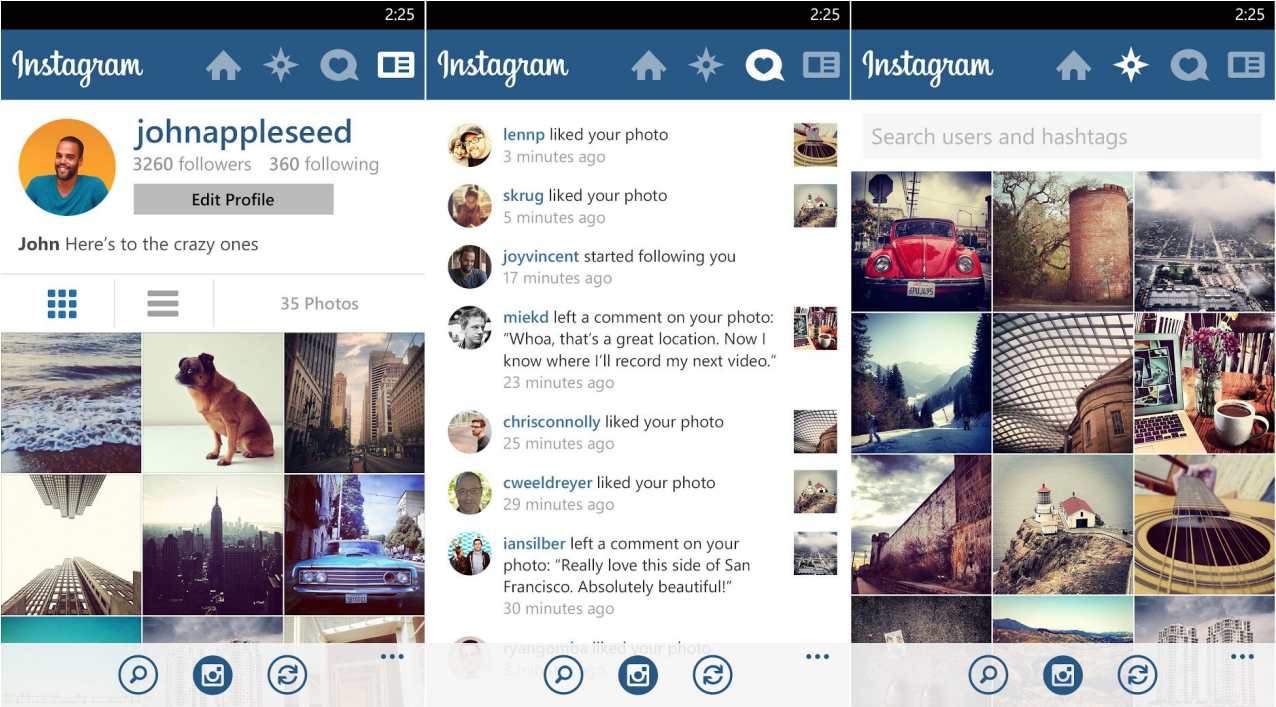


#thighgap to #thyghgapp: Incrementation of orthographic variation on Instagram

Ian Stewart and Jacob Eisenstein
Georgia Institute of Technology

Content warning: eating disorders

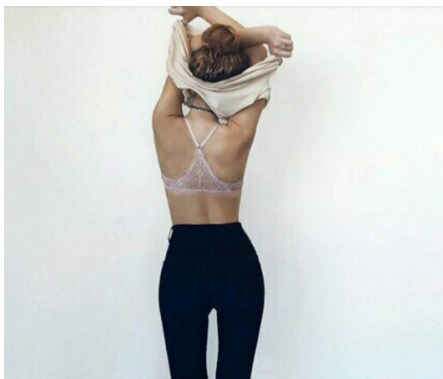
Instagram



Pro-ED Instagram

- Community that “share[s] content, advice and provide[s] social support for disordered or unusual eating choices” (Chancellor et al. 2015)

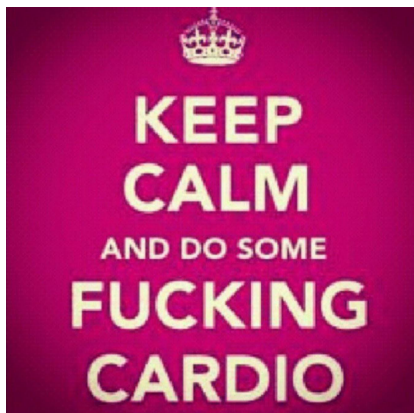
Pro-ED Instagram



7 likes

██████████ Today's 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

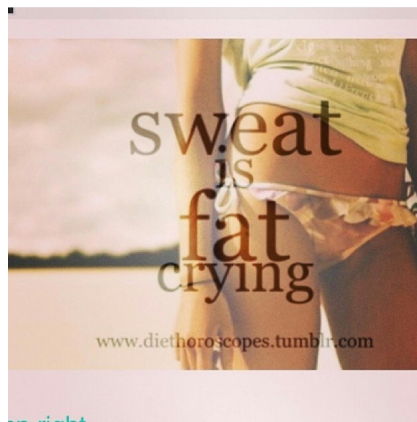
██████████ Great



6 likes

██████████ 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 #exercise #loseweight #workout #skinny #thin #thighgap #collarbones

