Investigating grammatical variation in African American English on Twitter

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Language variation

- How language varies between and within different groups of speakers
  - *pop* – *soda*
  - *We regret to inform you that…* – *Sorry, but…*
  - *I ain't done nothing like that before* – *I ain't done anything like that before*
- Tells us how we use language to construct identities, and how social contexts affect language use

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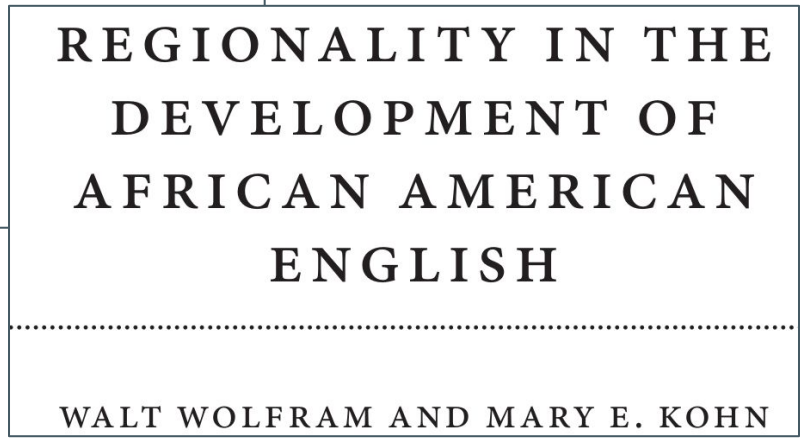
- Tells us how we use language to construct identities, and how social contexts affect language use
- To systematically measure variation (Labov 1984, Tagliamonte 2006):
  - Identify all instances of a certain linguistic feature in a dataset
  - Analyze the feature's distribution across speakers, regions, topics, etc

Variation in AAE

Sociolinguistic Folklore in the Study of African American English

Walt Wolfram*
North Carolina State University



A focus on a core set of basilectal structures in non-Southern urban communities obscured regional variation in early sociolinguistic studies of African American English (AAE). However, community comparisons, particularly in the rural South, indicate that regionality has played an essential role in the past and present development of the variety. This current analysis compares apparent time evidence for

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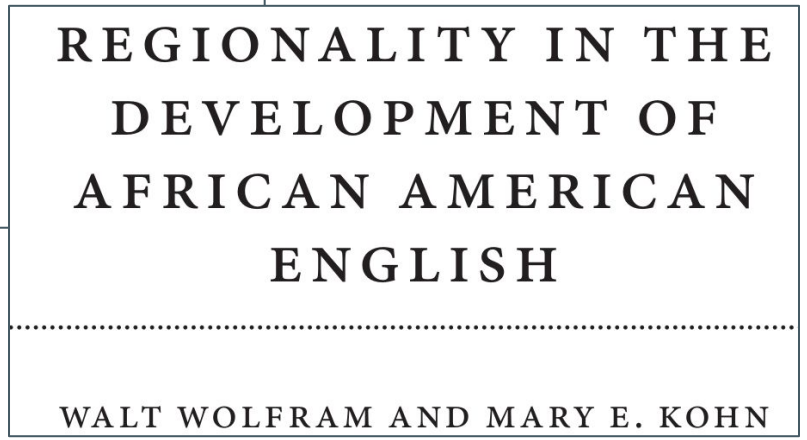

Yaeger-Dror (2007), Wroblewski et al. (2009), Yaeger-Dror & Thomas (2010), Lee (2016), Austen (2017), Jones (2020)

What is a grammatical feature?

- Negative concord
  - *I ain't done nothing like that before*

- Zero copula
  - *He on the five dollar bill*

- Habitual *be*
  - *I be out at my bus stop every day*

Research questions

- To what extent is there **systematic grammatical variation within AAE**?

- How much of this variation can be **accounted for by social factors** (i.e. region, race, age, socioeconomic status)?

