Social meanings from social media

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Taming the **SOCIAL** web

- Language is the dominant modality for web content.
- Syntax (parsing) provides the scaffolding that enables the construction of propositional meaning from words.
- But social dynamics play an important, underappreciated role:
  - Sociolinguistic **variation** affects the expression of propositional content.
  - People use language to create **social meaning**, thus situating themselves in the social world.

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- There's propositional content here!
  But variation makes it difficult to get.
- uu is neither shorter nor easier than u.
  This extra effort suggests that uu carries social meaning.

Here's looking at uu

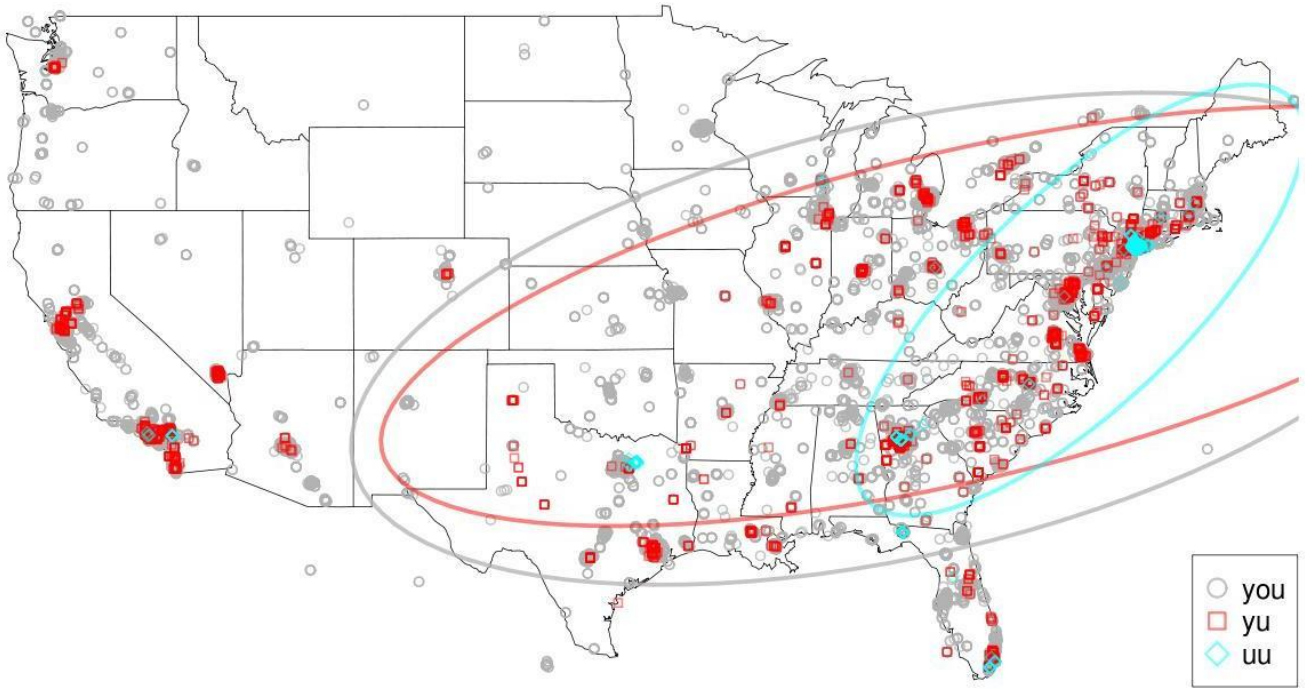
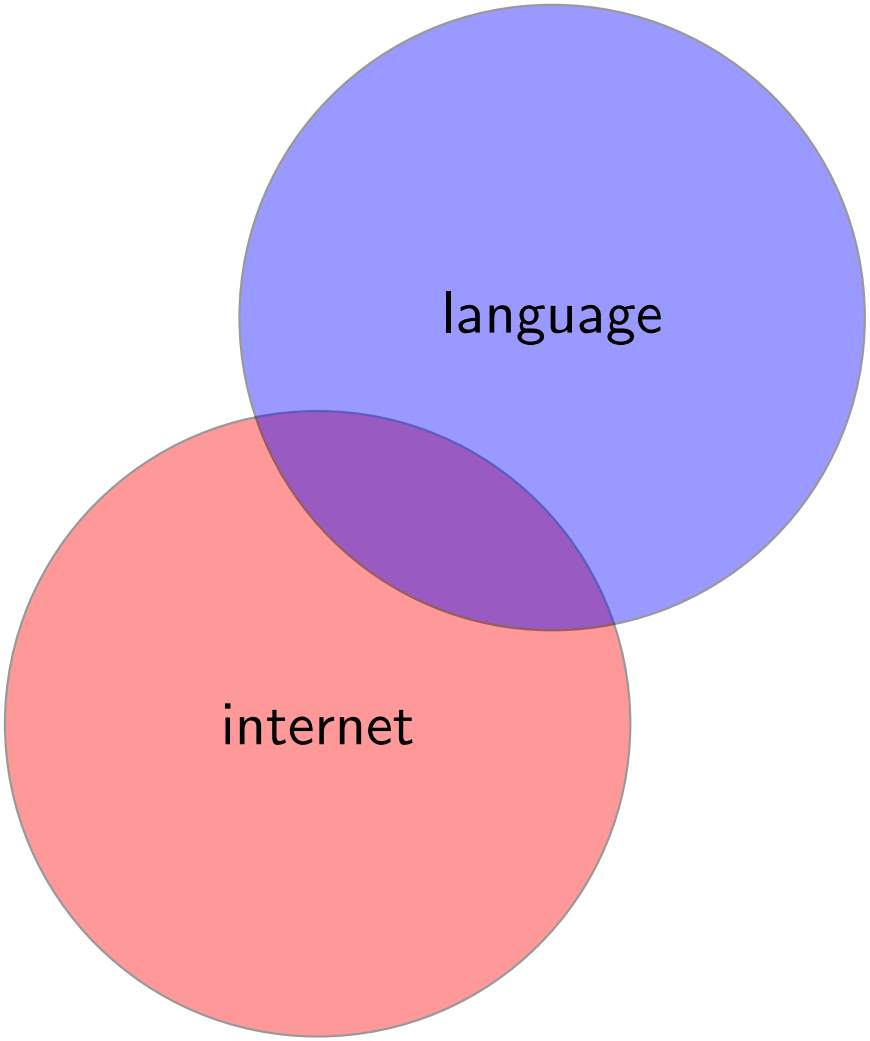


Figure: You and variants in March 2010

- Why uu instead of u?
- Why New York?
- Is it everyone in New York?

Taming the social web



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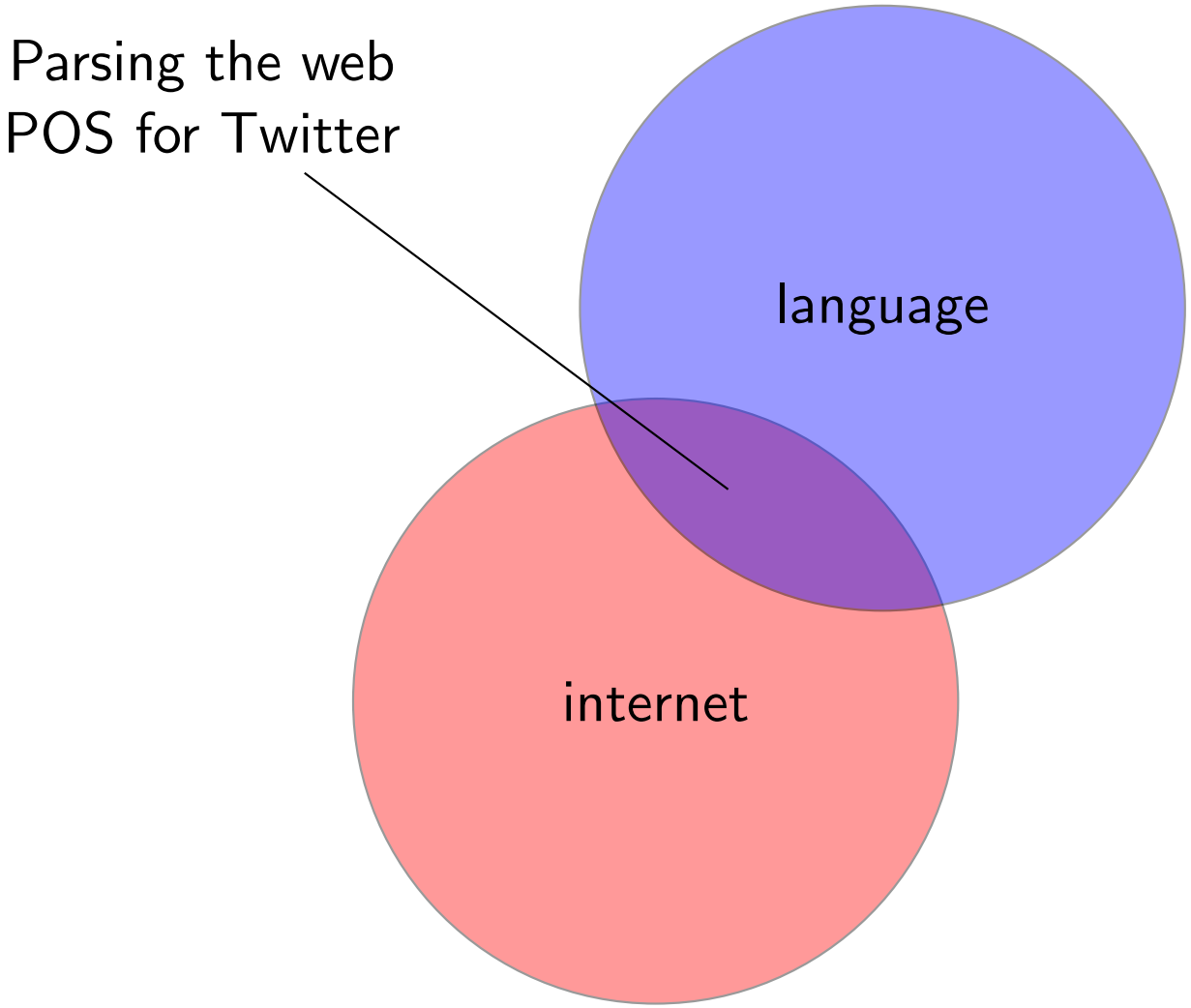
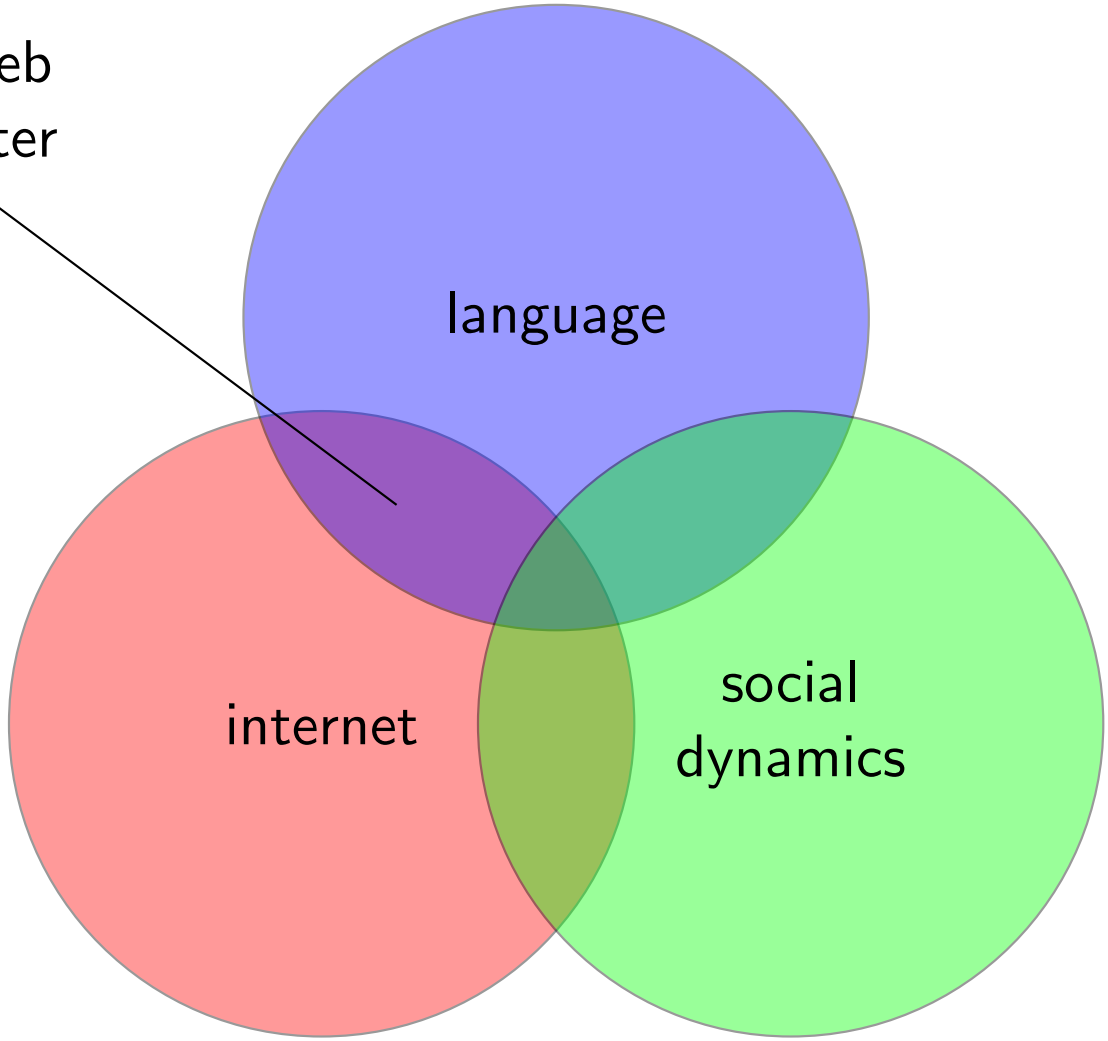


Taming the social web

Parsing the web
POS for Twitter



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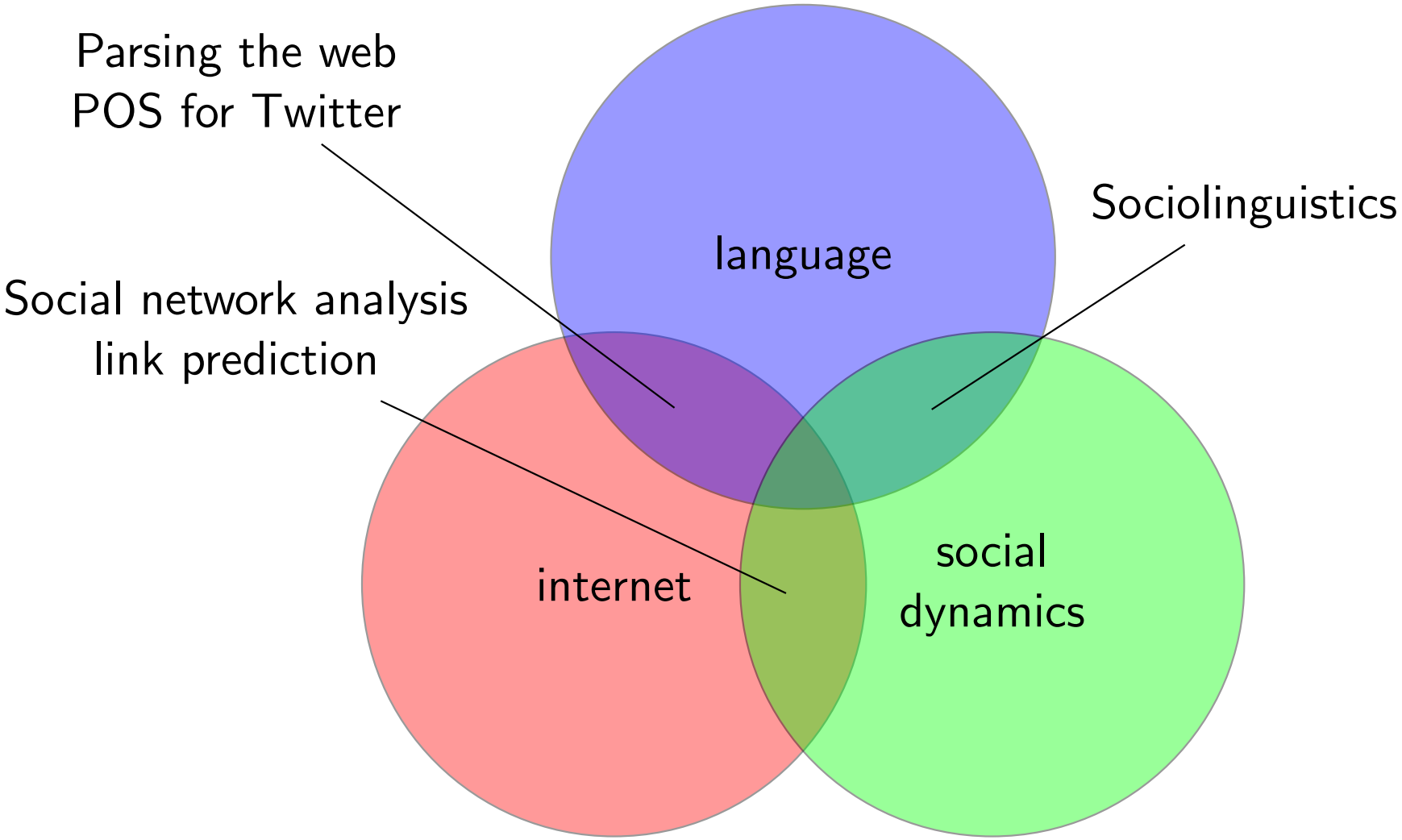

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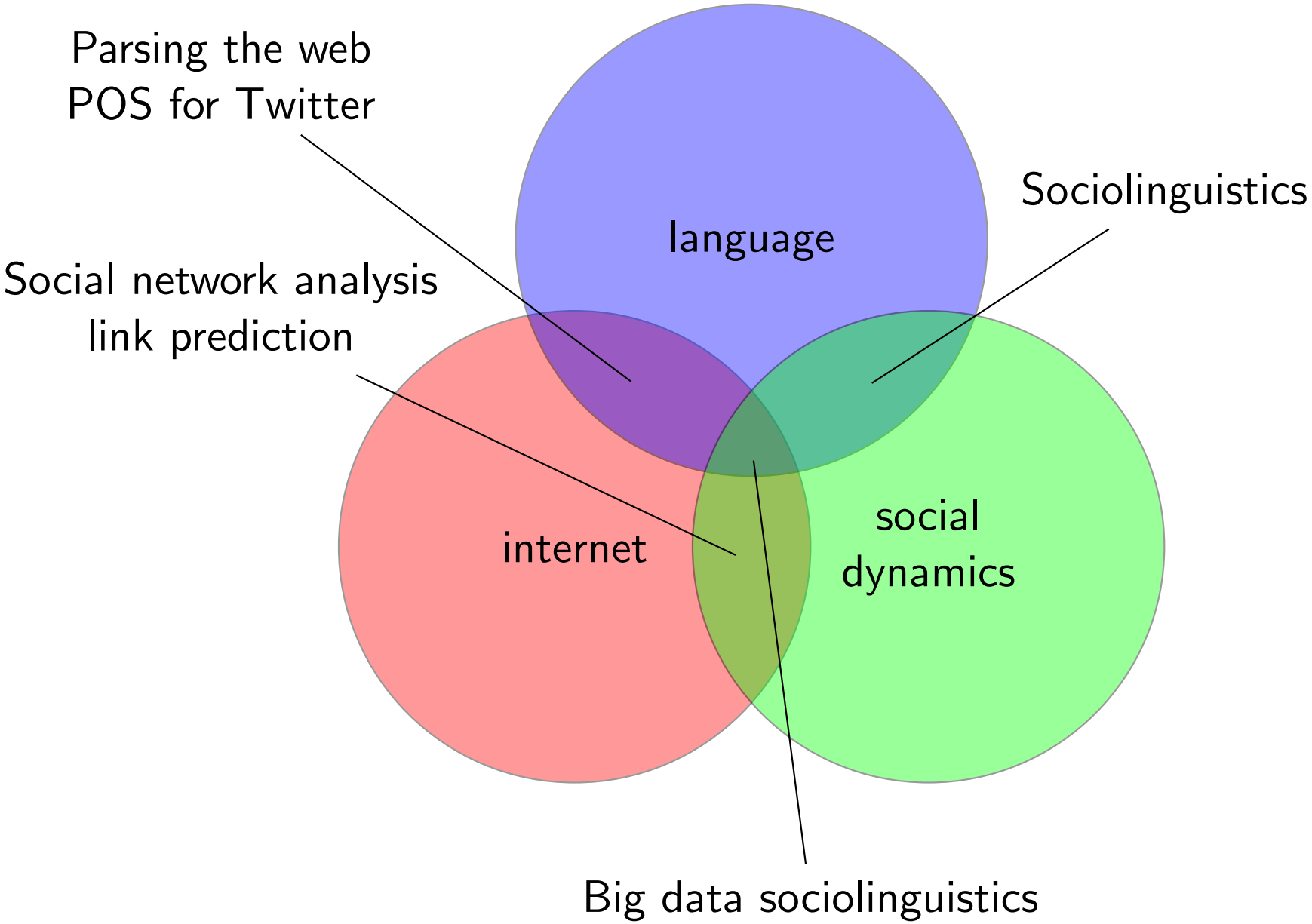