██████████ #thighgap



22 likes

██████████ #ana #mia #ed #bones #bonsepo #fitspo #thygap #thynsperation



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 ❤️ #ed #anorexia #bulimia #vegan #dinner #veganrecovery #thisorhospital #edfamily #anawho #2fab4ana #recover #edfighter #edwarriors #edwarrior #edsoldier #edfree #eatingdisorderrecovery

Pro-ED Instagram

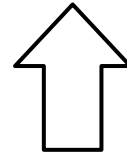
██████████ Feeling a little better..if i want to reach my goal i have to be patient and work harder. I hope you are doing the same :) #cardio #exercise #loseweight #workout #skinny #thin #thighgap #collarbones

██████████ #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 #exccercise #loseweight #workout #skinny #thin #thighgap #collarbones

██████████ #thighgap



thighgap

(space between thighs)

Orthographic variation

- “Represent spoken and vernacular forms, simulate prosody or shorten the message” (Androutsopoulos 2011)
- Tied to social differentiation, identity marking (Sebba 2009)
 - Community may only allow certain variants (Herring 2012)

Phonetic	<just> → <jus>
----------	----------------

Typographic	<leet speak> → <1337 5934K>
-------------	-----------------------------

Syllabograms	<before> → <b4>
--------------	-----------------

Dynamics of variation

- Writing conventions evolve over time (Sebba 2009)
- Communities are dynamic
 - Language change mirrors social dynamics (Danescu-Niculescu-Mizil et al. 2013)
 - Locally-defined social categories: newcomers vs. regulars
- Changing practices of pro-ED community
 - Community of practice: “aggregate of people who come together around mutual engagement in an endeavor” (Eckert & McConnell-Ginet 1992)

Community change: hashtag ban

SOCIETY

Instagram Bans Thinspo Content

Instagram is the latest social media platform to ban thinspiration content. But are these policies effective?

By Heba Hasan @Heba__H | April 26, 2012

[f Share](#) [Like 57](#) [Tweet](#) [G+1](#) [18](#) [in Share](#) [1](#) [Pin it](#) [Read Later](#)

Thinspo content will no longer be welcome on Instagram. Following in the footsteps of Pinterest and Tumblr, Instagram is the latest social media site to ban “thinspiration” photos — images that are meant to provide motivation for those who want to lose weight and which health experts say often contribute to eating disorders.

Instagram’s new policy doesn’t come as a surprise. The app came under scrutiny last week when celebrity and Instagram user Alexa Chung posted a photo of herself and was attacked by users for being too skinny.



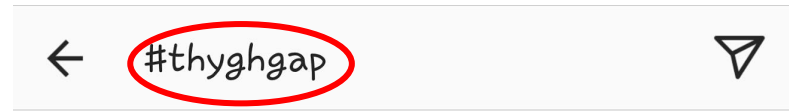
Michaela Begsteiger/Getty

Instagram bans thinspo content

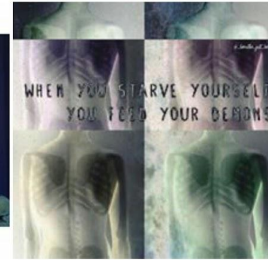
Ban effect



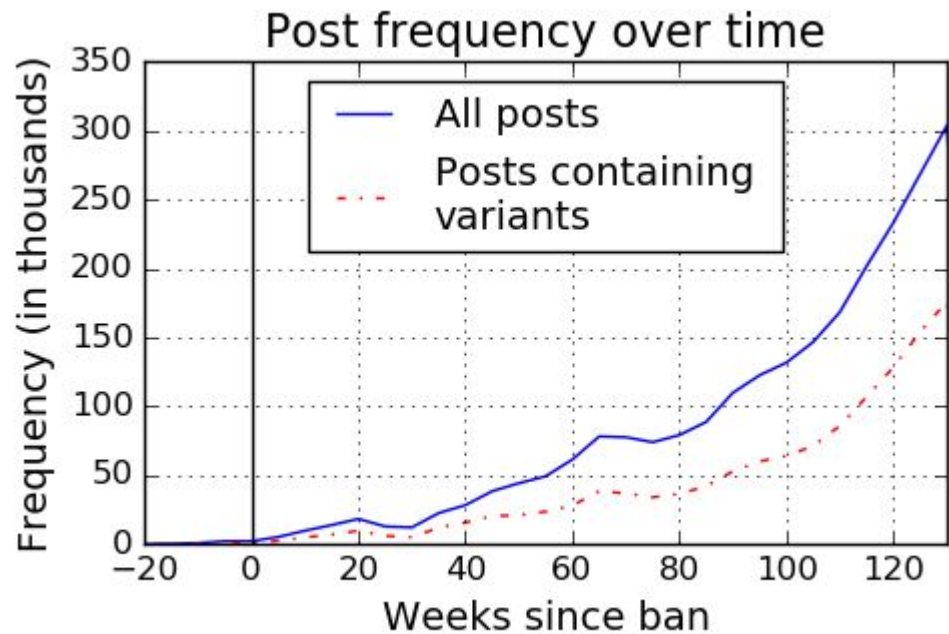
No photos or videos yet!