Data

- 227M geotagged tweets from Twitter Gardenhose
- Posted from the US during May 2011 - April 2015
- Filtered to prioritize conversational language and limit automated posts

- 5 orders of magnitude larger than previous Twitter corpus studies of AAE, with at least some data in all US counties

Grammatical features

Feature	Example
*Zero possessive	*they want to do they own thing*
Overt possessive	*they want to do their own thing*
*Zero copula	*she the folk around here*
Overt copula	*she's the folk around here*
*future *gone*	*we gone rock it out like*
*Habitual *be*	*I just be liking the beat*
*Resultant *done*	*you done lost your mind*
**be done*	*I be done died walking up that many*
**steady*	*and you steady talking to them*
**finna*	*she's finna have a baby*
*Negative concord	*I ain't doing nothing wrong*
Single negative	*I ain't doing anything wrong*
*Negative auxiliary inversion	*nobody don't say nothing*
*Preverbal negator *ain't*	*I ain't doing nothing wrong*
*Zero 3rd person singular present tense *-s*	*I don't know if it count*
**is/was* generalization	*they is die hard Laker fans*
*Double-object construction	*I got me my own car*
**Wh*-question	*what they were doing?*

Automatic feature detection

- Task: given a set of features F, for each f ∈ F identify utterances which contain f

- For our large dataset, automatic methods are a valuable alternative to manual annotation

Automatic feature detection: our framework

- Generate a small contrast set

- Fine-tune BERT on this contrast set, where each head is a binary classifier for a single feature

Automatic feature detection: our framework

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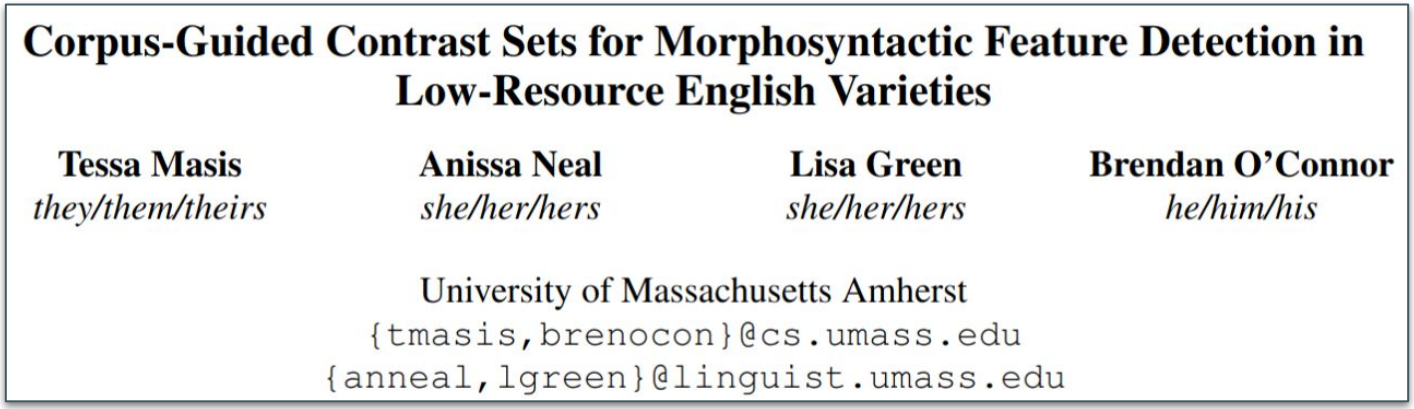

Corpus-Guided Contrast Sets for Morphosyntactic Feature Detection in Low-Resource English Varieties

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Brendan O'Connor *he/him/his*

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Field Matters @ COLING2022

Automatic feature detection: our framework

- Generate a small contrast set

- Fine-tune BERT on this contrast set, where each head is a binary classifier for a single feature