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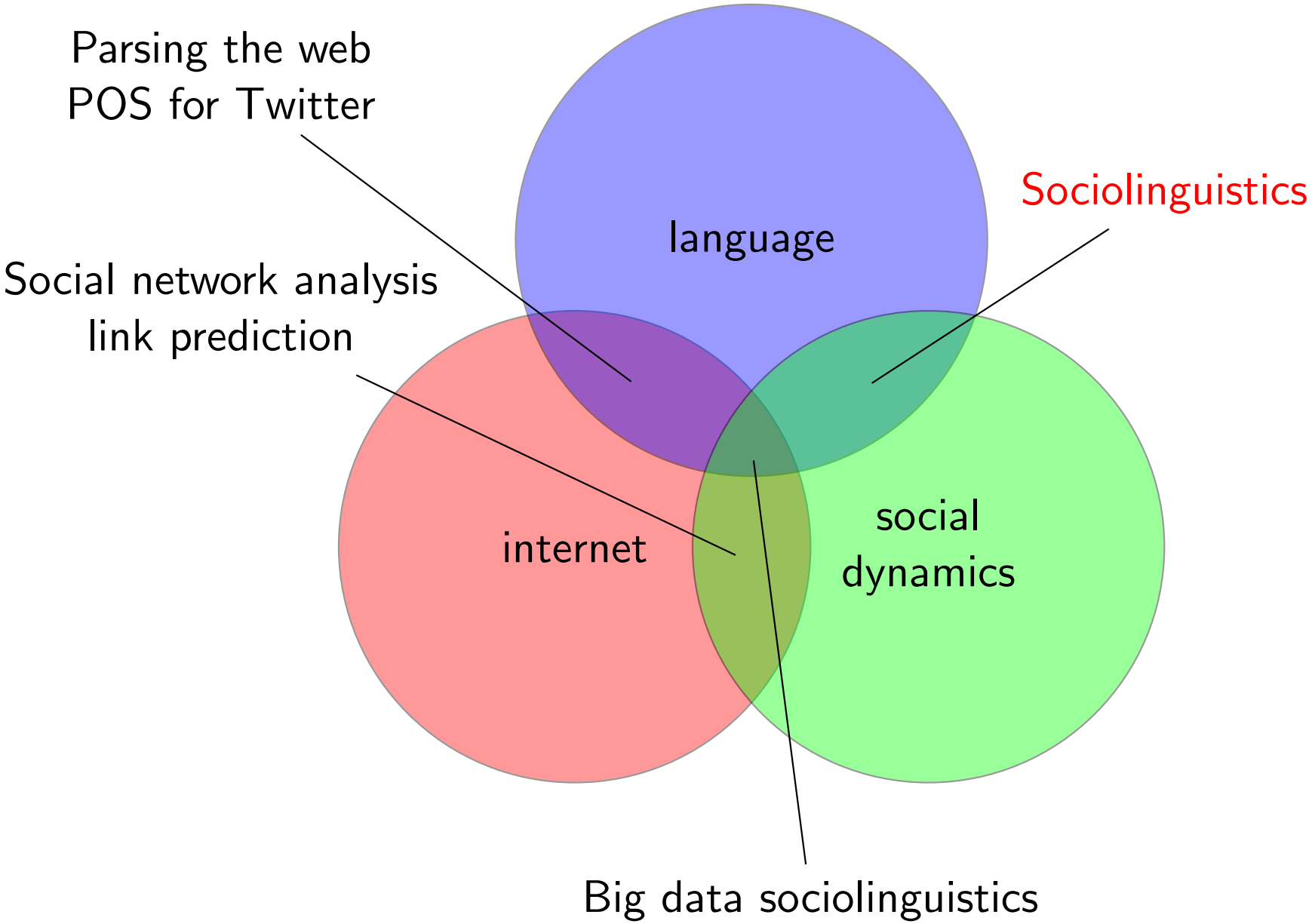

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ChuckGrassley @ChuckGrassley 13 Feb

I now h v an iphone

Retweeted by Jacob Eisenstein

Collapse Reply Retweeted Favorite

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Sociolinguists (and linguists generally) believe:

- Language standards are real. Obeying them can be important.
- But non-standard language is not illiteracy.
- Linguistic variation is not random noise; it carries social meaning.
- Our job is to understand the ways people use language, not to defend the linguistic status quo.

The department store study

"The Social Stratification of /r/ in New York City" [Lab66]

- Where can I return this tie?
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Findings of this study:

- Use of /r/ correlates with higher prices (Sak's > Macy's > Klein's)
- Use of /r/ increases with "attention to speech," especially in middle-class settings.

Variables, speakers, and context

- What did Labov have to know to do this research?
  - **language**: /r/-dropping as a linguistic *variable*
  - **speaker**: socioeconomic status as modulating regional dialect
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- These 3 elements define the playing field of sociolinguistics.
- Labov's work was seminal to *variationist* sociolinguistics, an approach which embodies a specific set of methological and theoretical commitments with respect to this playing field.

The methodology of "first-wave" variationism [Eck12]

language: focused on phonological variables

- can often be measured objectively
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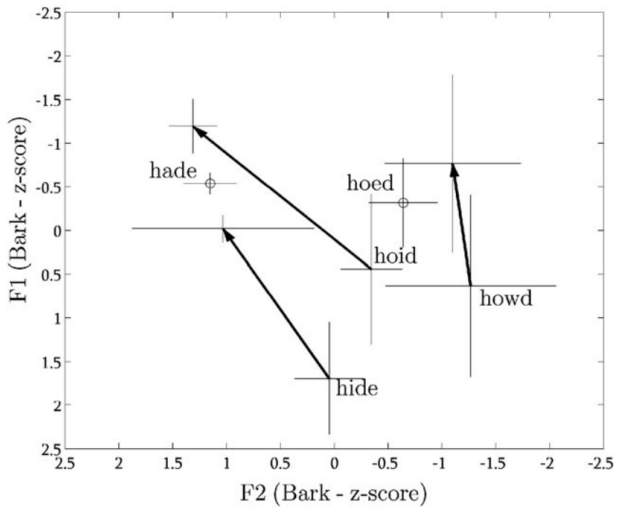

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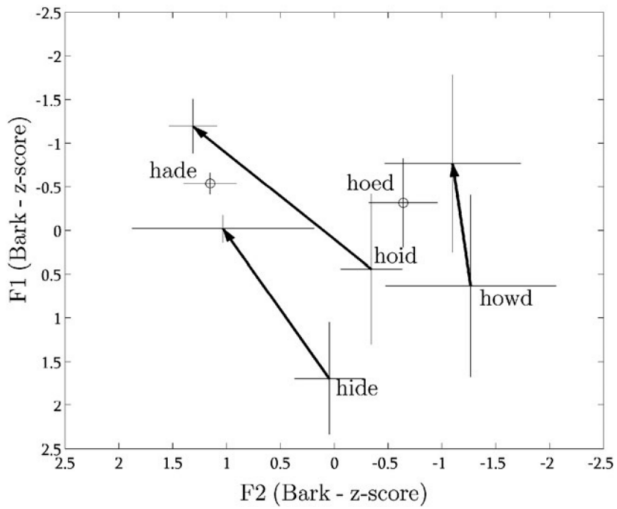

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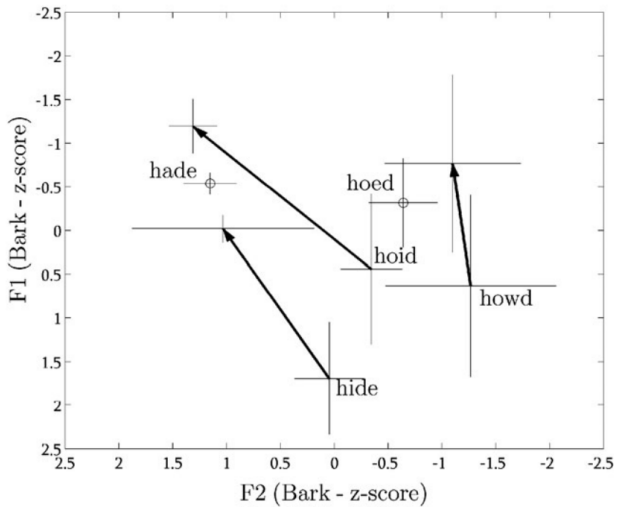

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context: distinction between *vernacular* and *prestige* forms

- The vernacular is inhibited by attention to speech.
- Careful interview methodology to elicit "truly" vernacular speech.

Insights from variationist sociolinguistics

- Language variation can be studied mathematically.
  (Logistic regression in the 1970s!)
- Cross-speaker variation is not purely geographical,
  but depends on multiple interacting social factors.
- Within-speaker variation is systematic, not random.
- Most importantly: **a coherent theory of language change**.

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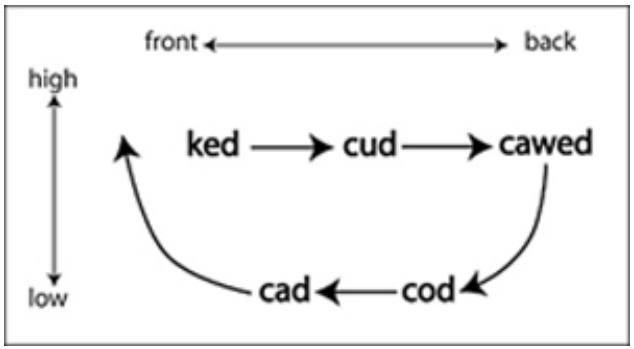

- Phonology is an integrated system.
- Change is triggered by social and historical factors.
- These factors can be understood by identifying the leaders of language change.

The Philadelphia study

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  - As in any good detective story, none of the usual suspects are guilty.

The Philadelphia study: methodology

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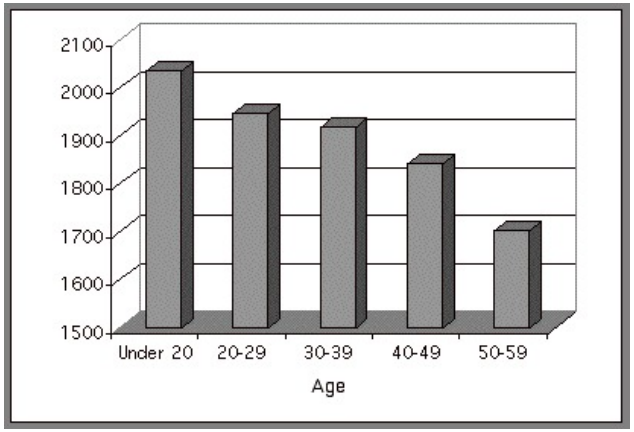
- **Apparent time**: differential language patterns by speaker age.



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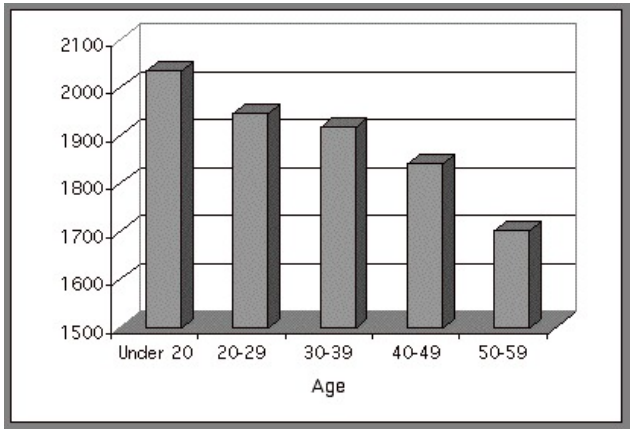

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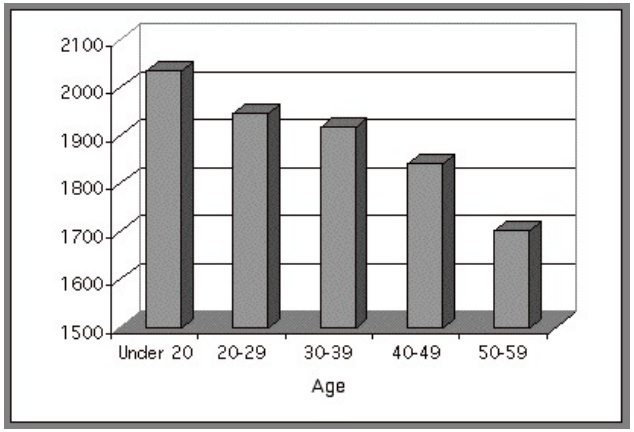
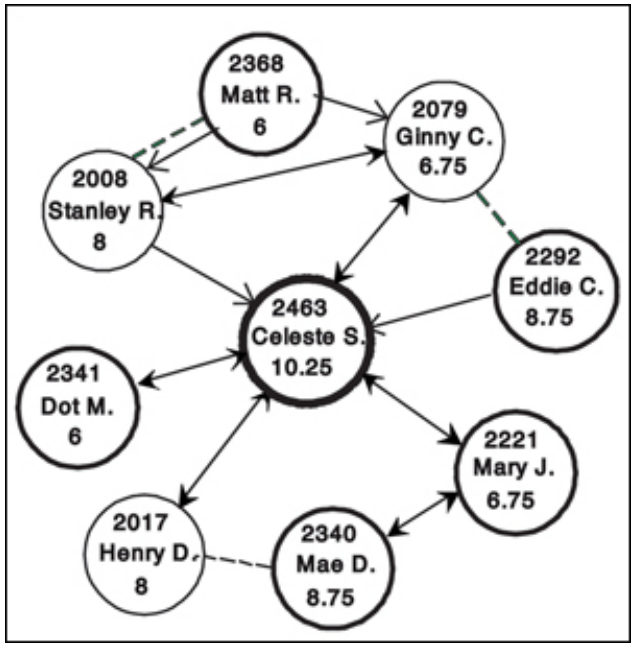


How to find the leaders of language change?

- Multiple local communities were studied over several months.
- The communities were differentiated by class and ethnicity, to measure the broad characteristics of language change.
- In-depth study within each community reveals the personal characteristics of change leaders, and their position in their local social network.



The Philadelphia study: results

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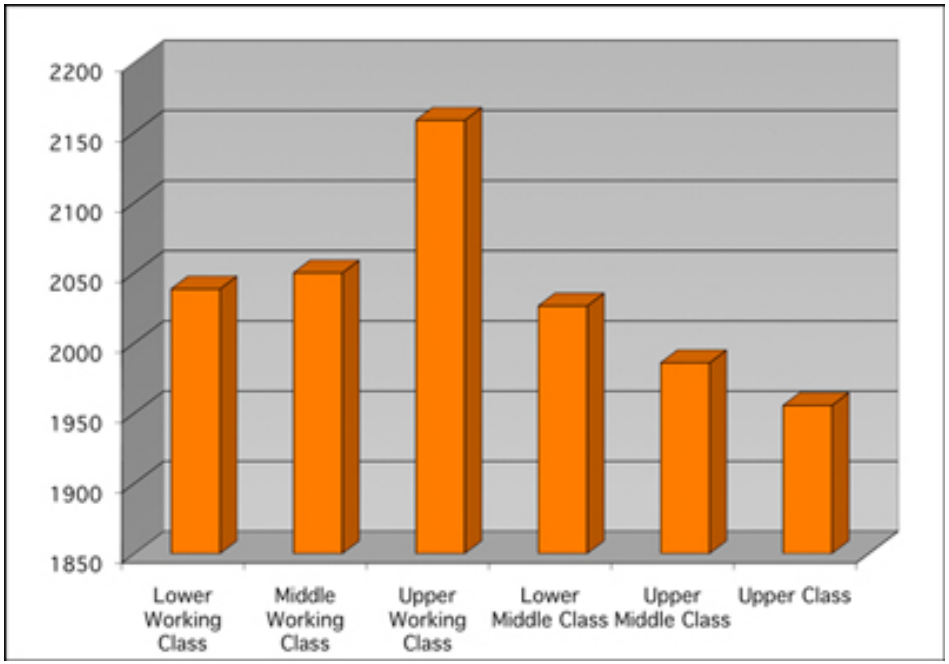

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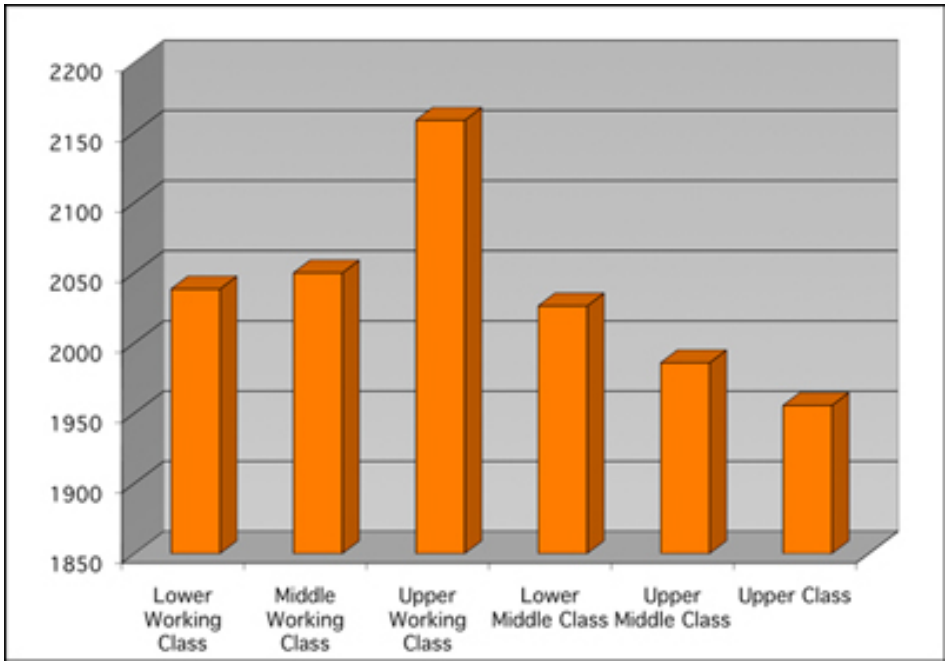

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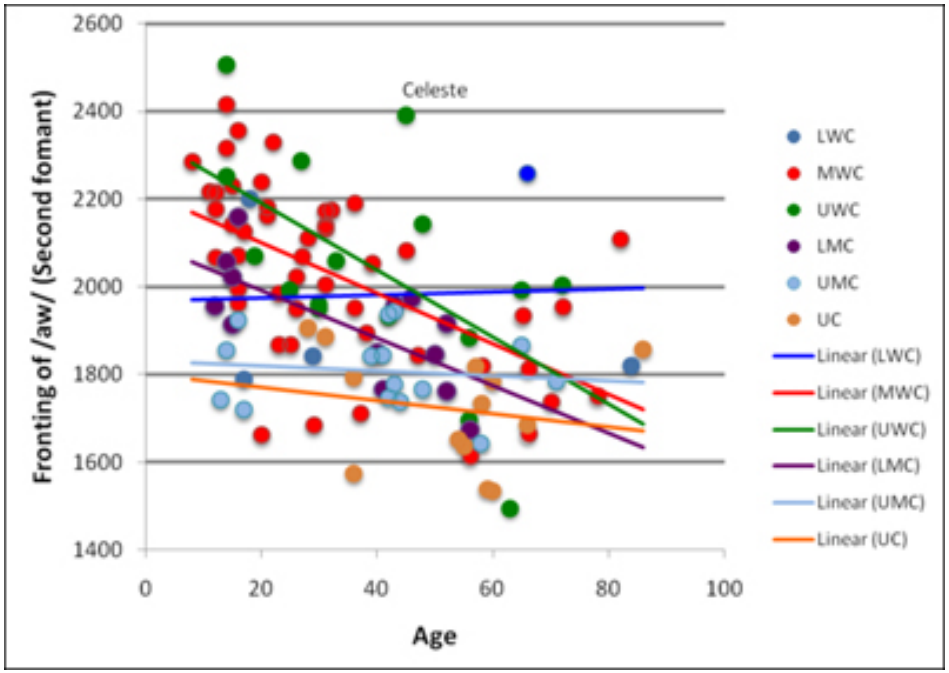

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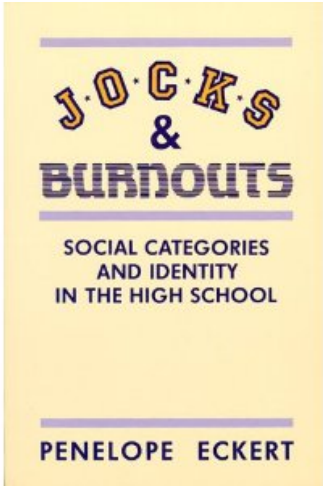
- But variation occurs even within homogeneous local communities.
- In the 1980s, Eckert studied a high school in suburban Detroit. The school was sharply divided into two groups [Eck89].
  - **Jocks** participate in school-sponsored activities, plan to go to college, and cultivate good relations with authority figures.
  - **Burnouts** reject the school, plan to work in Detroit, and cultivate friendships in the larger metropolitan area.