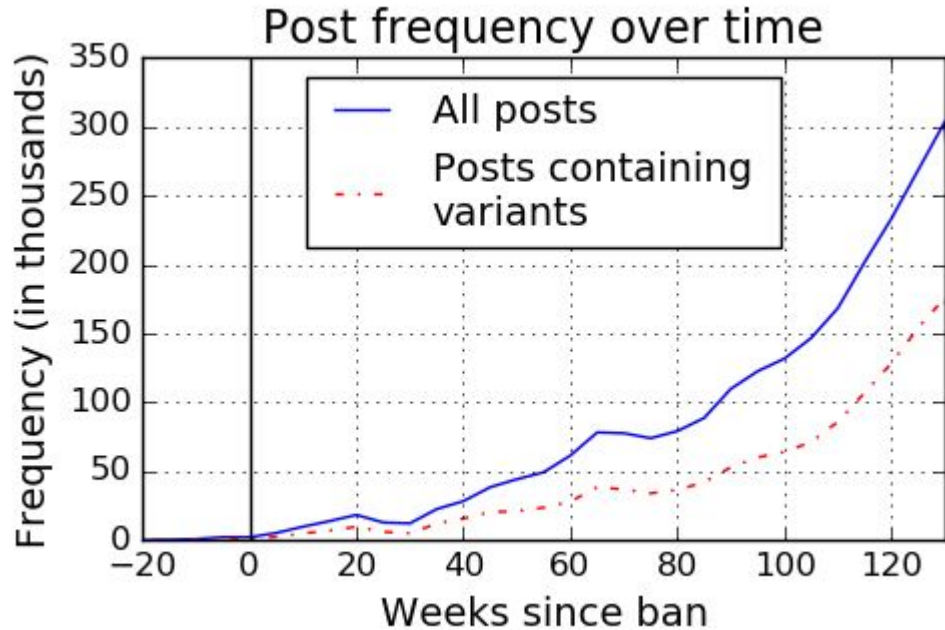
Top Posts



Ban response

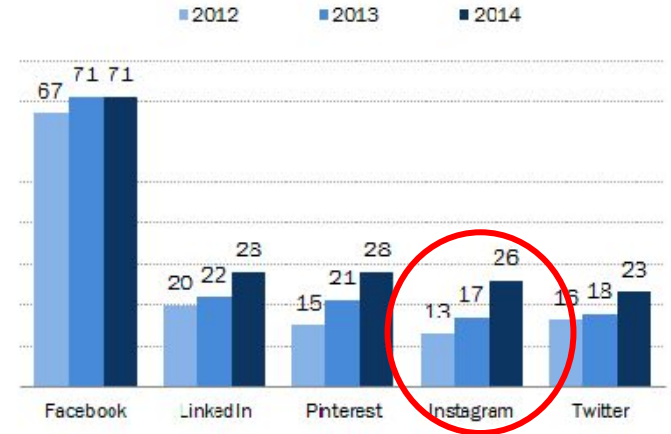


Ban response



Social media sites, 2012-2014

% of online adults who use the following social media websites, by year



Pew Research Center's Internet Project Surveys, 2012-2014. 2014 data collected September 11-14 & September 18-21, 2014. N=1,597 internet users ages 18+.

PEW RESEARCH CENTER

Research questions

RQ1: Which community members adopt more variants?

Example variants

thighgap

Example variants

	thyghgap	thyghgapp	thyygap	thyygapp
thighgap	thghgap	thiigap	thighgaappp	thygaps
	thightgap	thightgrap	thightpag	thygsp

Example variants

	thyghgap	thyghgapp	thyygap	thyygapp
thighgap	thghgap	thiigap	thighgaappp	thygaps
	thightgap	thightgrap	thightpag	thygsp



Depth

Example variants

	thyghgap	thyghgapp	thyygap	thyygapp
thighgap	thghgap	thiigap	thighgaappp	thygaps
	thightgap	thightgrap	thightpag	thygsp



Depth

Incrementation of variation

- Orthographic variation as continuum
- Similar to phonetic incrementation
 - “Successive cohorts and generations of children advance a change beyond the level of their caretakers and role models” (Labov 2001)
- Do community members adopt deeper variants differently than shallow ones?

Research questions

RQ1: Which community members adopt more variants?

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

Methods

- Data collection
- Compute orthographic depth (language variables)
- Compute membership attributes (community variables)
- Building regression models

Methods

- **Data collection**
- Compute orthographic depth (language variables)
- Compute membership attributes (community variables)
- Building regression models

Data collection (Chancellor et al. 2015)

- Collected in November 2014
 - Ban in April 2012
- 2.4 million posts
 - January 2011 to November 2014

Data collection (Chancellor et al. 2015)

Data collection (Chancellor et al. 2015)

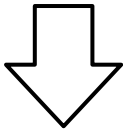
Identify pro-ED seed terms
(not banned), mine
Instagram

anorexia, ed, bulimia

Data collection (Chancellor et al. 2015)