Automatically detecting features

- Input: 227M geotagged tweets

- Output: Census tract-level relative frequencies for 18 grammatical features

$$rf_{feat} = \#\ \text{tweets with feature} / \#\ \text{total tweets}$$

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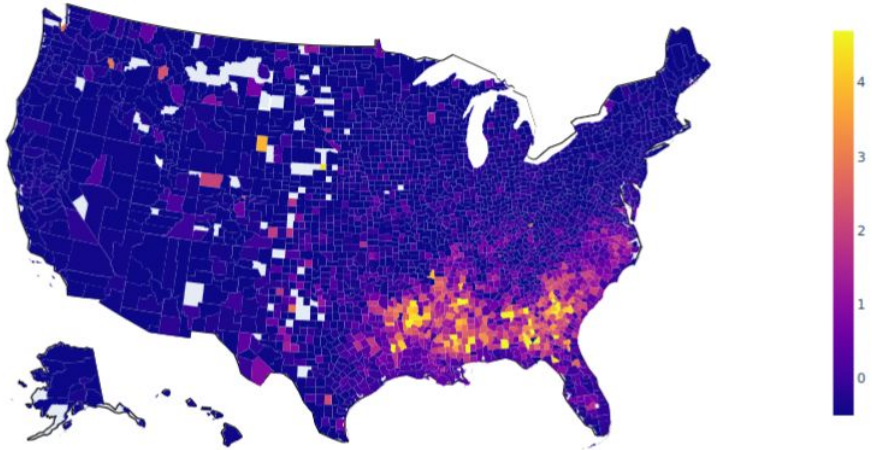
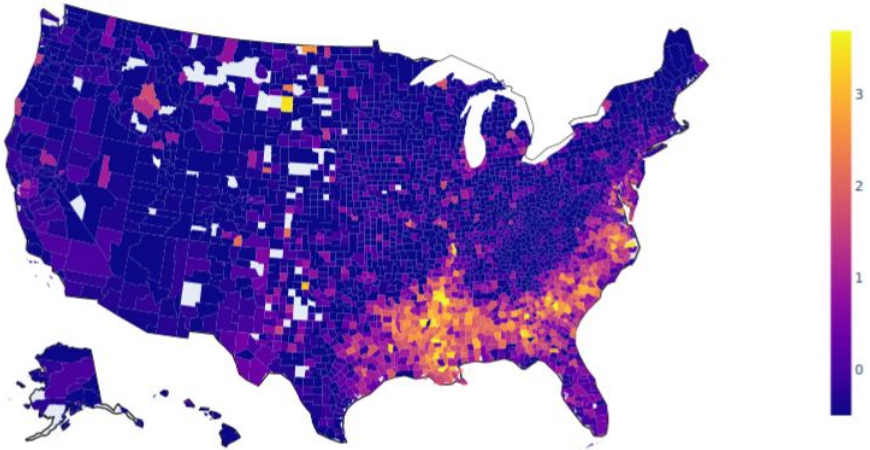
$$rf_{feat} = \#\ \text{tweets with feature} / \#\ \text{total tweets}$$

