RQ3
Regression	Logistic	Logistic	Poisson
Predicted	VARIANT	DIST_1, DIST_4	COMMENTS, LIKES
Predictors	SINCE_START, TILL_END, DATE_RANGE, DATE	SINCE_START, DATE_RANGE, DATE	SINCE_START, DATE_RANGE, MAX_EDIT, VARIANT, MAX_POP, fixed effect for member

RQ1: Who adopts new orthographic variants?

• Regression results

	β	SE	Effect size
SINCE_START	-0.00456***	2.97E-4	-0.348
TILL_END	0.00294***	2.88E-4	0.654
DATE	0.00529***	1.77E-4	0.746
	β	SE	Effect size
DATE_RANGE	0.00294***	2.89E-4	0.654
DATE	0.00541***	1.77E-4	0.746

*** = p < 0.001

RQ3: Does a variant's depth influence the post's social reception?

COMMENTS

	β	SE
SINCE_START	5.27E-3*	1.57E-3
TAGS	0.110***	2.57E-3
VARIANT	-7.89E-3	3.44E-3
MAX_POP	-2.33E-3	1.26E-3
MAX_EDIT	-3.72E-3	5.51E-3

LIKES

	β	SE
SINCE_START	-0.0319***	9.03E-4
TAGS	0.224***	1.47E-3
VARIANT	-0.00149***	1.98E-3
MAX_POP	-3.89E-3***	7.25E-4
MAX_EDIT	0.0130***	3.16E-3

*** = p < 0.001, * = p < 0.05, otherwise p > 0.05