Identify pro-ED seed terms
(not banned), mine
Instagram

anorexia, ed, bulimia

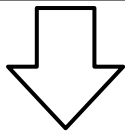


Filter for pro-ED content,
identify top 200 hashtags

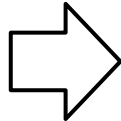
Data collection (Chancellor et al. 2015)

Identify pro-ED seed terms
(not banned), mine
Instagram

anorexia, ed, bulimia



Filter for pro-ED content,
identify top 200 hashtags



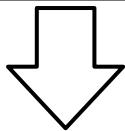
Manually identify 17 banned
source hashtags

ana, thighgap, thinspo

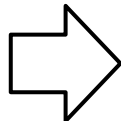
Data collection (Chancellor et al. 2015)

Identify pro-ED seed terms
(not banned), mine
Instagram

anorexia, ed, bulimia



Filter for pro-ED content,
identify top 200 hashtags



Extract 673 variants with
regular expressions

th*nsपो* => thynspoo



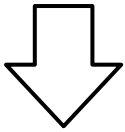
Manually identify 17 banned
source hashtags

ana, thighgap, thinspo

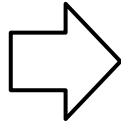
Data collection (Chancellor et al. 2015)

Identify pro-ED seed terms
(not banned), mine
Instagram

anorexia, ed, bulimia

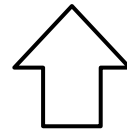


Filter for pro-ED content,
identify top 200 hashtags



Extract 673 variants with
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th*nsपो* => thynspo



Manually identify 17 banned
source hashtags

ana, thighgap, thinspo

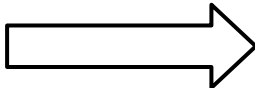
2.4 million posts
176,000 users
51% variant posts
673 variants
17 sources

Methods

- Data collection
- **Compute orthographic depth (language variables)**
- Compute membership attributes (community variables)
- Building regression models

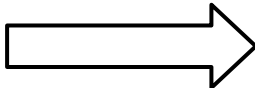
Compute depth: edit distance

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

thighgap  thyygapp

Compute depth: edit distance

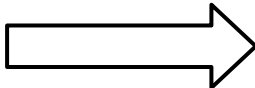
- Operations needed to transform source → variant hashtag
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thihgap  thyygapp

thihgap

Compute depth: edit distance

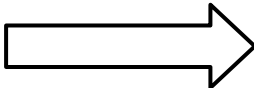
- Operations needed to transform source → variant hashtag
 - Used in dialectology (Nerbonne, Heeringa & Kleiweg 1999)

thighgap  thyygapp

thighgap ¹ th^yghgap

Compute depth: edit distance

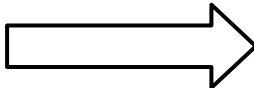
- Operations needed to transform source → variant hashtag
 - Used in dialectology (Nerbonne, Heeringa & Kleiweg 1999)

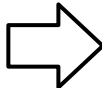
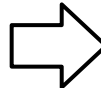
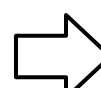

thighgap  thyygapp

thighgap ¹  th^yghgap ²  th^yhgap

Compute depth: edit distance

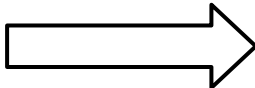
- Operations needed to transform source → variant hashtag
 - Used in dialectology (Nerbonne, Heeringa & Kleiweg 1999)