$$z_{feat} = (rf_{feat} - \mu_{feat}) / \sigma_{feat}$$

Automatically detecting features



(a) Distribution of resultant *done*



(b) Distribution of habitual *be*

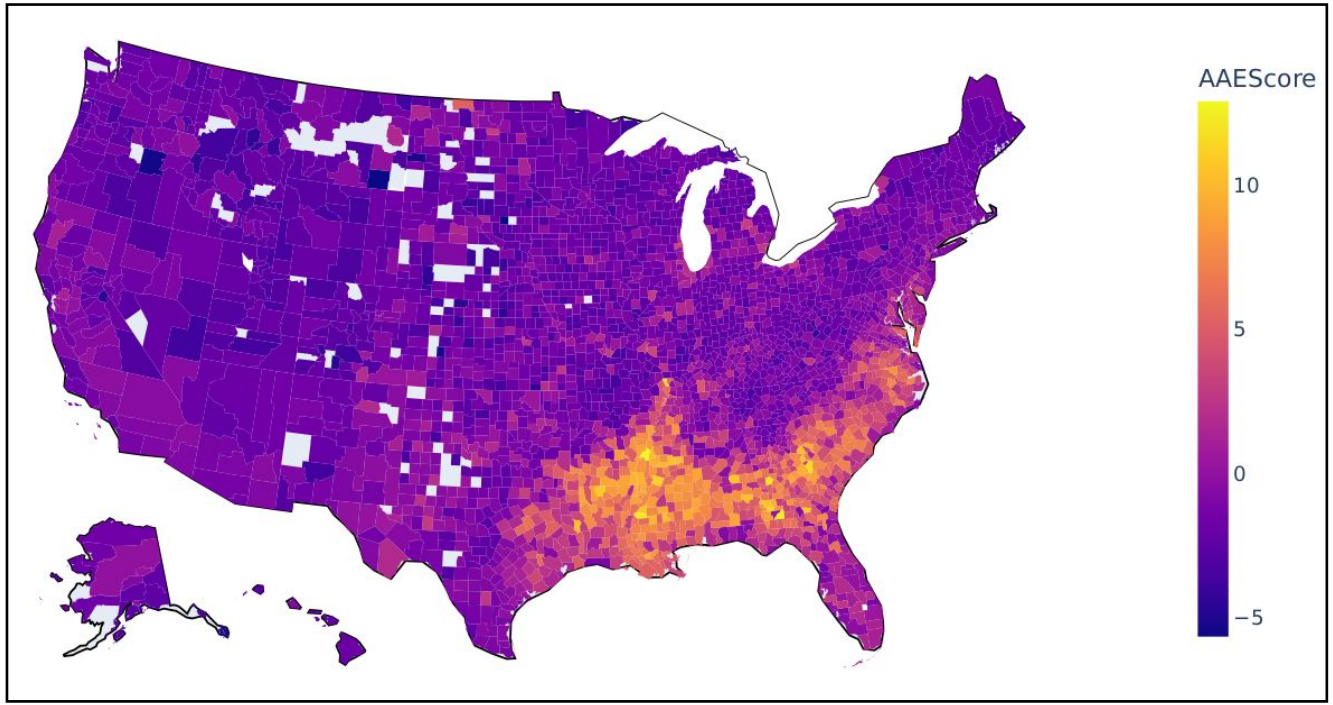
Research questions

- To what extent is there **systematic grammatical variation within AAE**?
  - Principal Components Analysis (PCA)

PCA: feature loadings

Feature	Frequency	AAEScore
ain't	2,168,105	.9156
Habitual *be*	947,900	.8436
future *gone*	477,514	.8409
Negative concord	1,473,423	.8258
Zero copula	7,726,637	.7867
Zero 3rd person singular present tense *-s*	1,100,333	.6721
finna	769,822	.6261
Negative auxiliary inversion	135,497	.6106
Resultant *done*	86,933	.5794
Wh-question	1,517,957	.5754
Zero possessive	239,302	.4587
Double object	486,346	.3767
Single negative	22,907,646	.3037
is/was generalization	1,321,730	.2814
steady	15,047	.2248
be done	146	.0509
Overt possessive	2,735,250	-.4840
Overt copula	53,925,152	-.7126
Percentage of variance		35.58

PCA: AAEScore



Research questions

- To what extent is there **systematic grammatical variation within AAE**?
  - Principal Components Analysis (PCA)

- How much of this variation can be **accounted for by social factors** (i.e. region, race, age, socioeconomic status)?
  - Correlation analysis
  - Linear regression

Correlation analysis

	Pearson's r
Afr.-Am. pop.	0.79
RUCA	-0.07
Latitude	-0.24
Mexican pop.	-0.04
PR pop.	0.07
Income	-0.39
…	…

Linear Regression analysis: RUCA

	Pearson's r	(1)
Afr.-Am. pop.	0.79	2.07
RUCA	-0.07	0.06
Latitude	-0.24	
Mexican pop.	-0.04	
PR pop.	0.07	
Income	-0.39	
…	…	

Linear Regression analysis: RUCA + latitude

	Pearson's r	(1)	(2)
Afr.-Am. pop.	0.79	2.07	2.03
RUCA	-0.07	0.06	0.09
Latitude	-0.24		-0.40
Mexican pop.	-0.04		
PR pop.	0.07		
Income	-0.39		
…	…		

Linear Regression analysis: Mexican pop.