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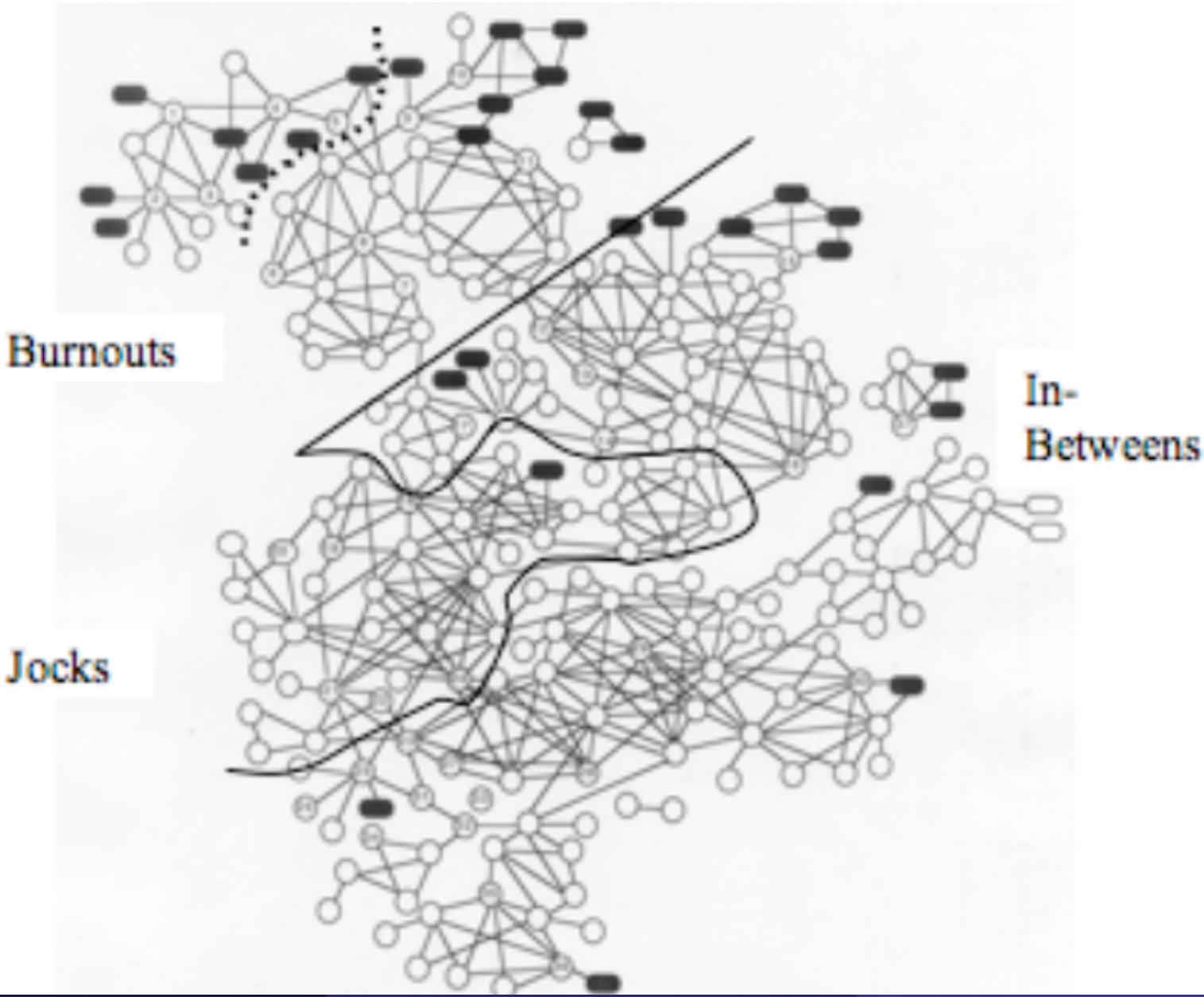

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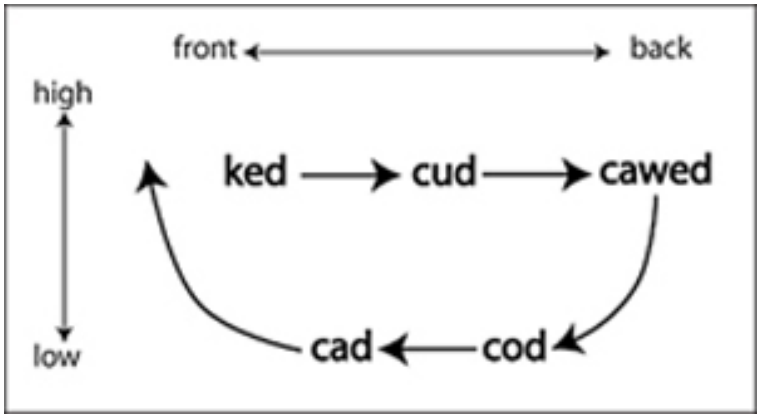

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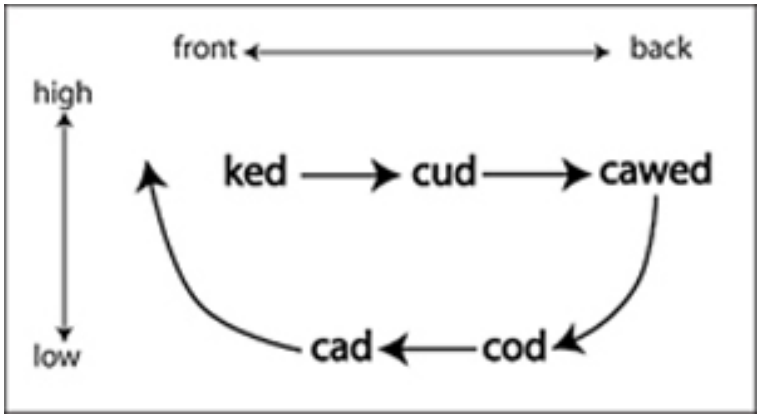

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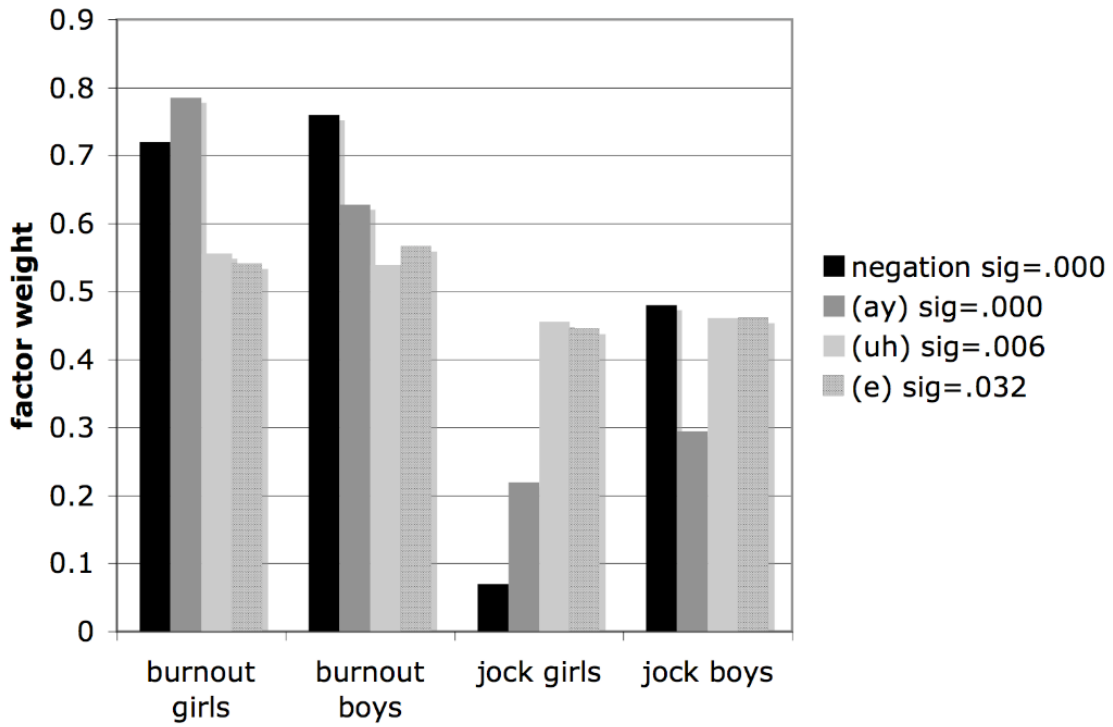
  - **language**: Northern Cities shifted vowels, multiple negation
  - **speaker**: locally-defined jock and burnout groups
  - **context**: ethnographic interviews

Jocks and burnouts: results

Jocks and burnouts differ markedly on the northern cities shift:

- Burnouts adopt a more Detroit-oriented style.
- Jocks adopt a style that is closer to the national standard.



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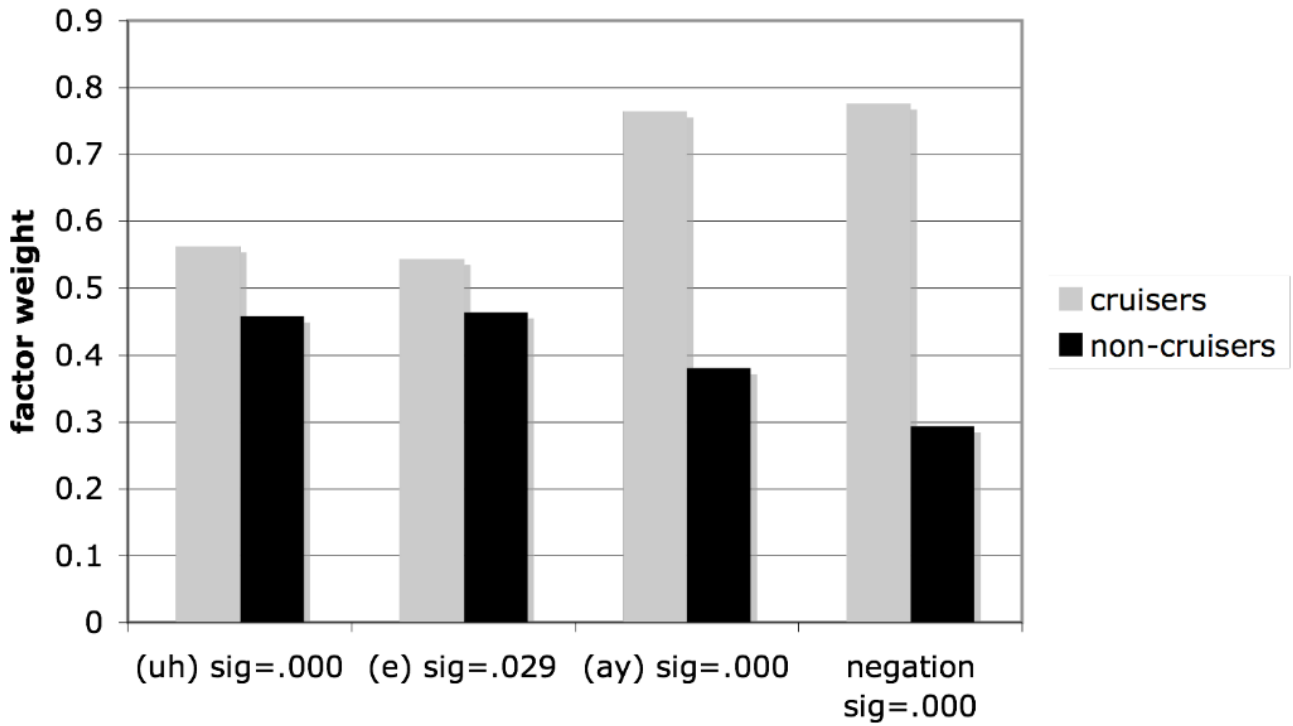

Variation in local communities

A related example from Ucieda, in the Spanish Pyrenees [Hol85]

- Castilian: El trabajo del campo no lo saben
- Ucieda: El trabaj**u** del camp**u** no lo saben

This is a change in progress, towards the Castilian standard.

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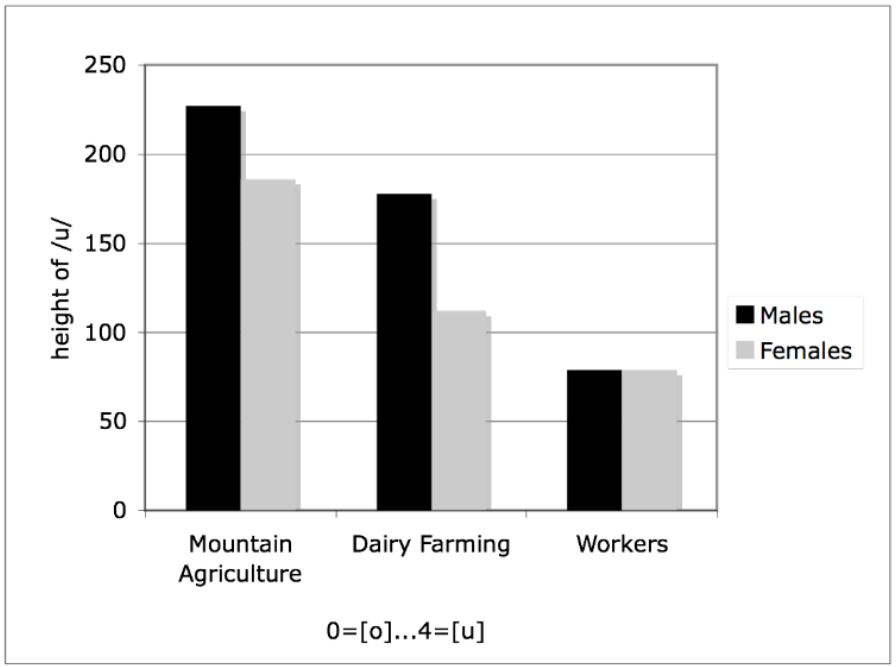

- Uciedans doing less traditional work are changing most quickly.
- The change is led by women. Eckert argues that this reflects the particular undesirability of mountain agriculture for women [Eck12].

Variationist sociolinguistics today

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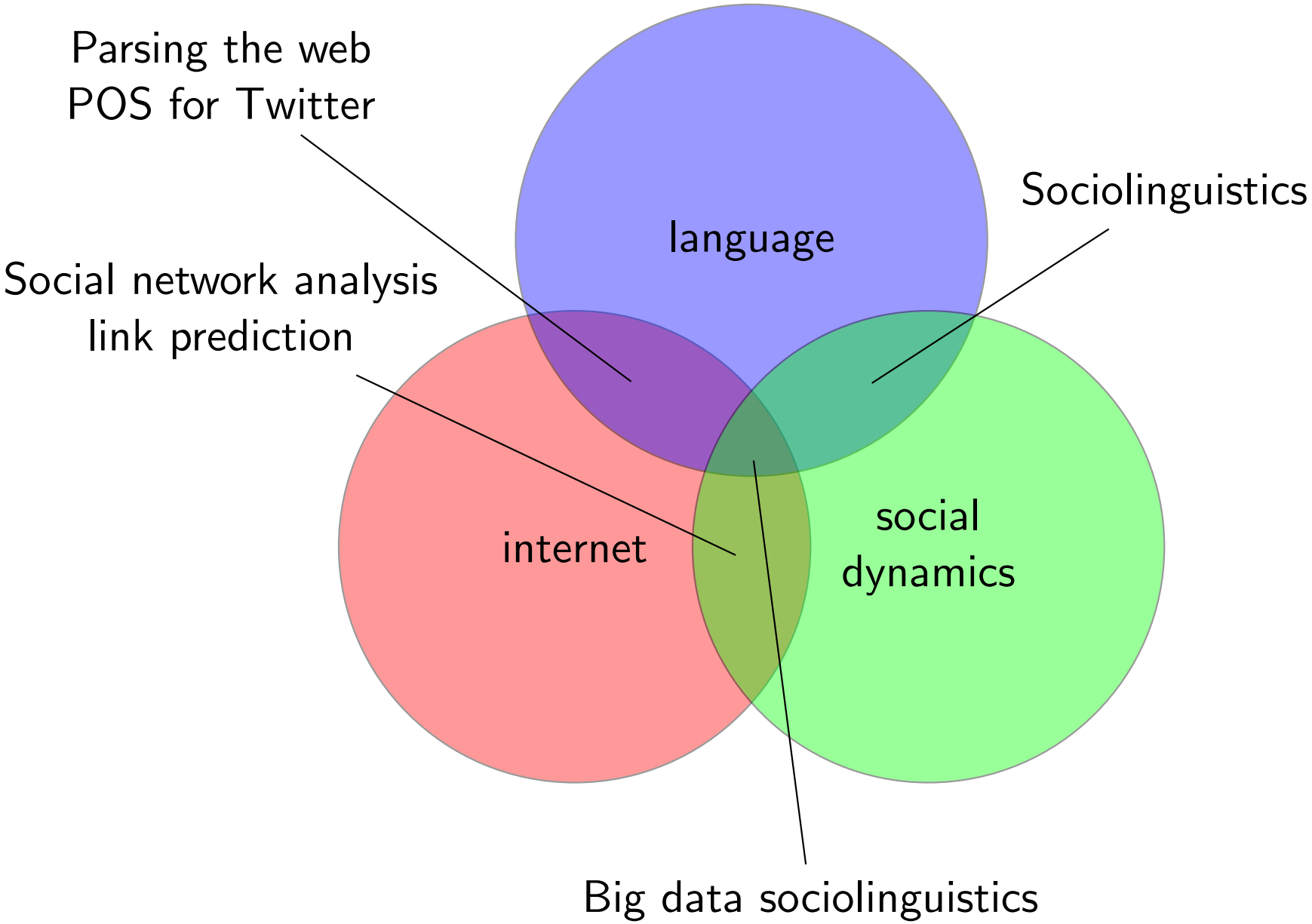
This is not a disavowal of quantitative "1st wave" sociolinguistics.

- But interest has shifted to more deeply contextual settings, and quantitative methods seem unable to contribute.
- (but is this true?)

Taming the social web



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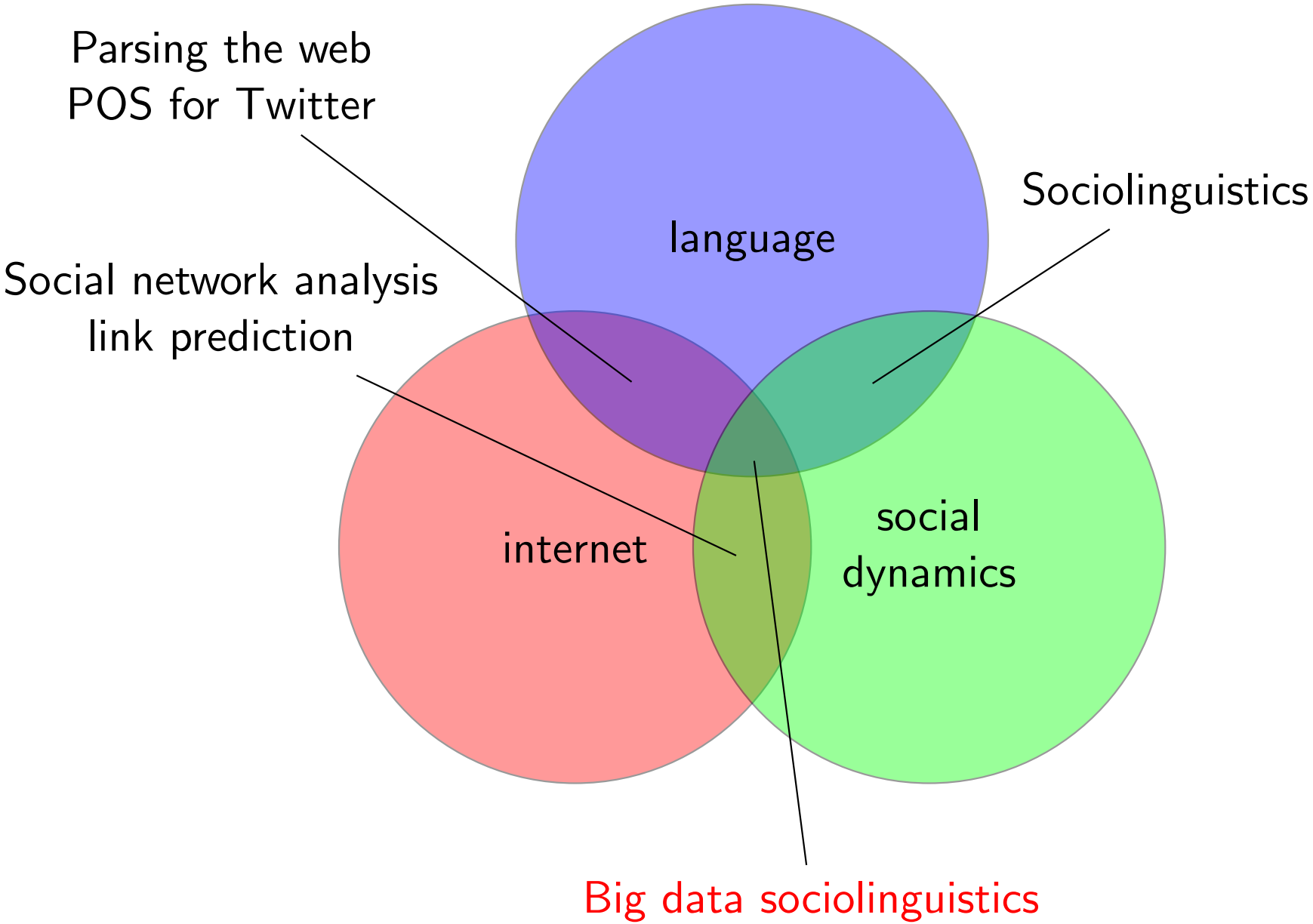

Towards big data sociolinguistics

Social media corpora open the possibility of a new, "big data" methodology for sociolinguistics.