thighgap  thyygapp

thighgap ¹  th^yghgap ²  th^yhgapp ³  thyy  gap

Compute depth: edit distance

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

thighgap  thyygapp

thighgap ¹  th^yghgap ²  th^yhgapp ³  thyy  gap ⁴  thyygapp^p

Compute depth: edit distance

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

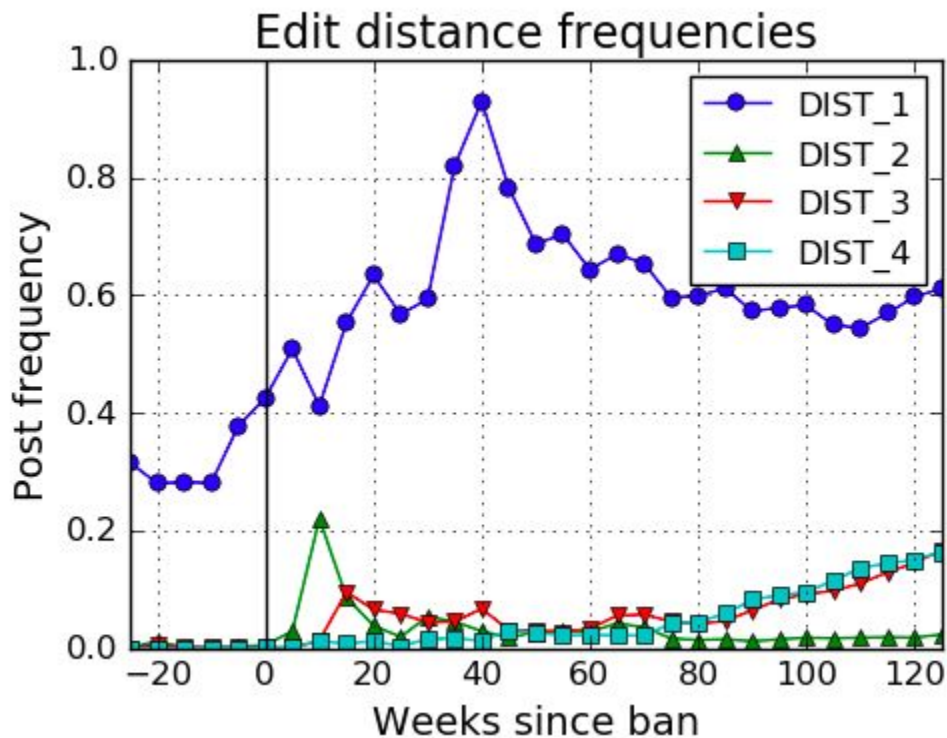
thighgap $\xrightarrow{4}$ thyygapp

thighgap $\xrightarrow{1}$ th^yghgap $\xrightarrow{2}$ thyy^hgap $\xrightarrow{3}$ thyy█gap $\xrightarrow{4}$ thyygap^p

Edit distance: Distribution of variants

Edit distance	Variants	Top 3 variants
1	253	anarexia, bulimic, eatingdisorders
2	221	anarexyia, thinspooo, thynspoo
3	108	secretociety123, thinspoooo, thygap
4	50	secret_society123, secretociety_123, thinspooooo

Edit distance: Adoption over time

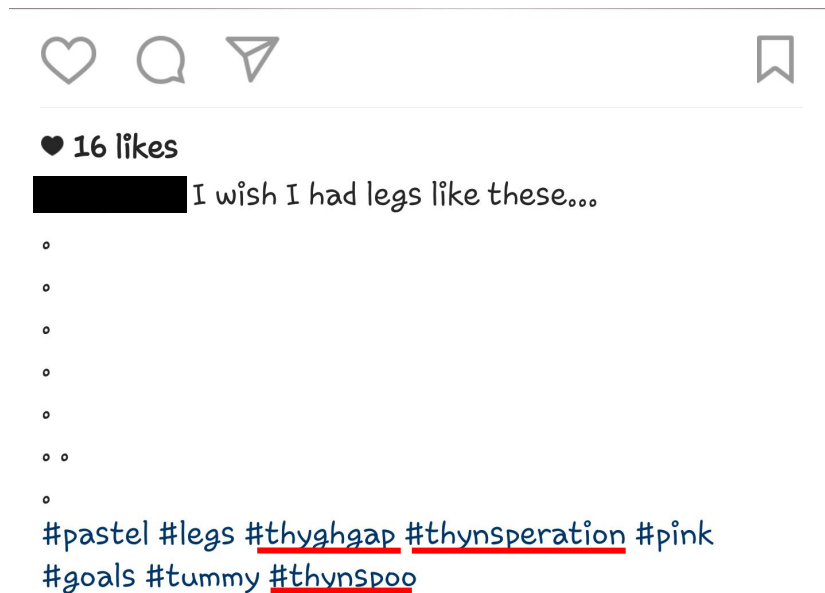


Language variables

- per post:
 - TAGS, VARIANT, MAX_EDIT, DIST_1, DIST_4

Language variables

- per post:
 - TAGS, VARIANT, MAX_EDIT, DIST_1, DIST_4



Language variables

- per post:
 - TAGS, VARIANT, MAX_EDIT, DIST_1, DIST_4

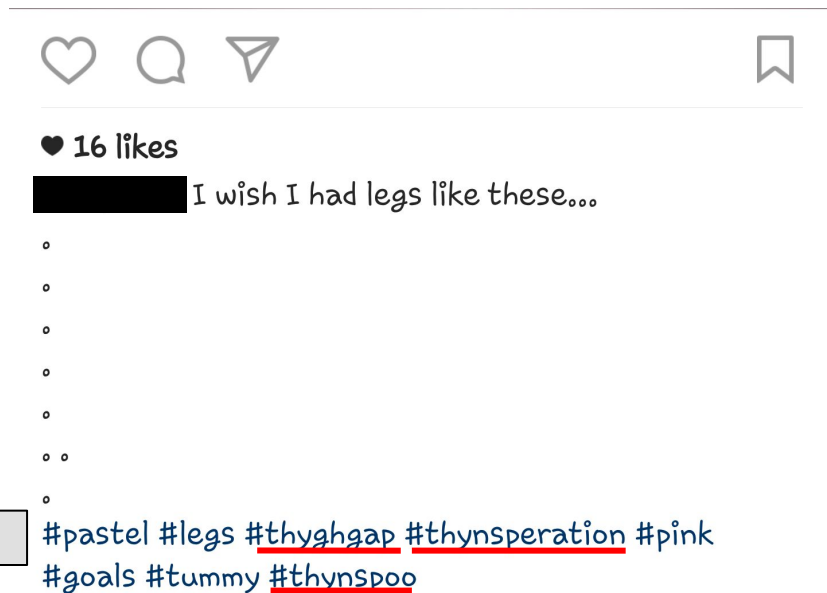
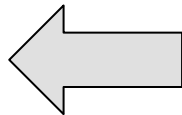
TAGS=3

VARIANT=1

MAX_EDIT=2

DIST_1=1

DIST_4=0



Methods

- Data collection
- **Compute orthographic depth (language variables)**
- **Compute membership attributes (community variables)**
- Building regression models