	Pearson's r	(1)	(2)	(3)
Afr.-Am. pop.	0.79	2.07	2.03	2.09
RUCA	-0.07	0.06	0.09	
Latitude	-0.24		-0.40	
Mexican pop.	-0.04			0.19
PR pop.	0.07			
Income	-0.39			
…	…			

Conclusions

- To what extent is there **systematic grammatical variation within AAE**?
  - There is systematic variation, which can be characterized by our first principal component (AAEScore)

- How much of this variation can be **accounted for by social factors** (i.e. region, race, age, socioeconomic status)?
  - Can mostly be explained by relative African American population; but urbanization, geographic region, racial identity also play a role

Thank you!

Slides and abstract available at
tmasis.github.io/

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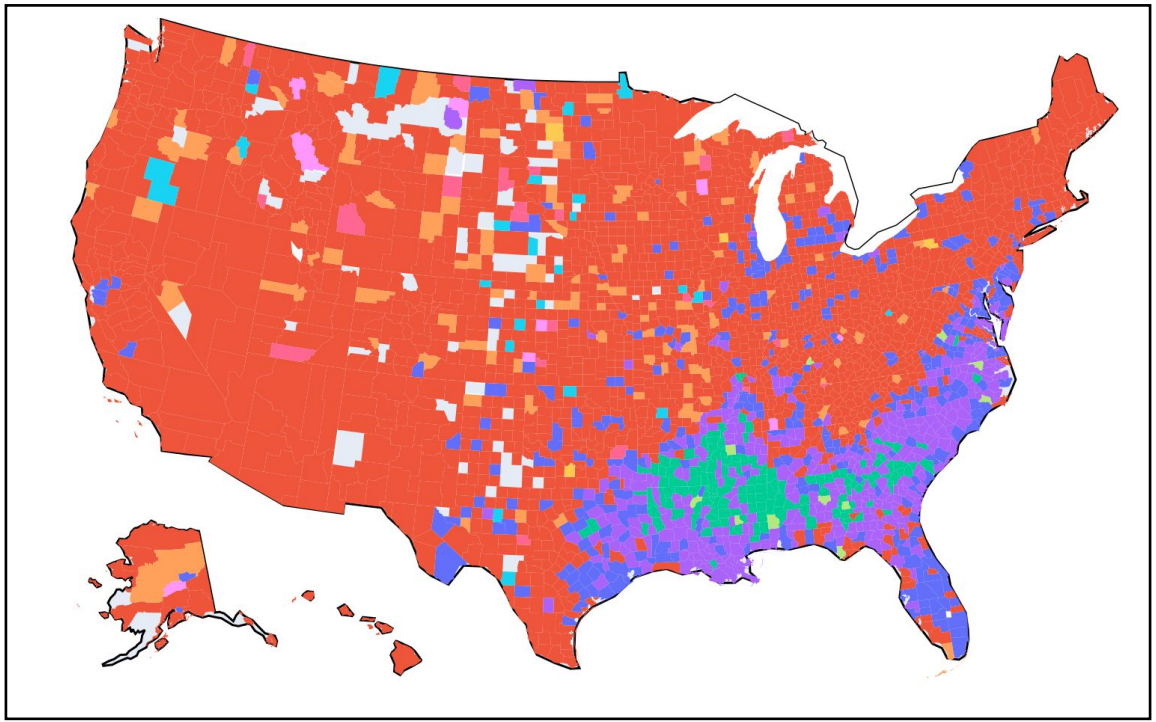
Hampden County example tweets

- *finna*
  - *“@ShawnM1ller: finna hang”*
  - *“Your boy really still waiting on that pizza. Dominoes finna close soon.”*