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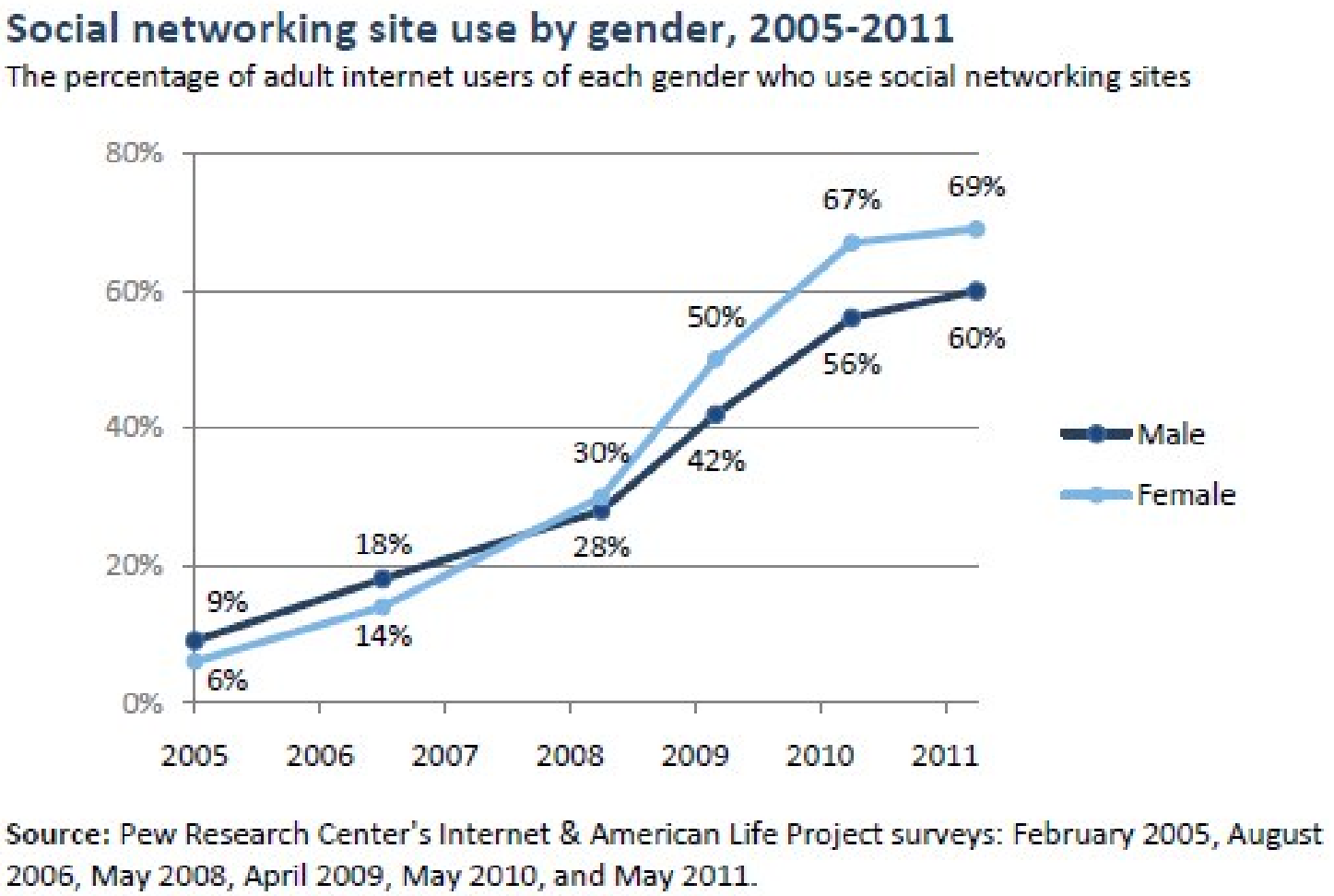
Social media corpora open the possibility of a new, "big data" methodology for sociolinguistics.

- **Exploratory analysis**
  find linguistic variables in the data, rather than relying on experimenter's intuition.
- **Limited observer bias**
  language from real (public) social interactions, outside a lab.
- **Law of large numbers**
  a big pool of participants means less sensitivity to outliers.

Who uses social media?



(Pew Research Center, Aug 2011)

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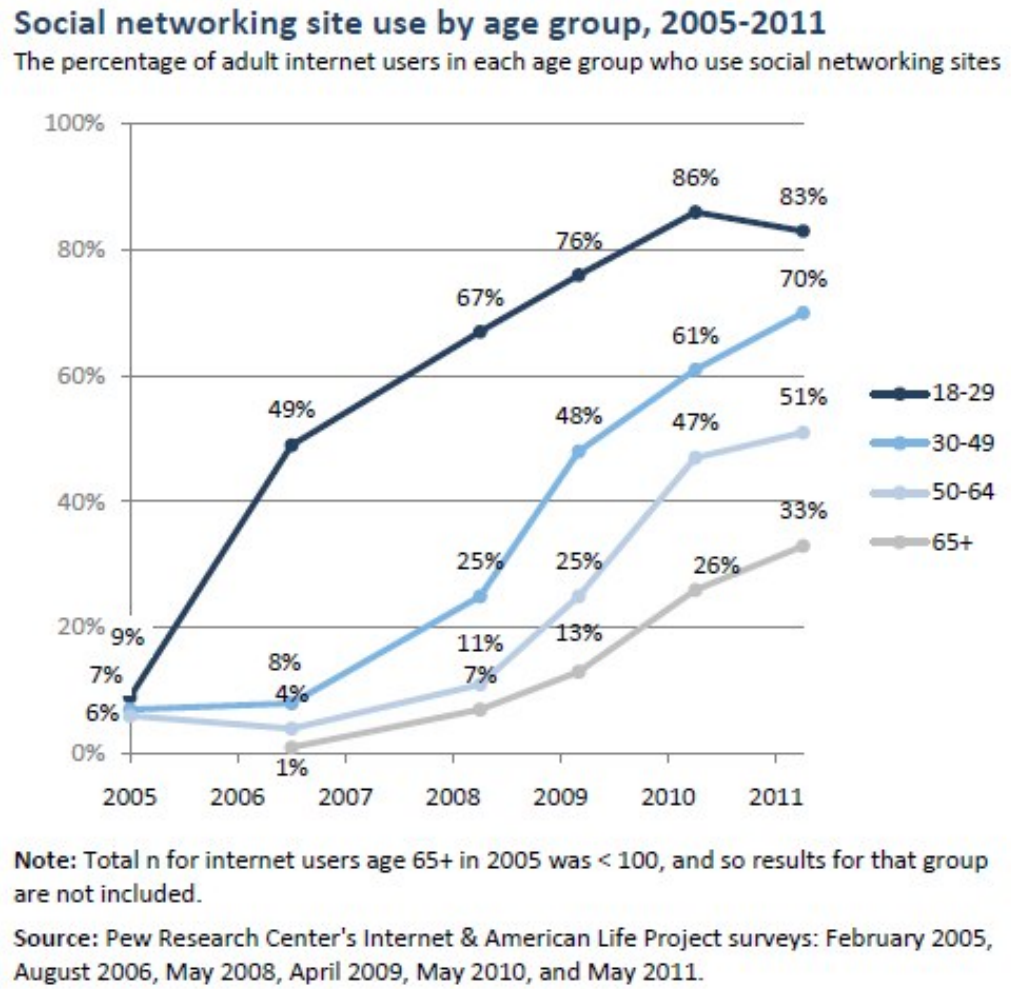

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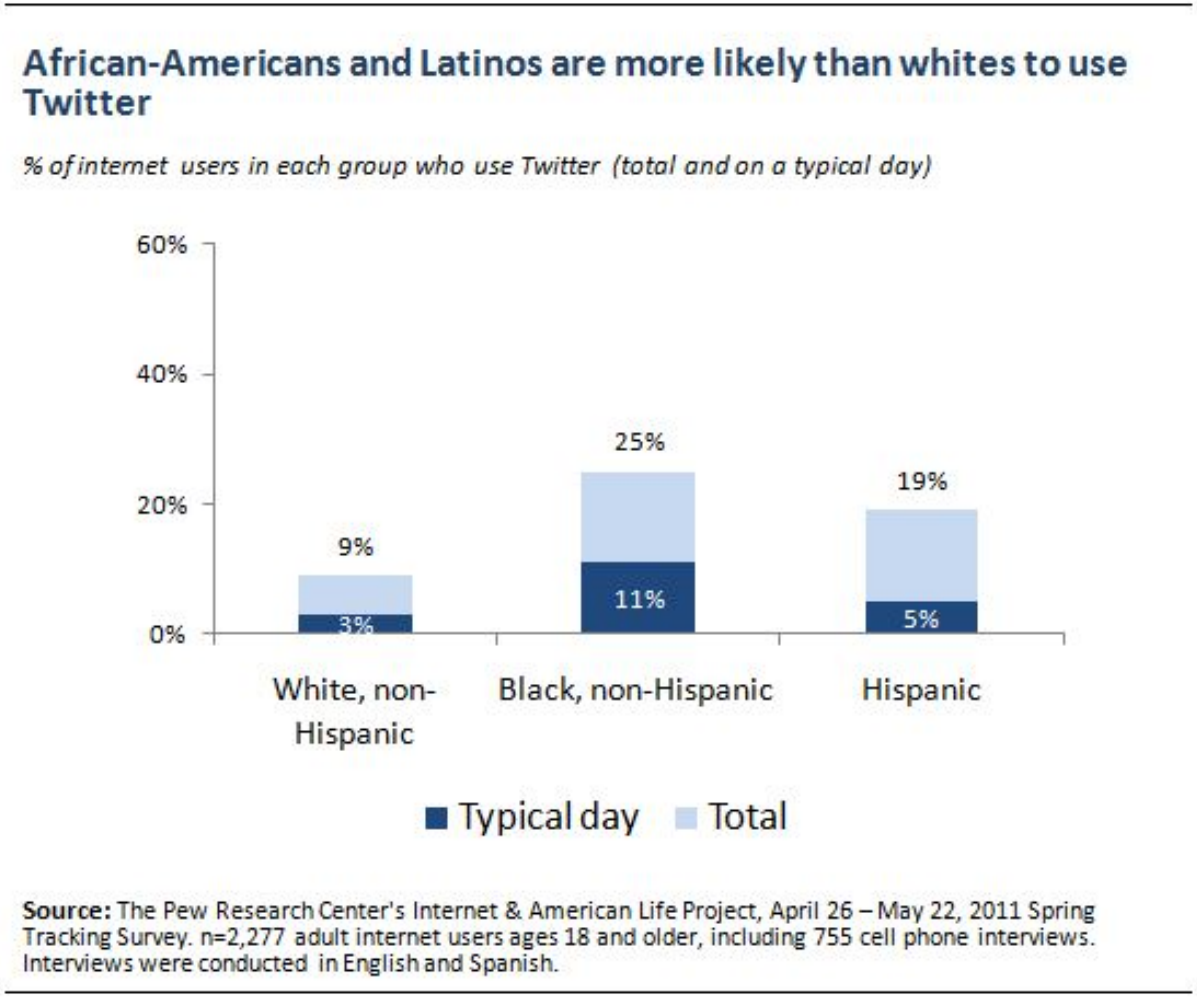
Twitter

- Weak tie to real-life identity
- Short, unstructured content (140 characters)
- Unidirectional social network connections
- Public but not redistributable

Who uses Twitter?



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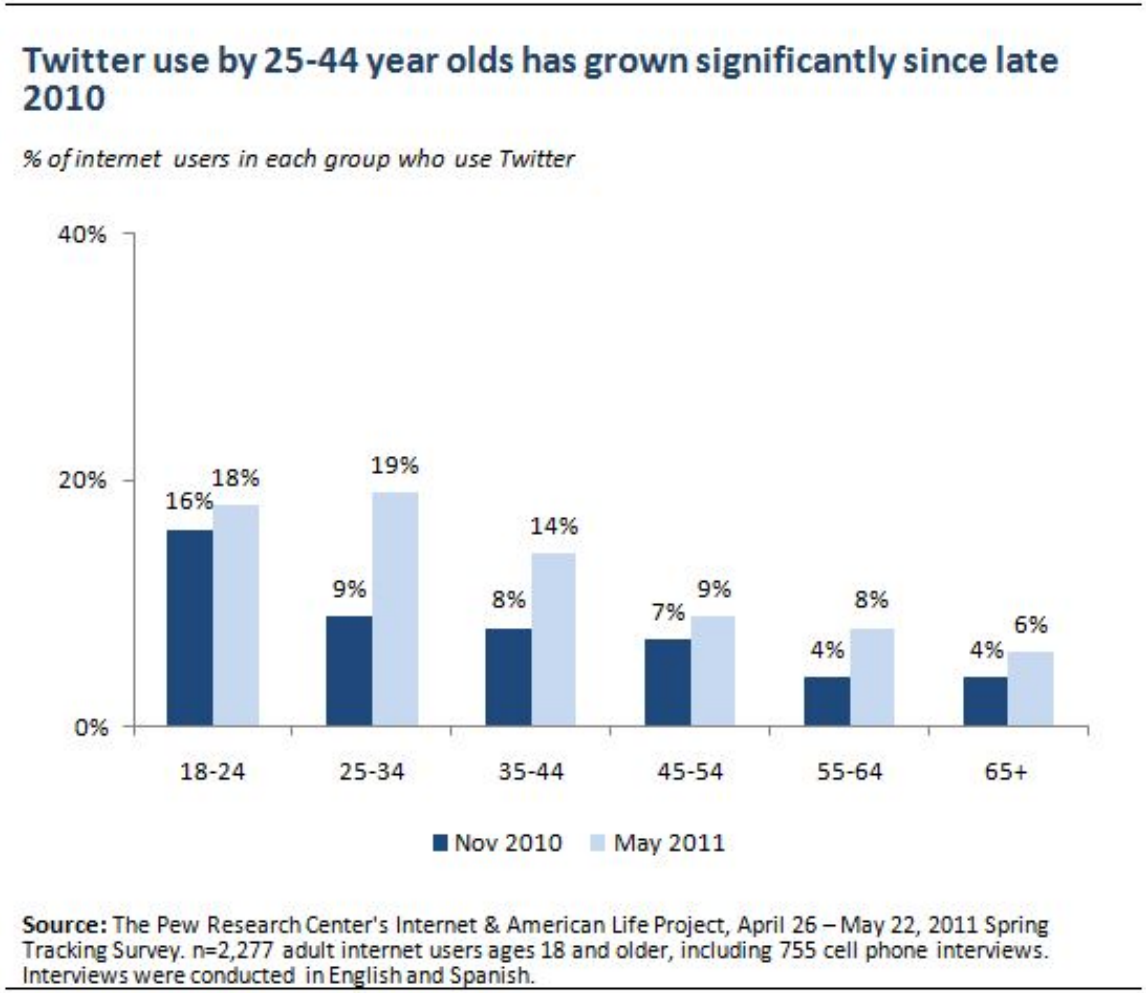

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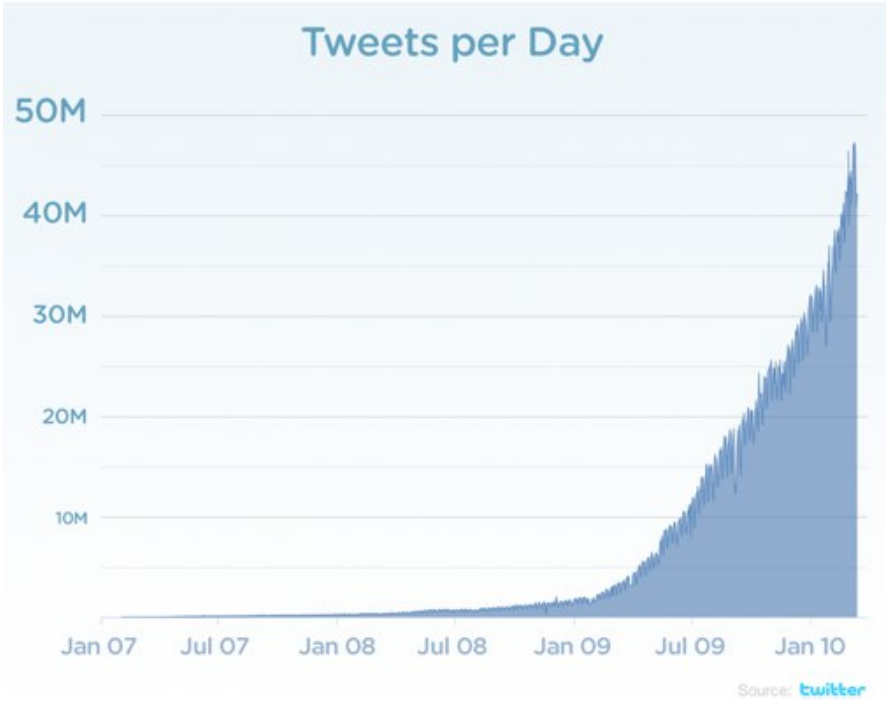
How much?