Community data: membership attributes

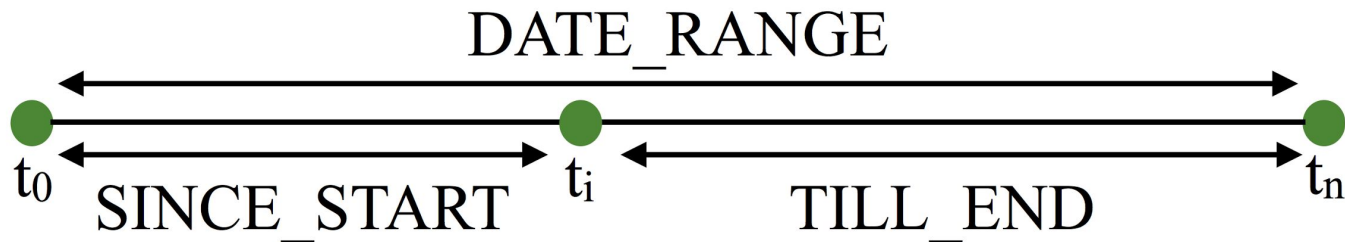
- Locally-defined variables (within pro-ED community):
 - relative age
 - lifespan

Community data: membership attributes

- per post:
 - `SINCE_START, TILL_END`
- per user:
 - `DATE_RANGE`

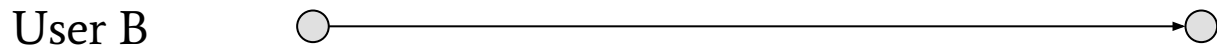
Community data: membership attributes

- per post:
 - `SINCE_START, TILL_END`
- per user:
 - `DATE_RANGE`



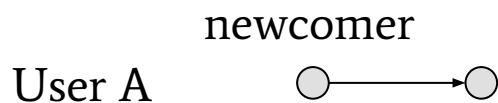
Community data: membership attributes

- newcomer = low **SINCE_START** (< 10 weeks)
- committed user = high **DATE_RANGE** (≥ 10 weeks)



Community data: membership attributes

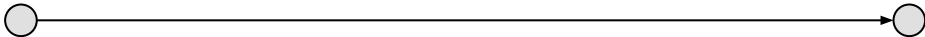
- newcomer = low **SINCE_START** (< 10 weeks)
- committed user = high **DATE_RANGE** (≥ 10 weeks)



Community data: membership attributes

- newcomer = low **SINCE_START** (< 10 weeks)
- committed user = high **DATE_RANGE** (≥ 10 weeks)

User A 
transient

User B 
committed

Recap: all variables

- per post:
 - **VARIANT**, **DIST_1**, **DIST_4**, **MAX_EDIT**, **TAGS**, **SINCE_START**, **TILL_END**, **DATE**
- per user:
 - **DATE_RANGE**

Methods

- Data collection
- **Compute orthographic depth (language variables)**
- Compute membership attributes (community variables)
- **Building regression models**

Questions

RQ1: Which community members adopt variants?

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

Regression: predictors

	RQ1	RQ2
Regression	Logistic	Logistic
Predicted	VARIANT	DIST_1 DIST_4
Predictors	SINCE_START TILL_END DATE_RANGE	SINCE_START TILL_END DATE_RANGE

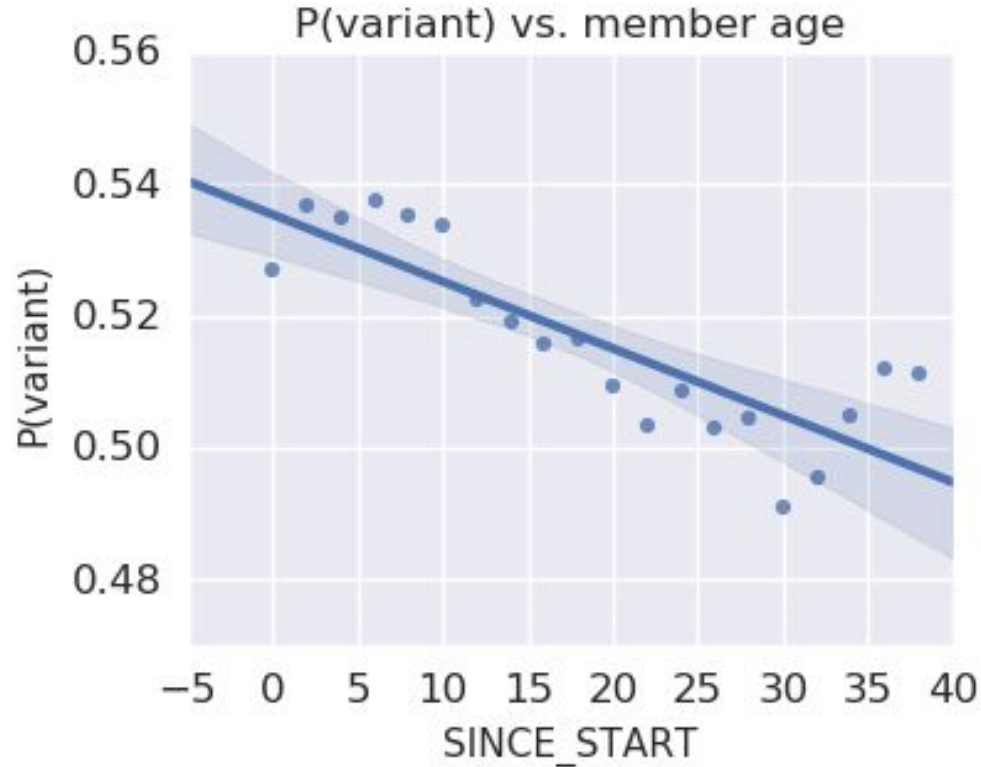
Results

RQ1: Which community members adopt variants?

RQ1: Which community members adopt variants?

- Newcomers and committed (long-lifespan) users

RQ1: Which community members adopt variants?



RQ1: Which community members adopt variants?

- Regression results

RQ1: Which community members adopt variants?

- Regression results
- Predicting **VARIANT**
 - **SINCE_START** negatively correlated ($\beta = -0.00456$, $p < 0.001$)
 - **TILL_END** positively correlated ($\beta = 0.00294$, $p < 0.001$)
 - **DATE_RANGE** positively correlated ($\beta = 0.00294$, $p < 0.001$)

RQ1: Which community members adopt variants?

- Regression results
- Predicting **VARIANT**
 - **SINCE_START** negatively correlated ($\beta = -0.00456$, $p < 0.001$)
 - **TILL_END** positively correlated ($\beta = 0.00294$, $p < 0.001$)
 - **DATE_RANGE** positively correlated ($\beta = 0.00294$, $p < 0.001$)
- Conclusion: variants adopted more often by newcomers and committed members

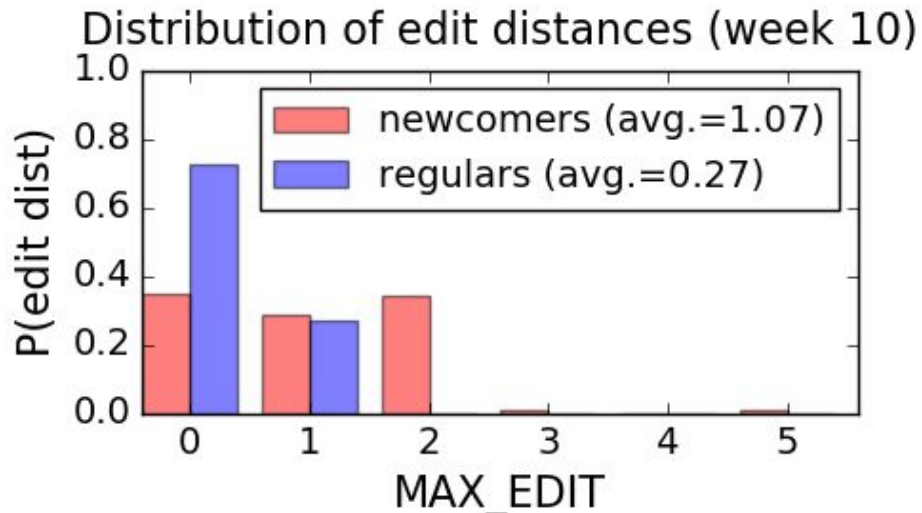
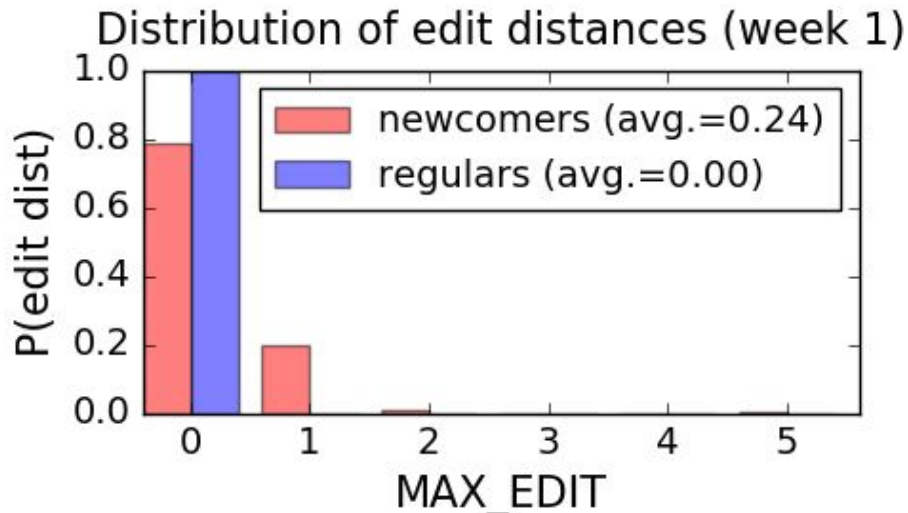
RQ2: Does a variant's depth influence its likelihood of adoption?

RQ2: Does a variant's depth influence its likelihood of adoption?