- Twitter claims:
  100 million active users, 177 million tweets per day in March 2011

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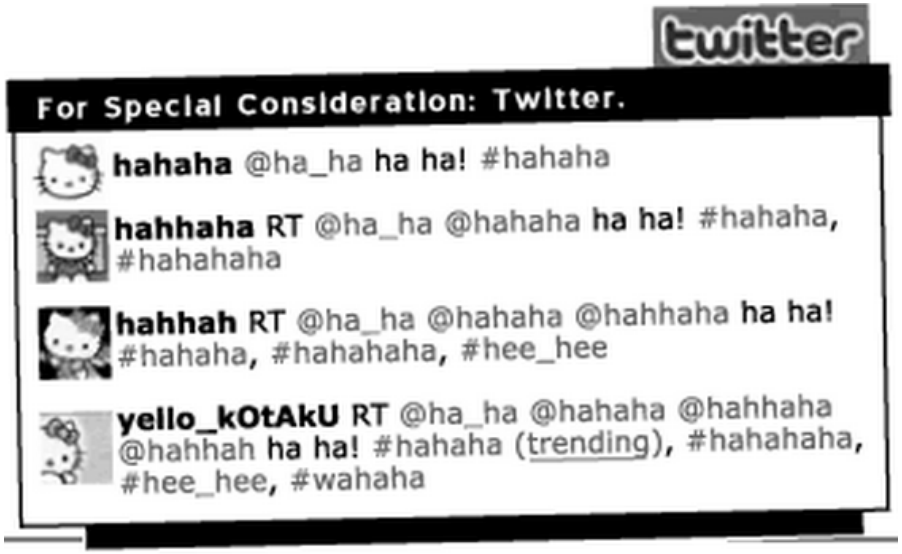

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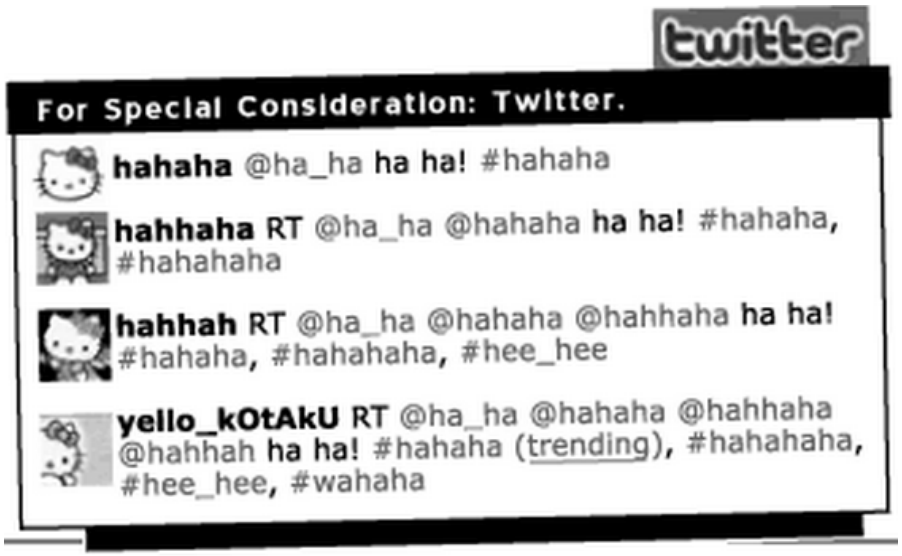

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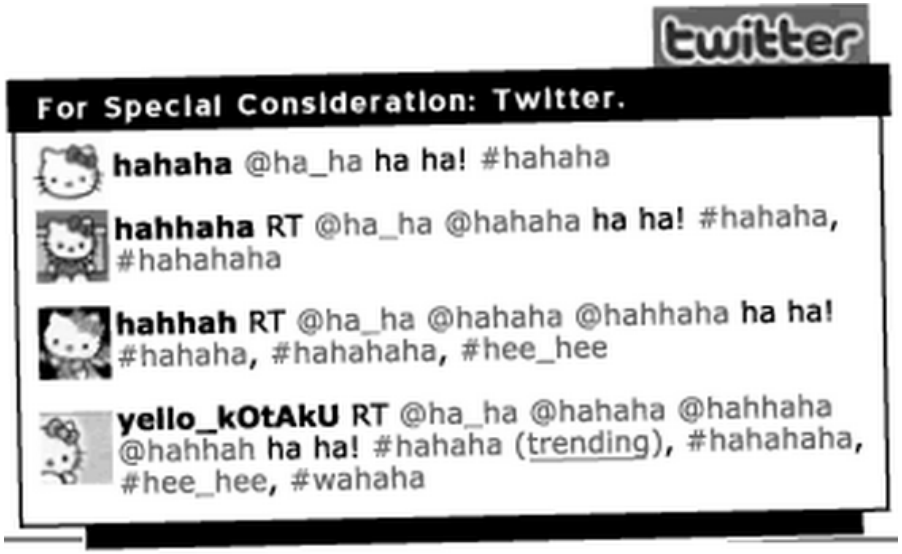

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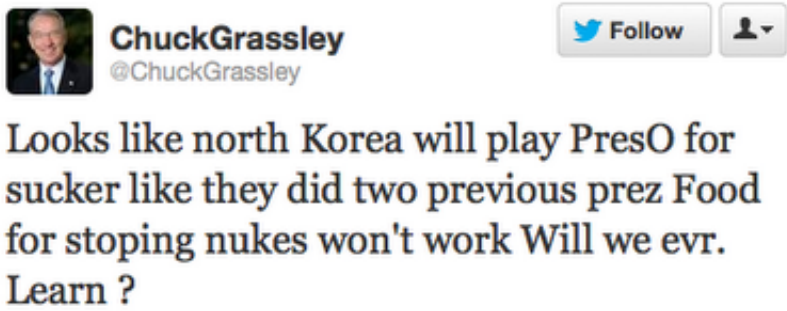

Three studies in computational sociolinguistics

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- **Context**: public Twitter messages.

Geographical Language Variation

A Latent Variable Model for Geographical Lexical Variation
Eisenstein, O'Connor, Smith, and Xing. EMNLP 2010.

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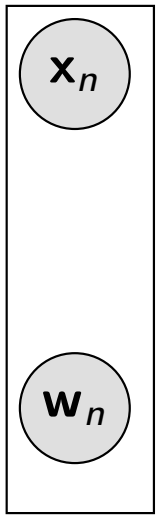
- Does language display geographical variation in social media?
- If so, does it match spoken language variation?
- What are the main linguistic divisions of the United States?
- Can we predict where people are from based on only their text?

Dataset

- 9250 authors with GPS locations
- 380K messages from one week in March 2010
- 4.9M tokens
- Vocabulary limited to 5000 words (expanded later)
- Filters
  - At least 20 messages (in Gardenhose)
  - Must include GPS within a USA zipcode
  - No more than 1000 followers, followees

A mixture model for dialect

- For each author, we observe text $\mathbf{w}_n$ and GPS $\mathbf{x}_n$. Imagine these observations are generated from a random process:



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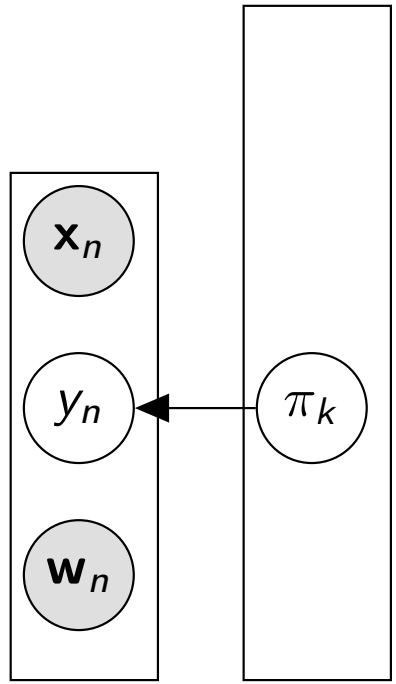

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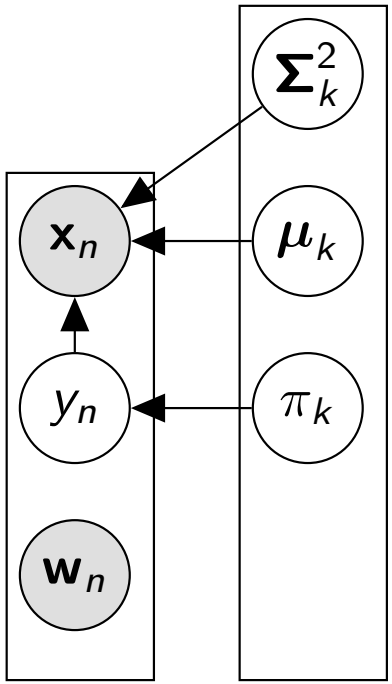

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  - Draw the text $\mathbf{w}_n \sim \beta_{y_n}$,

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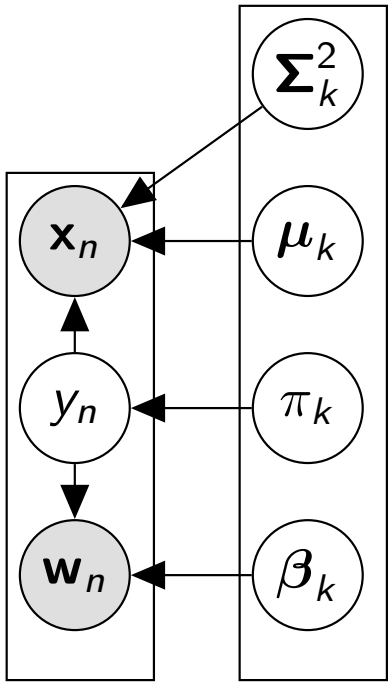

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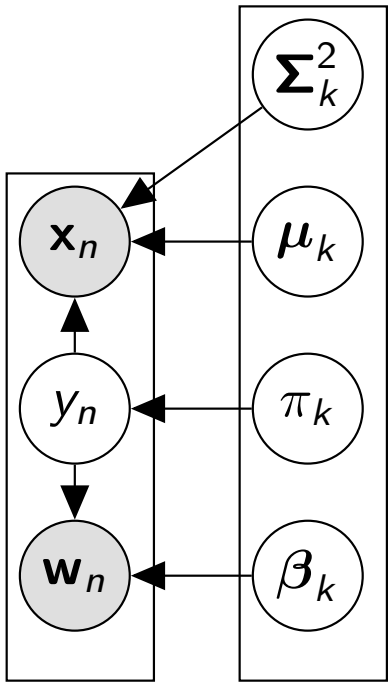

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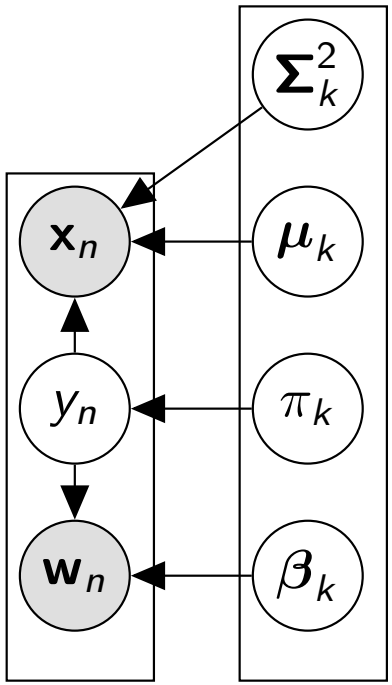

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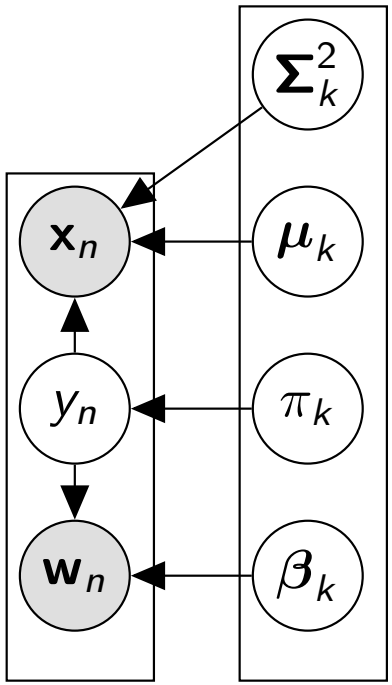

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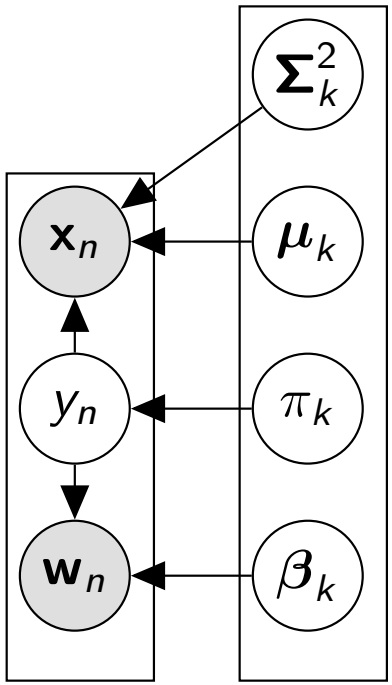
  - **Gibbs sampling**: randomly sample from the posterior for each variable. Iterate until convergence.
  - **Variational inference**: design a tractable approximation, and optimize its similarity to the true distribution.



Adding topics

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- To account for non-geographical variation, we add **latent topics**: groups of words which are used by the same authors.
  - album, music, beats, artist, video, #lakers, itunes, tour
  - bieber, justin, gaga, jonas, pants, beiber, ring, annoying
  - da, dat, dis, wat, dats, dey, gud, watz, wats

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  - draw location $\mathbf{x}_n \sim \mathcal{N}(\mu_{y_n}, \Sigma^2_{y_n})$.
  - For each token t,
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- We must now maximize an approximation to $P(y, \beta, \boldsymbol{\mu}, \boldsymbol{\Sigma}^2, \mathbf{z}, \boldsymbol{\theta} | \mathbf{w}, \mathbf{x})$.
- This is more work, but it's worth it.

Predictive accuracy

We can predict the location of unlabeled authors by summing over regions:

$$\hat{x}_n = \arg\max_x \sum_k P(x|\mu_k, \Sigma_k^2) Pr(y_n = k|\mathbf{w}_n, \boldsymbol{\beta}_\mathbf{k})$$

error in kilometers $\rightarrow$	**mean**	**median**
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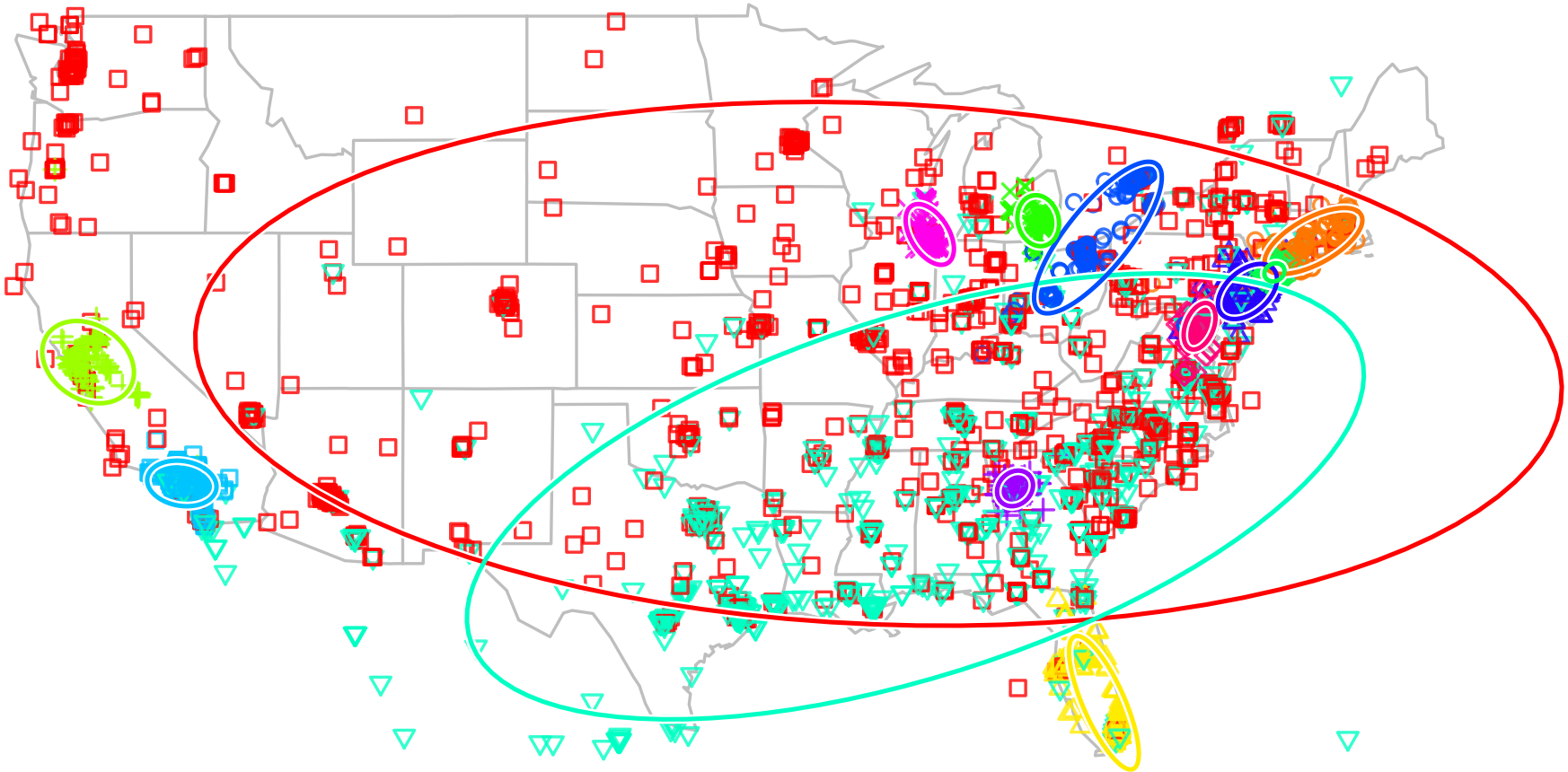
+sparsity [EAX11]	845	501
+larger vocab	791	461

Text+geography model output



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For each cluster,[1] we rank words by log-odds: $\log \beta_i - \log \frac{1}{K} \sum_j \beta_j$:

- **New York**: brib, lml, wassupp, uu, werd, deadass, flatbush, odee, dha
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- **Cleveland/Detroit**: ctfu, detroit, foolin, .!!, cleveland, geeked, salty, ikr
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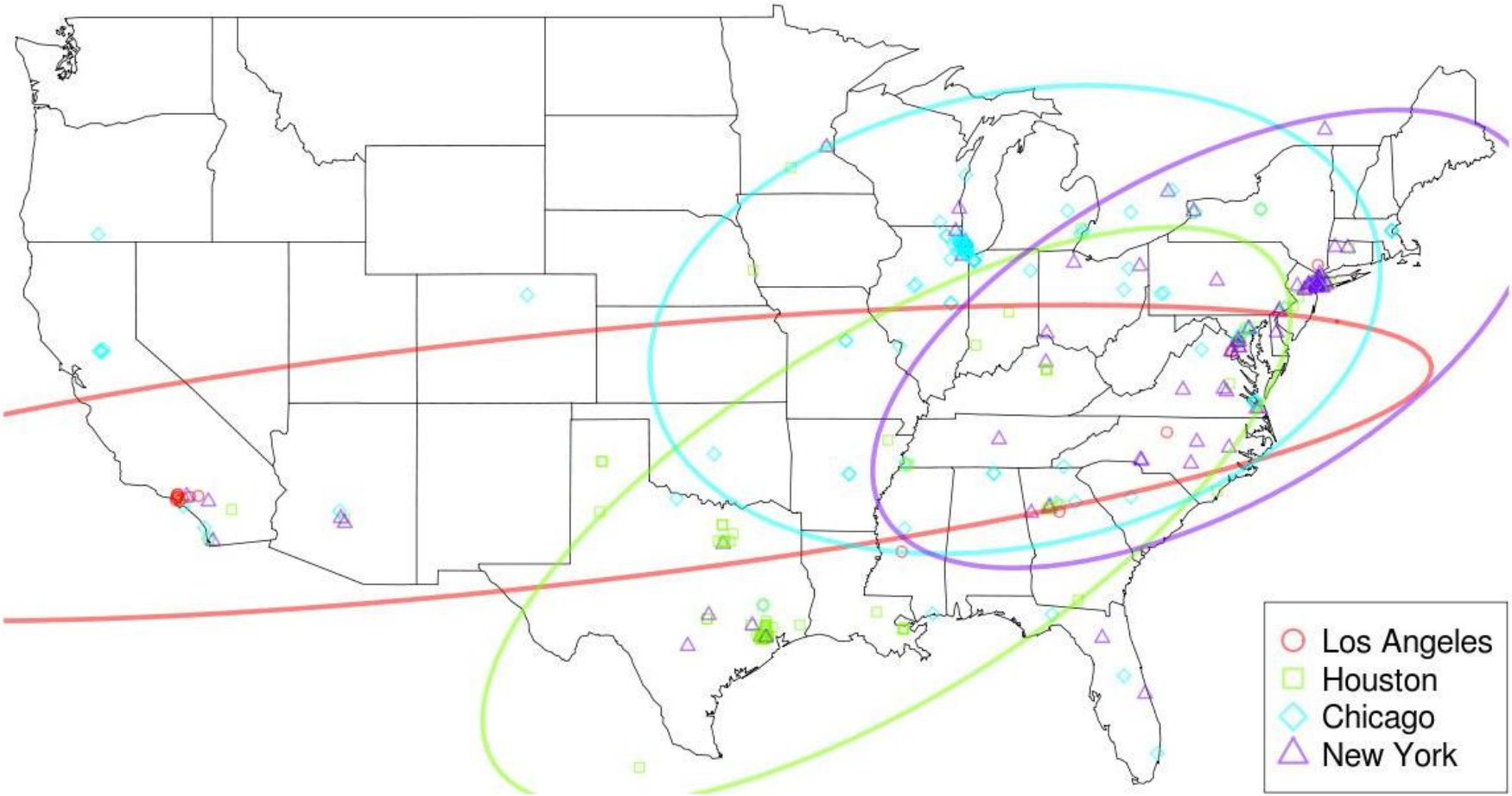
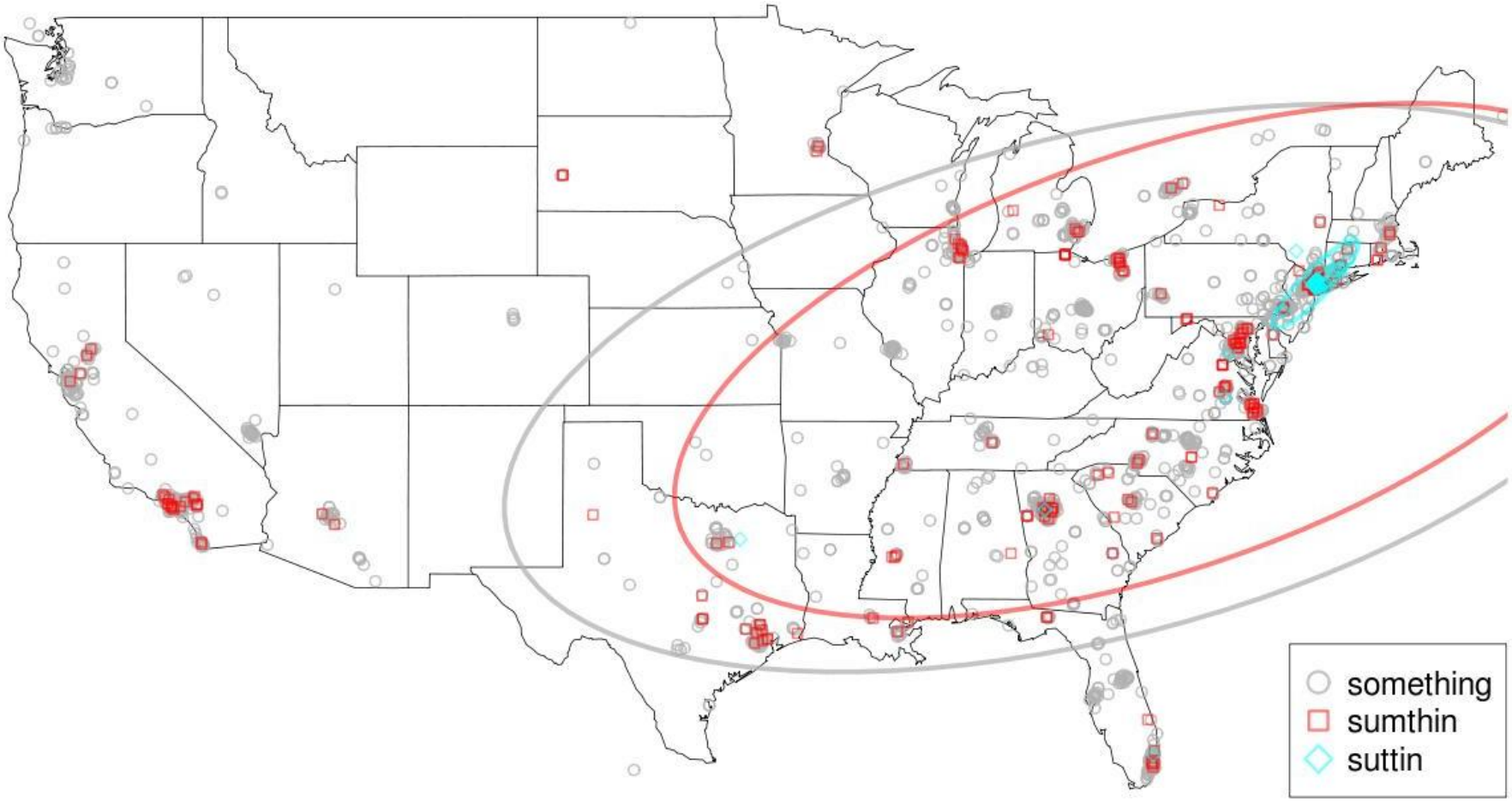
Mentions of city names