- Deeper variants associated with newcomers and committed members

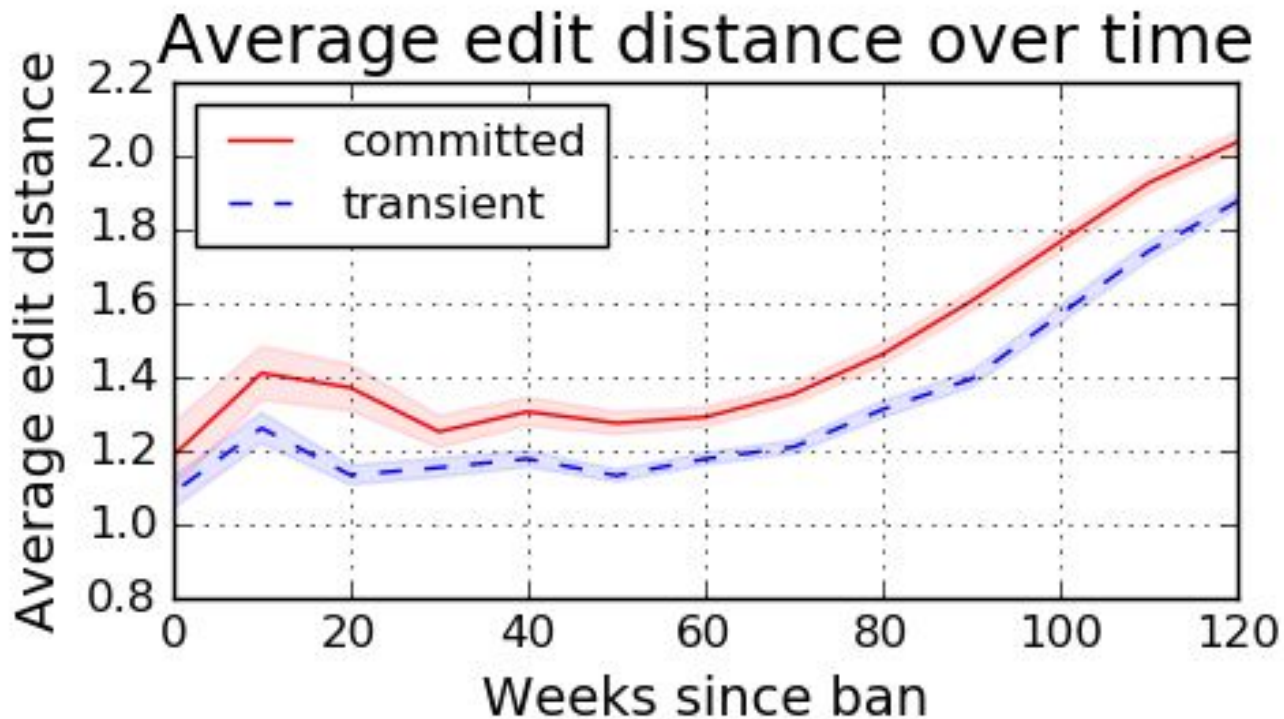
RQ2: Does a variant's depth influence its likelihood of adoption?

Newcomers versus regulars



RQ2: Does a variant's depth influence its likelihood of adoption?

Committed versus transient



RQ2: Does a variant's depth influence its likelihood of adoption?

- Regression results

RQ2: Does a variant's depth influence its likelihood of adoption?

- Regression results
- Predicting **DIST_1**
 - **SINCE_START** $\beta = -0.00177$, ($p < 0.001$)
 - **TILL_END** $\beta = 0.00311$ ($p < 0.001$)

RQ2: Does a variant's depth influence its likelihood of adoption?

- Regression results
- Predicting **DIST_1**
 - **SINCE_START** $\beta = -0.00177$, ($p < 0.001$)
 - **TILL_END** $\beta = 0.00311$ ($p < 0.001$)
- Predicting **DIST_4**
 - **SINCE_START** $\beta = -0.00450$ ($p < 0.001$)
 - **TILL_END** $\beta = 0.0133$ ($p < 0.001$)

RQ2: Does a variant's depth influence its likelihood of adoption?

- Regression results
- Predicting **DIST_1**
 - **SINCE_START** $\beta = -0.00177$, ($p < 0.001$)
 - **TILL_END** $\beta = 0.00311$ ($p < 0.001$)
- Predicting **DIST_4**
 - **SINCE_START** $\beta = -0.00450$ ($p < 0.001$)
 - **TILL_END** $\beta = 0.0133$ ($p < 0.001$)
- Conclusion: depth of variation correlates more strongly with adoption by newcomers and committed members

Summary of findings

- Newcomers use more variants, deeper variation
 - Supports prior findings (Danescu-Niculescu-Mizil et al. 2013)
- Committed members also use more/deeper variants
- Deeper variants → stronger effects
 - Depth may influence orthographic perception in pro-ED community
- Additional: unclear social reception
 - Mixed results (likes ≠ comments)

Implications and future work

- Implications

- Online communities provide useful setting to study large-scale, long-term language variation
- Orthographic variation as incrementation
- Sociotechnical effect on language variation

- Future work

- Different processes of orthographic variation: deletion, lengthening, metathesis

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Thank you!

Special thanks: Stevie Chancellor and Munmun De Choudhury
(Georgia Institute of Technology)

Questions?