Something & variants



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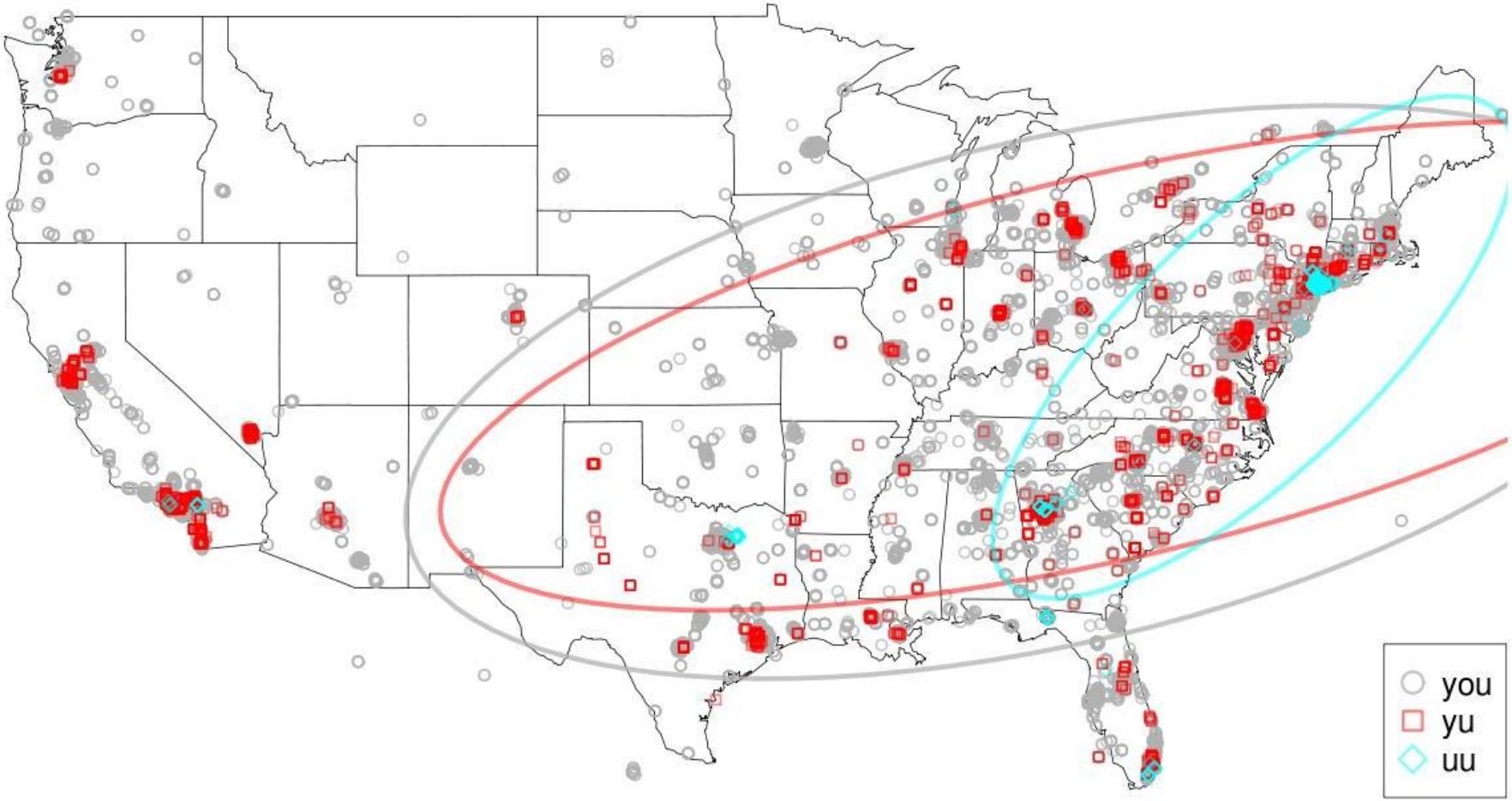
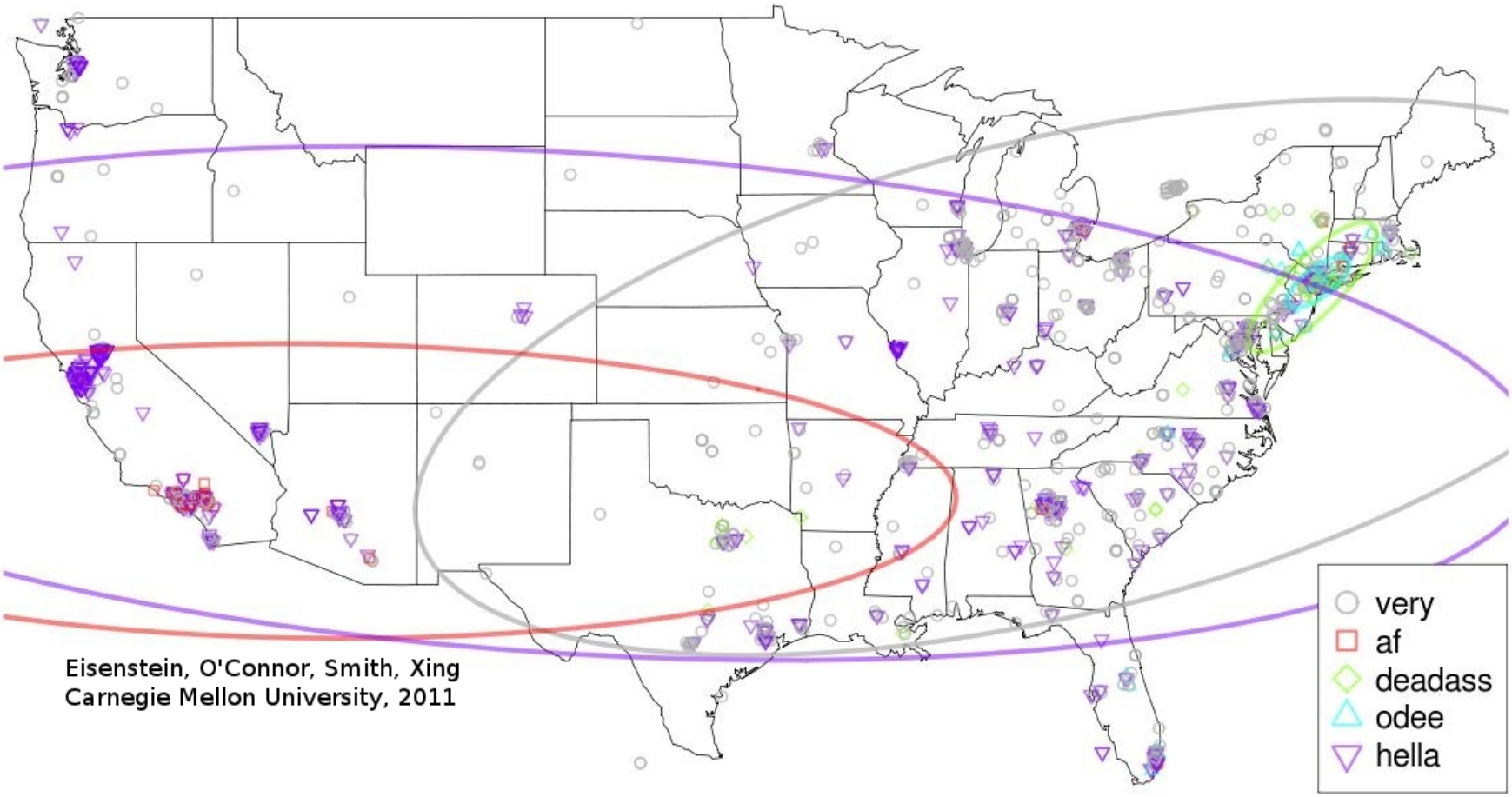


Intensifiers



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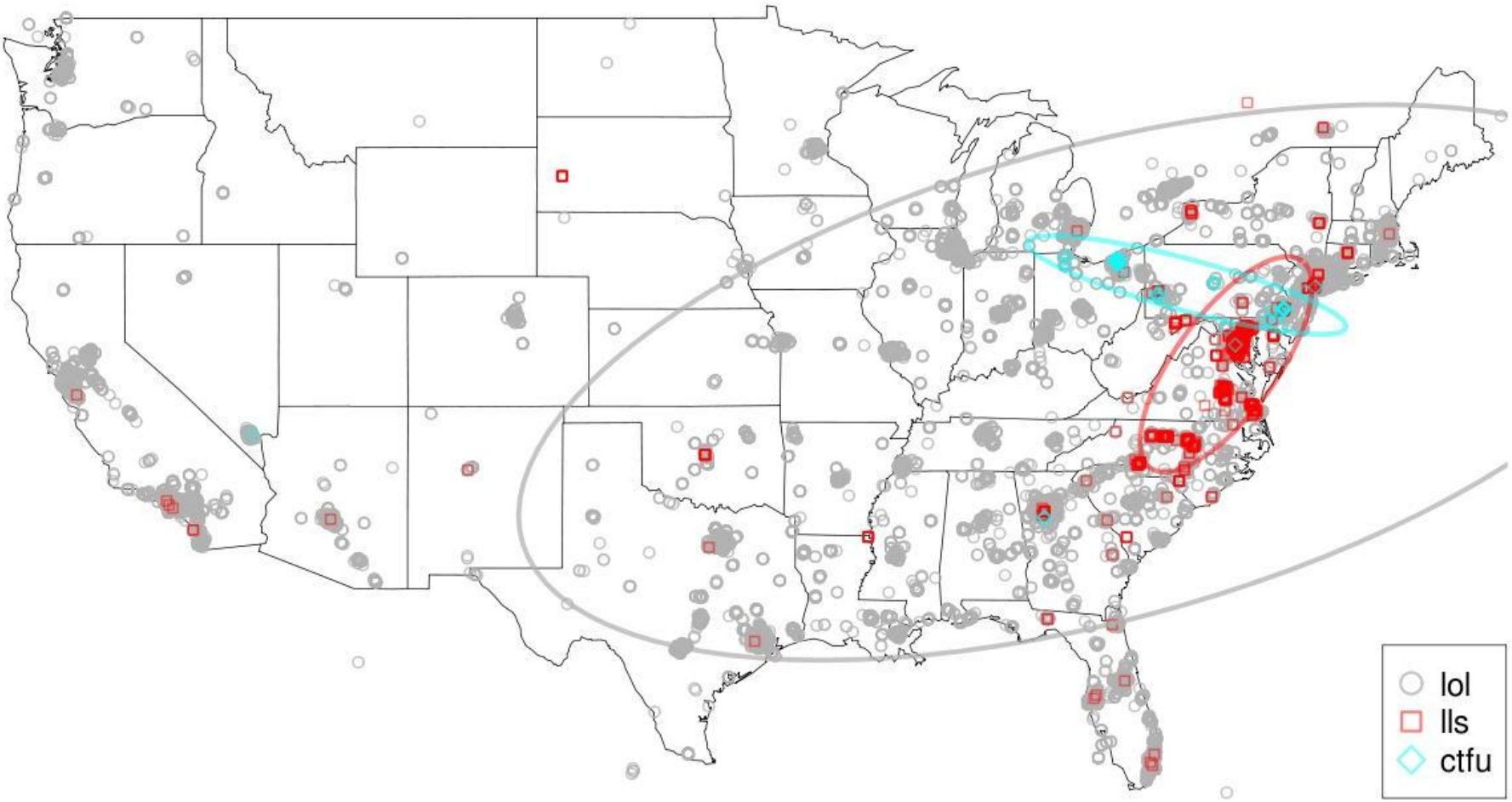

Overview of geographical variation

- Social media introduces new lexical variables which are not possible in speech, e.g. ctfu, koo, uu
- The geographical distribution of these variables may not follow speech dialect regions.
- A more flexible models of author identity is both more plausible and more accurate.

Demographic language variation

Discovering Sociolinguistic Associations with Structured Sparsity, Eisenstein, Smith, and Xing. ACL 2011.

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Our goal: rather than directly model personal identity, can we induce a vocabulary of lexical variables **jointly** across many demographic attributes.

Data

We use the same Twitter data from the geography study, but augment it with demographic attributes.

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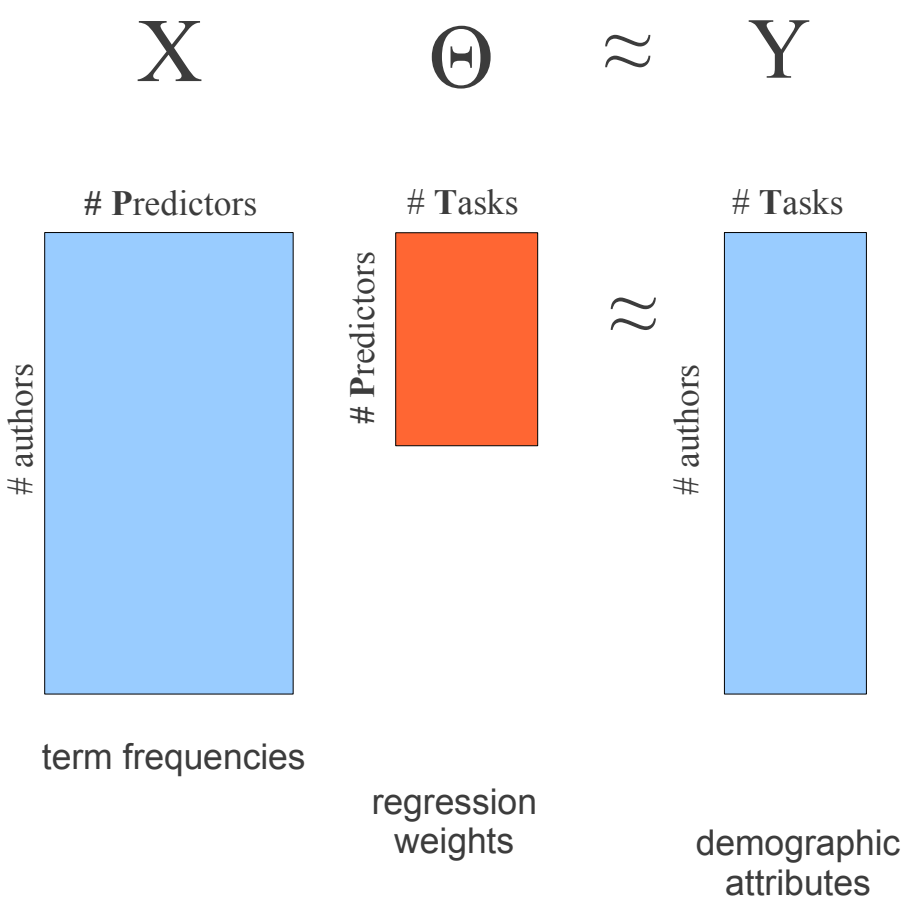
	mean	std. dev.
race & ethnicity		
% white	52.1	29.0
% African American	32.2	29.1
% Hispanic	15.7	18.3
language		
% English speakers	73.7	18.4
% Spanish speakers	14.6	15.6
% other language speakers	11.7	9.2
socioeconomic		
% urban	95.1	14.3
% with family	64.1	14.4
% renters	48.9	23.4
median income ($)	42,500	18,100

- We are using zipcode to proxy for demographics.
- This is standard in public health research, but...
- Careful! Twitter users are not an unbiased sample from a zipcode.

Data summary

	mean	std. dev.
race & ethnicity		
% white	52.1	29.0
% African American	32.2	29.1
% Hispanic	15.7	18.3
language		
% English speakers	73.7	18.4
% Spanish speakers	14.6	15.6
% other language speakers	11.7	9.2
socioeconomic		
% urban	95.1	14.3
% with family	64.1	14.4
% renters	48.9	23.4
median income ($)	42,500	18,100

Model



- Regress demographics against term frequencies
- $\min_{\mathbf{\Theta}} \ell(\mathbf{X\Theta} - \mathbf{Y}) + \Omega(\mathbf{\Theta})$
  - Loss: $\ell(\mathbf{X\Theta} - \mathbf{Y})$
  - Regularizer: $\Omega(\mathbf{\Theta})$

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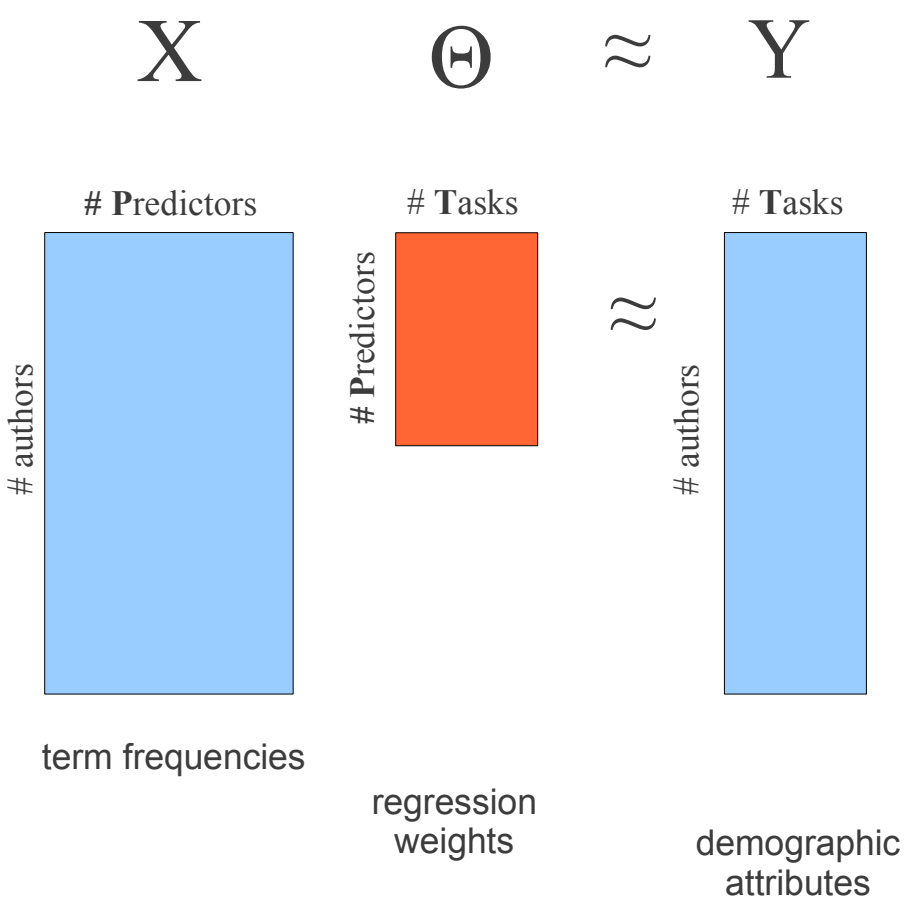

- Regress demographics against term frequencies
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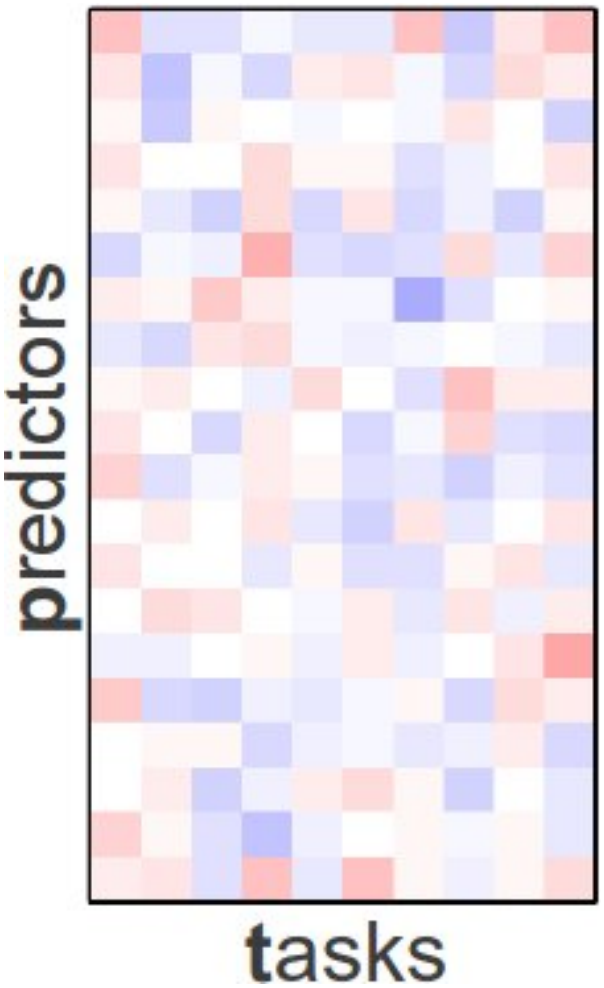
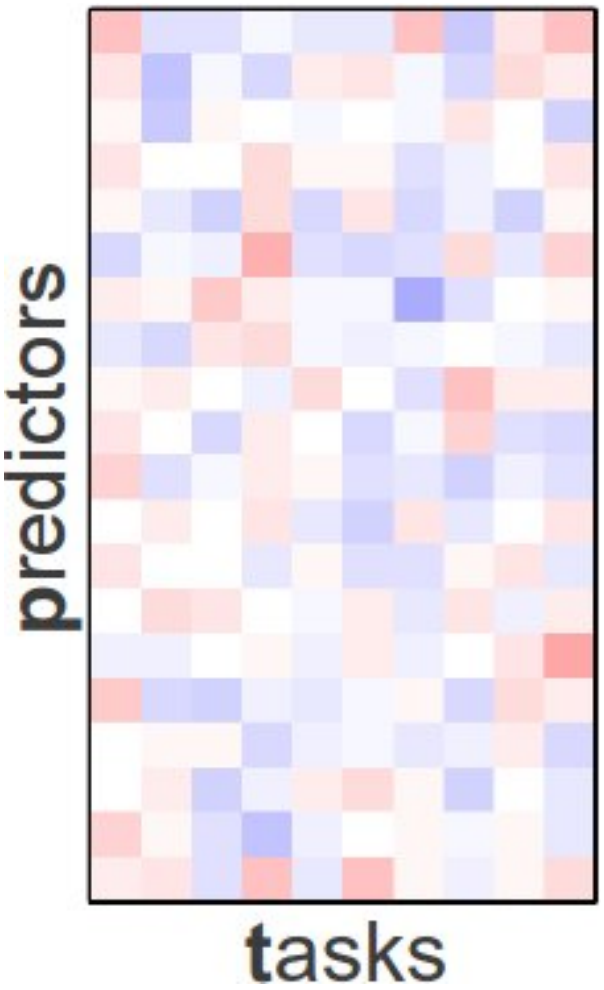
  - Loss: $\ell(\mathbf{X\Theta} - \mathbf{Y})$
  - Regularizer: $\Omega(\mathbf{\Theta})$
- We'll use the regularizer to make the $P \times T$ weights into an interpretable model.

Three regularizers



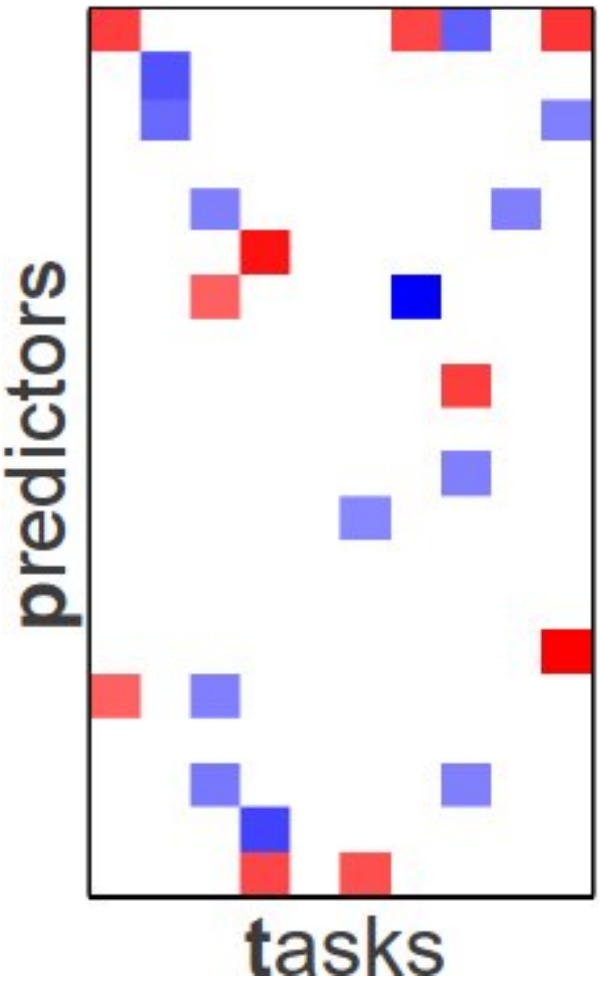
- L2 regularizer: $\Omega(\mathbf{\Theta}) = \sum_t \sum_p \theta_{pt}^2$
- encourages small regression coefficients
- equivalent to running T separate ridge regressions

Three regularizers



- L2 regularizer:
  $\Omega(\mathbf{\Theta}) = \sum_t \sum_p \theta_{pt}^2$
- encourages small regression coefficients
- equivalent to running T separate ridge regressions
- Interpretable? No.
  Every word-demographic association has a non-zero weight.

Three regularizers



- $L1$ regularizer [FHT10]: $\Omega(\mathbf{\Theta}) = \sum_t \sum_p |\theta_{pt}|$
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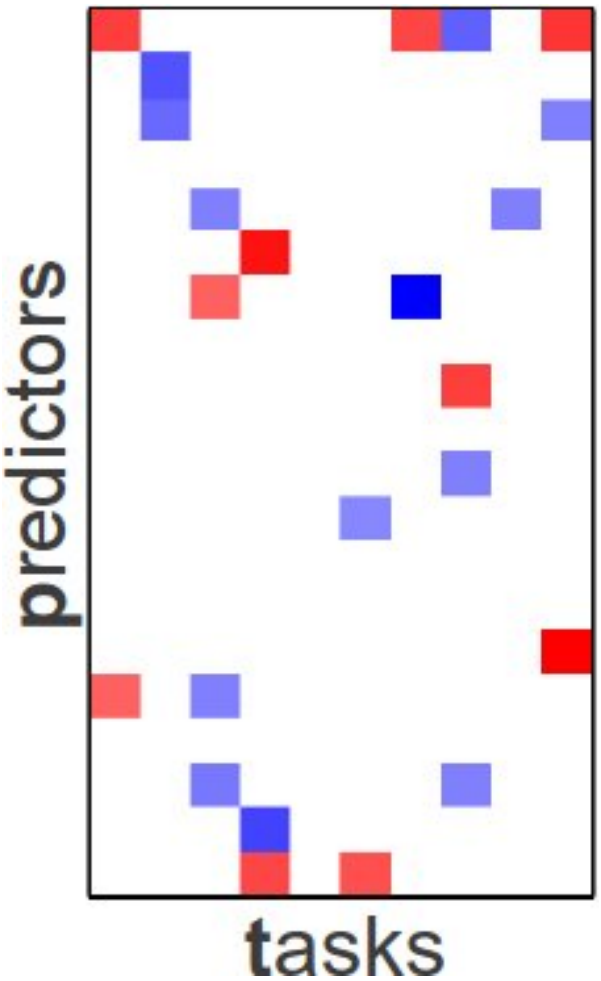
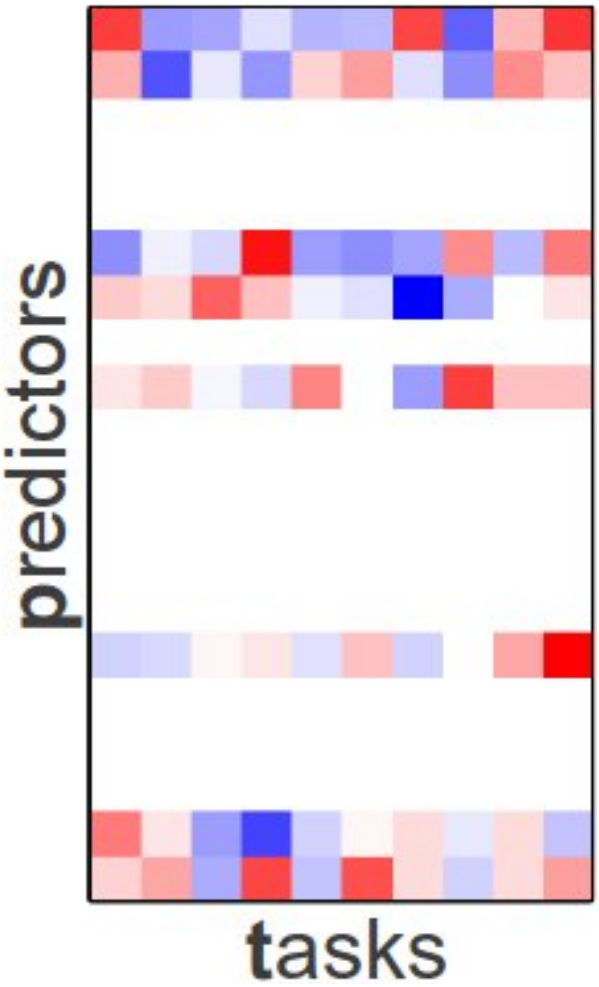
Three regularizers



- $L1$ regularizer [FHT10]: $\Omega(\mathbf{\Theta}) = \sum_t \sum_p |\theta_{pt}|$
- encourages regression coefficients to be zero
- equivalent to running T separate lasso regressions
- Interpretable? Sort of. L1 isolates a few robust associations, but it forces us to think about each demographic attribute separately.

Structured regularization

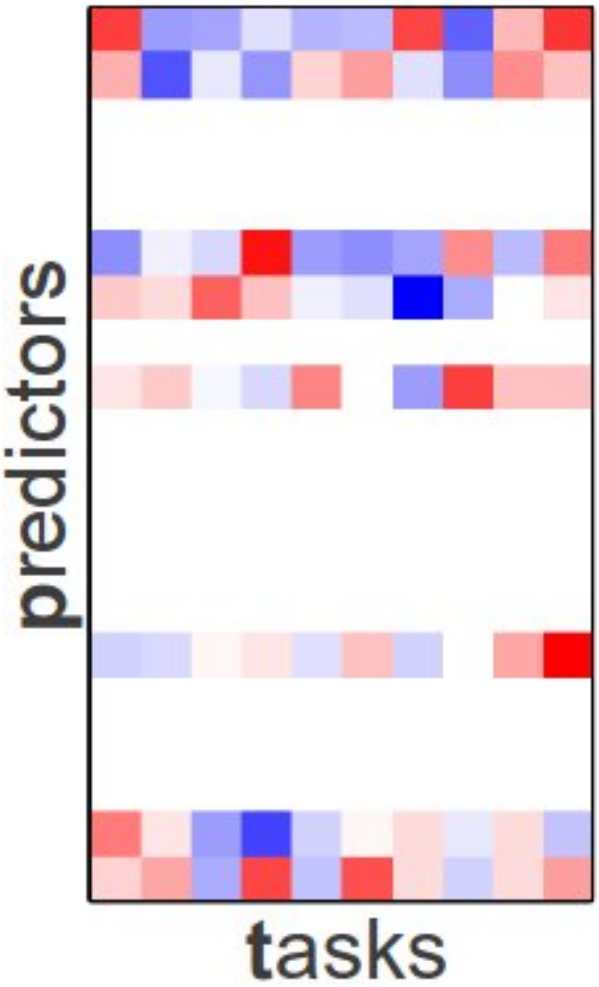


$L1/L\infty$ regularizer

$$\Omega(\mathbf{\Theta}) = \sum_t \max_p |\theta_{pt}|$$

aka **multi-output lasso** [TVW05]

Structured regularization



$L1/L\infty$ regularizer

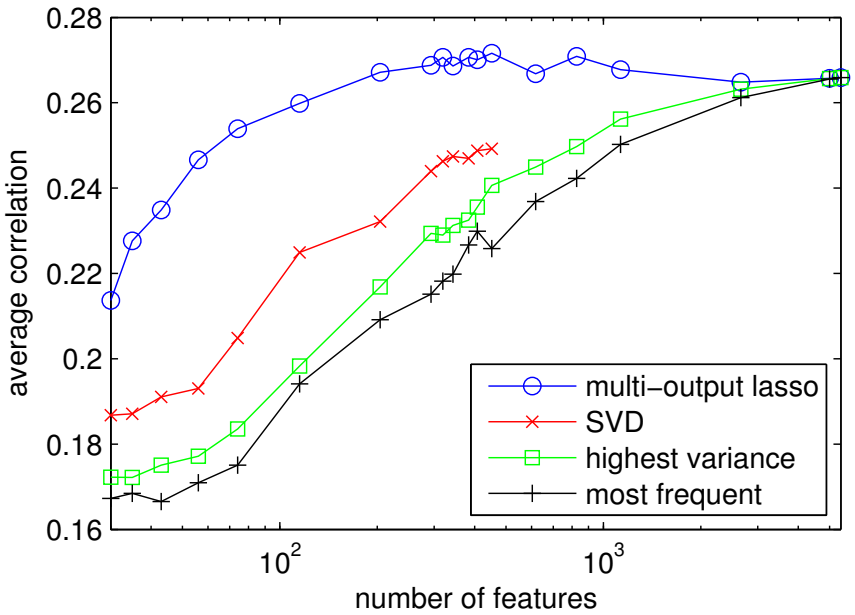
$$\Omega(\mathbf{\Theta}) = \sum_t \max_p |\theta_{pt}|$$

aka **multi-output lasso** [TVW05]

- pushes entire rows to zero
- not decomposable, must be solved jointly
- Interpretable? Yes: it identifies words with strong associations across a range of demographic attributes

Regularization path

By increasing the strength of the regularizer, we discard more terms from the vocabulary.



- Predictive accuracy remains high even when the vocabulary is reduced by more than an order of magnitude.
- Other dimensionality-reduction techniques suffer dramatically.

Predictive accuracy

vocabulary	**# features**	average	white	Afr. Am.	Hisp.
full	5418	0.260	0.337	0.318	0.296
multi-output lasso	394.6	0.260	0.326	0.308	0.304
SVD		0.237	0.321	0.299	0.269
highest variance		0.220	0.309	0.287	0.245
most frequent		0.204	0.294	0.264	0.222

- **metric**: Pearson correlation between predicted and true values of demographic attributes
- **baselines**:
  - SVD of author-term matrix
  - highest variance words
  - most frequent words

Predictive accuracy

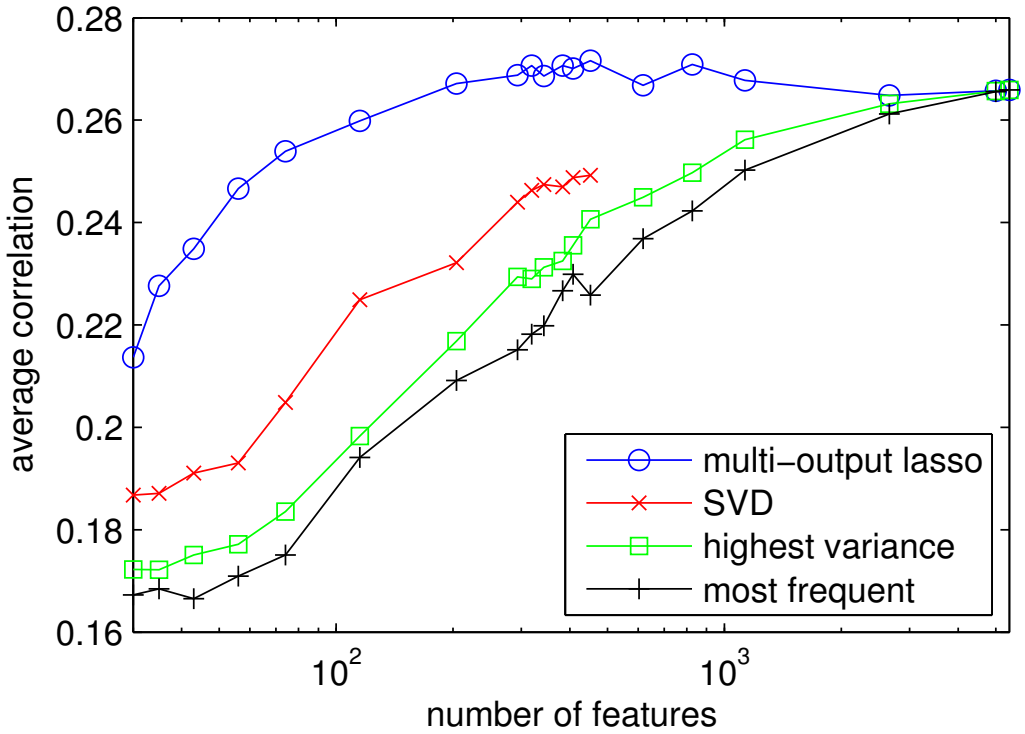
vocabulary	**# features**	average	Eng. lang.	Span. lang.	other lang.
full	5418	0.260	0.384	0.296	0.256
multi-output lasso	394.6	0.260	0.383	0.303	0.249
SVD		0.237	0.352	0.272	0.226
highest variance		0.220	0.315	0.248	0.199
most frequent		0.204	0.293	0.229	0.178

Predictive accuracy

vocabulary	**# features**	average	urban	family	renter	med. inc.
full	5418	0.260	0.155	0.113	0.295	0.152
multi-output lasso	394.6	0.260	0.153	0.113	0.302	0.156
SVD		0.237	0.138	0.081	0.278	0.136
highest variance		0.220	0.132	0.085	0.250	0.135
most frequent		0.204	0.129	0.073	0.228	0.126

- All confidence intervals are tighter than ± 0.02.
- 93% reduction in model size, no loss in performance.
- Socioeconomic attributes are more difficult to predict than race, ethnicity, and language.

Qualitative analysis



- In predictive experiments, regularization chosen on dev set
- Now we tune it to identify a more compact set of 69 terms

Place names and foreign language

	white	Afr. Am.	Hisp.	Eng. lang.	Span. lang.	other lang.	urban	family	renter	med. inc.
atlanta			-	+	-	-				
famu		+	-	+	-	-				-
harlem				-					+	
con			+	-	+				+	
la		-	+	-	+					
si		-	+	-	+					

The symbols + and - indicate significant positive or negative association, as measured by a Wald Test, with Bonferroni correction.

Dictionary Words

	white	Afr. Am.	Hisp.	Eng. lang.	Span. lang.	other lang.	urban	family	renter	med. inc.
as			-	+	-					
awesome	+	-					-		-	+
break			-	+	-	-				
campus			-	+	-	-				
dead	-	+		-	+		+		+	
hell			-	+	-	-				
shit	-								+	
train				-	+				+	
will			-	+	-					
would				+					-	

Abbreviations

	white	Afr. Am.	Hisp.	Eng. lang.	Span. lang.	other lang.	urban	family	renter	med. inc.
bbm	-	+		-		+	+		+	
lls		+	-	+	-	-				
lmaoo	-	+	+	-	+	+	+		+	
lmaooo	-	+	+	-	+	+	+		+	
lmaoooo	-	+	+	-	+	+			+	
lmfaoo	-		+	-	+	+			+	
lmfaooo	-		+	-	+	+			+	
lml	-	+	+	-	+	+	+		+	-
odee	-		+	-	+		+		+	
omw	-	+	+	-	+	+	+		+	
smfh	-	+	+	-	+	+	+		+	
smh	-	+					+		+	
w	-		+	-	+	+	+		+	

Emoticons

	white	Afr. Am.	Hisp.	Eng. lang.	Span. lang.	other lang.	urban	family	renter	med. inc.
-_-	-		+	-	+	+	+			
;)		-	+	-	+					
:(		-								
:)		-								
:d	+	-	+	-	+					

Other

	white	Afr. Am.	Hisp.	Eng. lang.	Span. lang.	other lang.	urban	family	renter	med. inc.
dats	-	+		-					+	-
deadass	-	+	+	-	+	+	+		+	
haha	+	-							-	
hahah	+	-								
hahaha	+	-							-	+
ima	-		+	-	+				+	
madd	-			-		+		+		
nah	-		+	-	+	+			+	
ova	-	+		-					+	
sis	-	+							+	
skool	-	+		-		+	+		+	-
wassup	-	+	+	-	+	+	+		+	-
wat	-	+	+	-	+	+	+		+	-
ya	-	+							+	
yall	-	+								
yep			-	+	-	-	-		-	
yoo	-	+	+	-	+	+	+		+	
yooo	-	+		-	+				+	

Overview of demographic variation

- Some observations
  - **Paralinguistic commentary** is an area of major differences between demographic groups.
    - **Emoticons** correlate with % Whites, English speakers, Hispanics
    - **Abbreviations** correlate % African Americans, Hispanics, renters
  - **Phoneticization** correlates with % African American
    - May reflect phonological features of AAE (“dats”, “wassup”, “ima”)

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  - **Phoneticization** correlates with % African American
    - May reflect phonological features of AAE ("dats", "wassup", "ima")
- Jointly modeling many demographic attributes makes lexical analysis more robust, limiting multiple comparisons.

Gender, language and social networks

Gender in Twitter: Styles, stances, and social networks.
Bamman, Eisenstein, and Schnoebelen. In preparation.

Gender, language and social networks

Gender in Twitter: Styles, stances, and social networks.
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- Social networks are often homophilous with respect to gender.
- We started with a simple idea:
  use the social network to improve gender prediction.

Data

- 14,464 Twitter users (56% male)
  - geolocation in USA
  - must use 50 of 1000 most frequent words
  - no more than 1000 follow connections
- 9.2M tweets, from January to June 2011
- Author gender induced from first name and census records
- Social network induced from mutual @-mentions
  - Women have 58% female friends
  - Men have 67% male friends

Adding network features

Logistic regression, 10-fold cross-validation:

- Text alone: 89% accuracy

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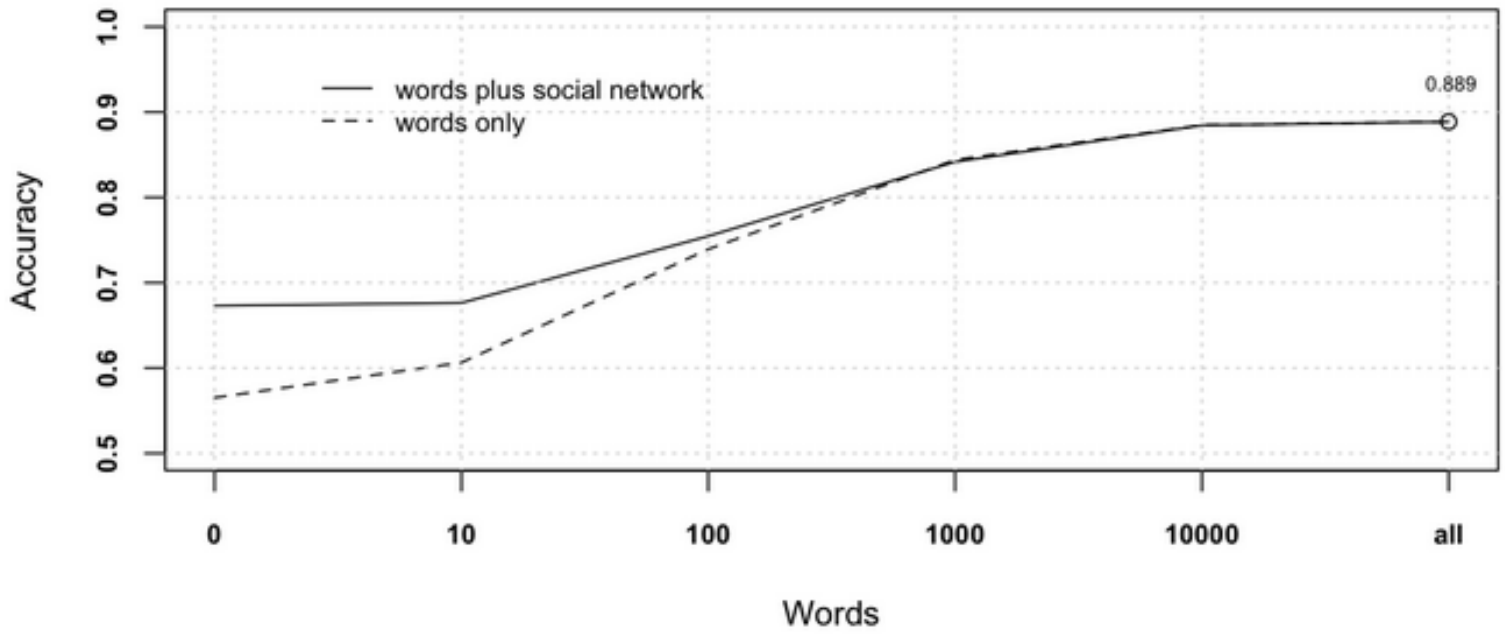
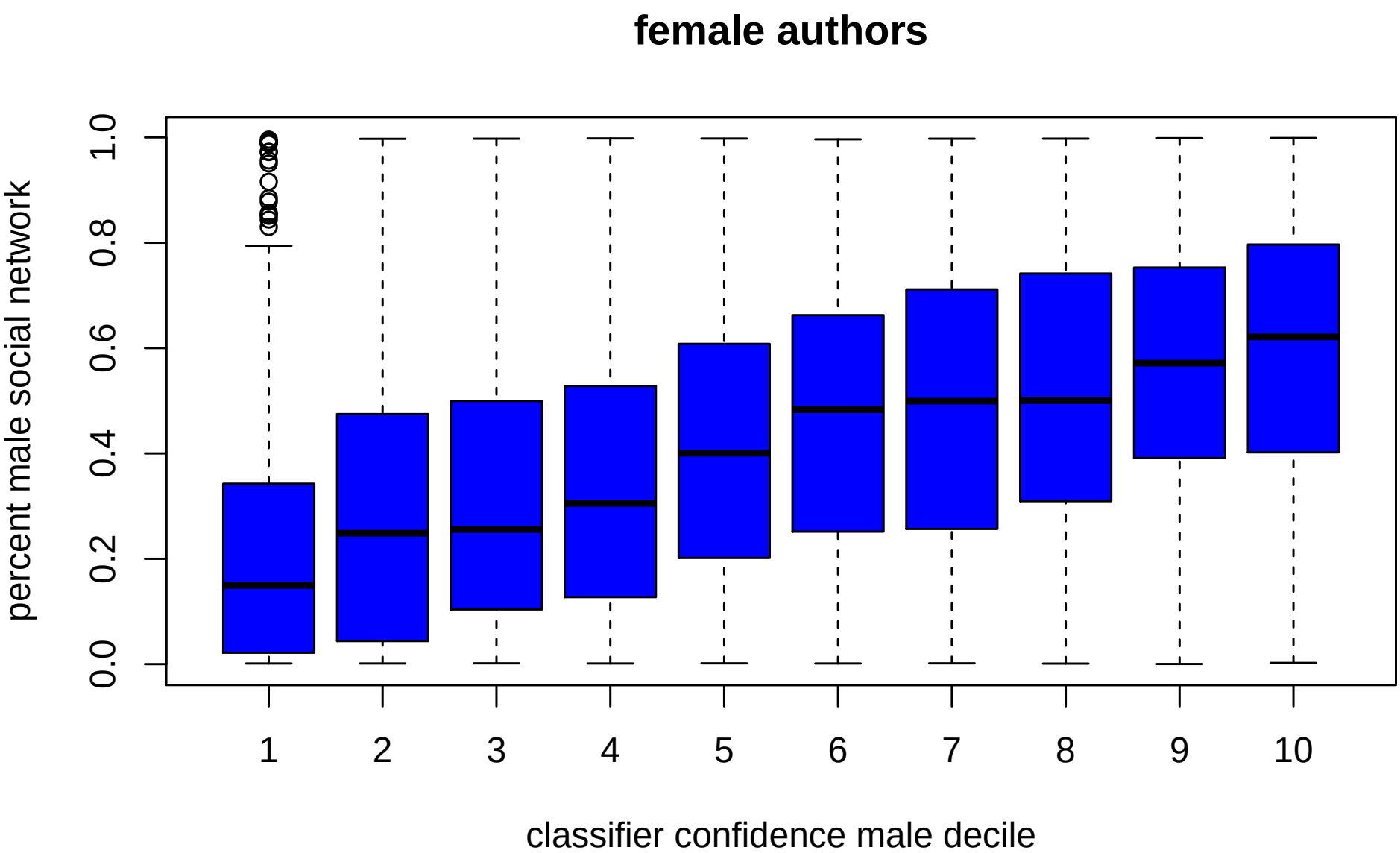
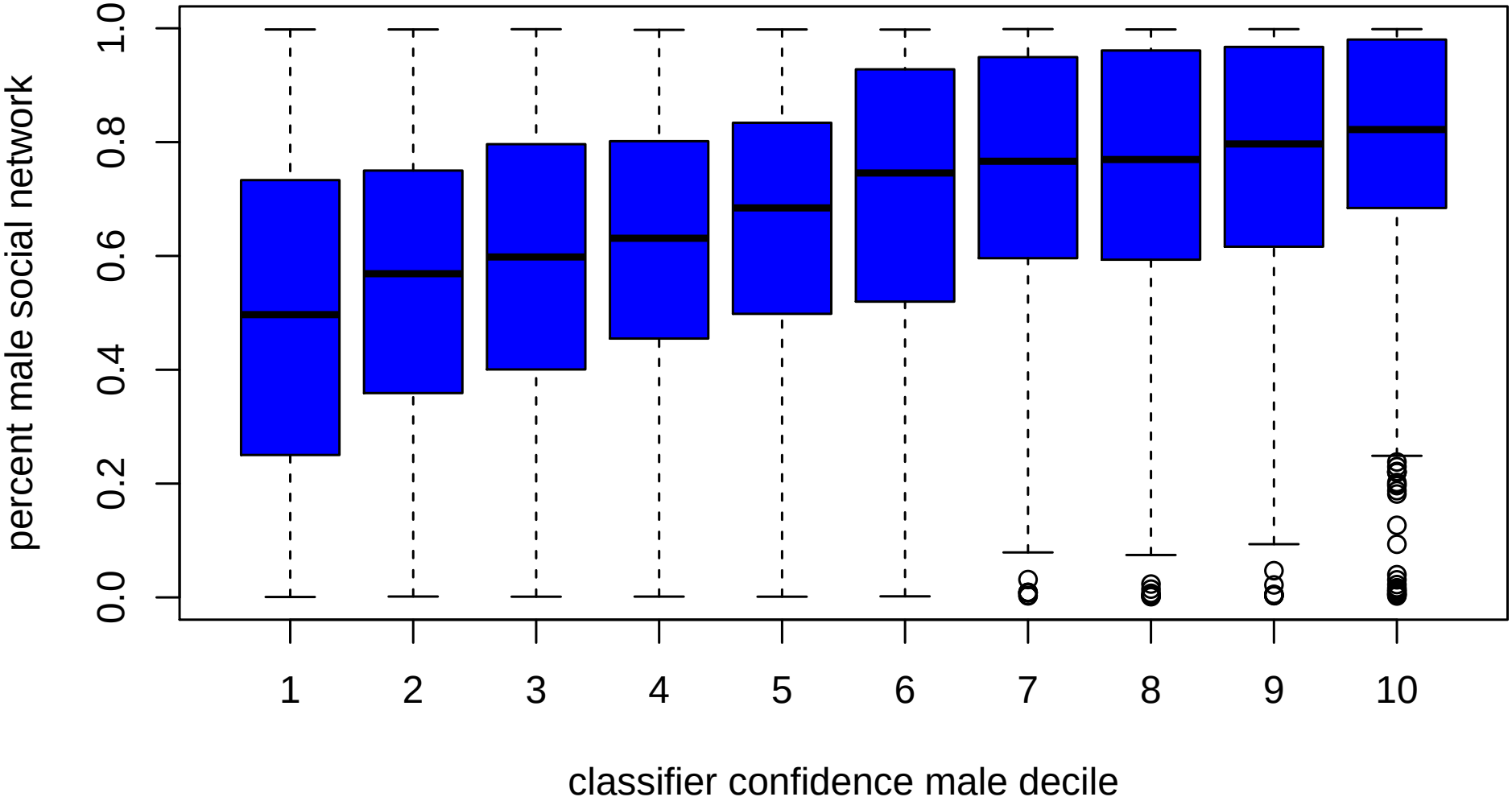


Once we have 1000 words per author, adding network information does not improve performance. **Why not?**


female authors
percent male social network
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
9
10
classifier confidence male decile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Why social network features don't help

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classifier vs. network	0.38 ($.35 \leq r \leq .40$)	0.33 ($.30 \leq r \leq .36$)

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- Network features will improve gender classification only to the extent that they are adding new information.
- But language and social network are **not** independent views on gender as a discrete, binary variable [EMG03].
- Language and the social network are correlated because they are noisy views on gender as a continuous space of possibilities.

Text-based gender prediction

- To determine the language features that drive the classifier's performance, we computed the 500 words that were the strongest predictor of each gender.
- We then manually divided these words into categories.

		female	male
Dictionary words		325	295
Shortenings	ballin	19	16
Named entities	ipad	13	134
Taboo/swear words	fuck	1	10
Other, pronounceable	awww	80	8
Other, unpronounceable	<3	46	23
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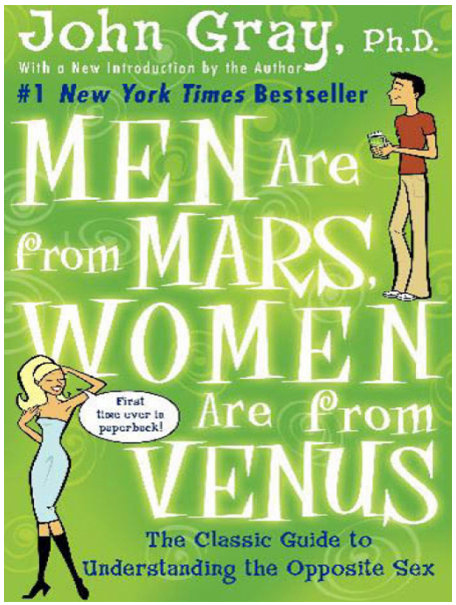
Clustering by content

- At the corpus level, women use more non-dictionary words and men mention more named entities.
- This fits snugly into an airport bookstore pop psycholinguistics of gender...



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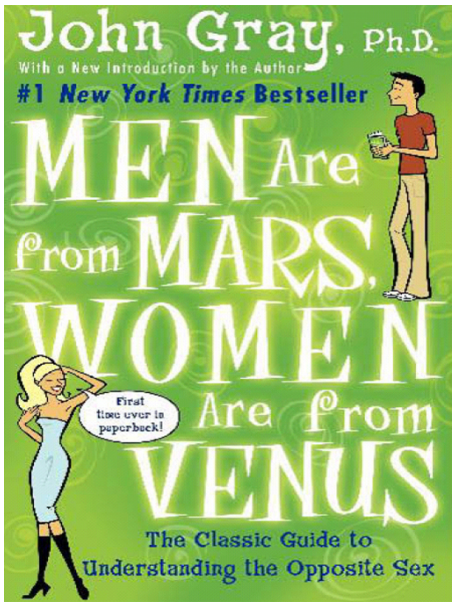
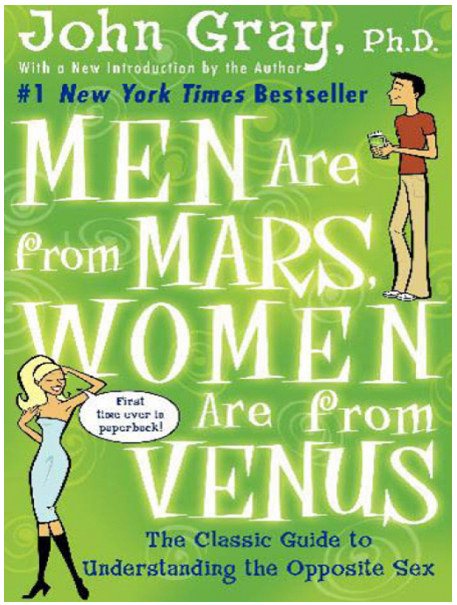


Clustering by content

- At the corpus level, women use more non-dictionary words and men mention more named entities.
- This fits snugly into an airport bookstore pop psycholinguistics of gender...
- But we have already seen that we should distrust the binary male/female opposition.
- For a closer look, we clustered all authors by text.
  - K-means ($K = 20$)
  - Clusters represent shared interests and/or styles.
  - Many clusters **happen to have** strong demographic orientations, including gender, race, and age.



Female clusters

% fem	words
0.84	fabric blogged hubs recipe recipes delish @starbucks almond howdy baking cocktails
0.79	;o xx hun xxx hump sweetie x xoxoxo cena becky
0.78	xo elizabeth gr8 -) ranked ty blessings thnx fr 2day
0.76	muah darren bo sry xoxoxo sux ,,, scotty lmbo hun
0.75	**clark pokemon ash arc #idol authors unicorns terrifying romance chapter**
0.75	:') (: <333 @justinbieber (; xxx <33333 </3 <33 ;d

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- At the population level, women use few named entities and many non-dictionary words.
- But there are clusters of (mostly) women who do the opposite.

Male clusters

% fem	words
0.29	dems gop democrats unions conservative senate muslim israel liberal republicans
0.28	**niggaz shyt dats dey wats lmmfao lik dis neva lls**
0.19	e3 gears psn 360 kombat halo gaming portal console marvel
0.19	bama @darrenrovell @espn severe auburn ky #heat thunderstorm au #marchmadness
0.15	#nba mets #jets #mavs #knicks crawford @ochocinco pacers #lakers wright
0.14	api ui ios apple's developers developer dev hardware plugin interface
0.07	#nhl nhl prospect #bruins qb roster timeout 2-1 boozer 1-0

- At the population level, men use many named entities and few non-dictionary words.
- But there are clusters of men who do the opposite.

Overview of gender variation

- From a theoretical perspective, the sociolinguistics of gender has moved beyond the binary male/female opposition [EMG03]
- Our work provides new quantitative support for this theory.
  - The social network analysis supports the view of gender as a continuous – rather than binary – variable.
  - The clustering analysis supports the view that gender is a social construction, with linguistic properties that are contingent on the *local meaning* of broader gender categories.

Summary

We have examined sociolinguistics on three main axes

- **language** – what aspects of language are affected by social dynamics?
- **speakers** – how does personal identity relate to language variation?
- **context** – how does language carry social meaning in various social and linguistic contexts?

Summary

Computational social media analysis can provide a new perspective:

- **language** – automatically identifying new lexical variables through structured sparsity
- **speakers** – modeling speaker identity through latent variables (such as geographical regions, topics, and clusters).
- **context** – the next frontier?

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