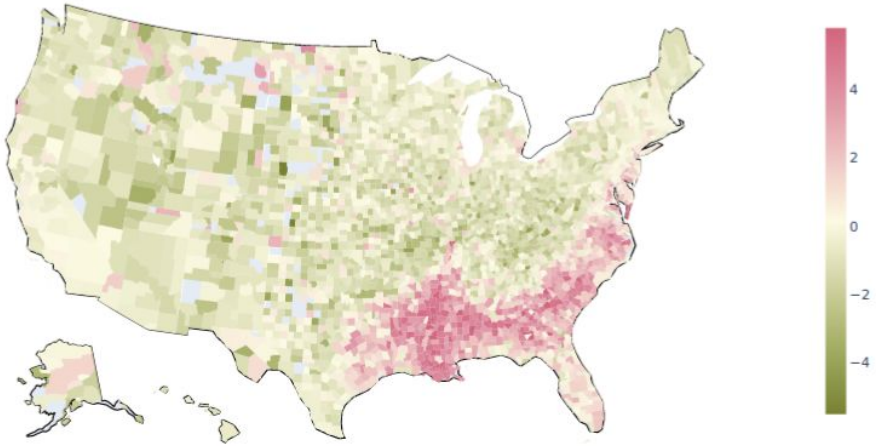
- Zero copula
  - *“I hope my boy @JodyyyyP good”*
  - *“@neaglesbagels you trying to get involved in the half christmas”*

- Habitual *be*
  - *“I b catching them subtweets”*
  - *“These little kids basketball games be gettin intense as fuck lol.”*

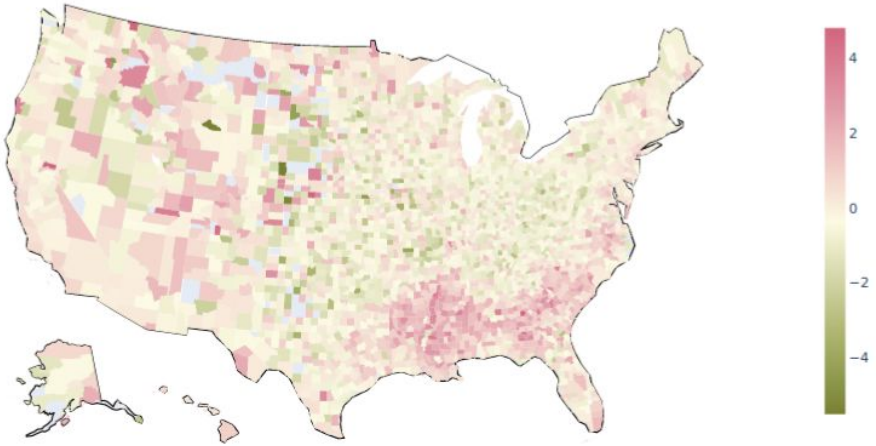
Clustering



Automatically detecting features

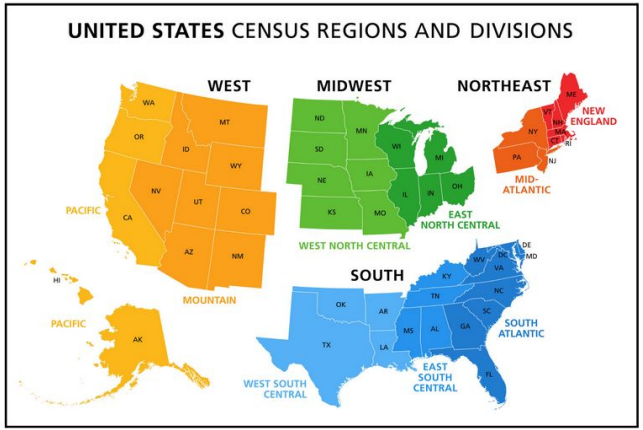


(c) Distribution of zero copula versus overt copula



(d) Distribution of negative concord versus single negative

Linear regression



	Northeast		South		Midwest	
	Metro	Non-metro	Metro	Non-metro	Metro	Non-metro
n	884	32	2612	494	876	60
PC1 averages:	0.4319	0.4595	1.3350	2.6181	1.1427	0.8089
Feature	Z-score	Z-score	Z-score	Z-score	Z-score	Z-score
ain't	0.0789	0.1960	0.5259	1.1415	0.4354	0.4605
habitual be	0.4005	0.2029	0.3703	0.5933	0.4869	0.1514
gone	-0.1550	0.0361	0.4125	0.9186	0.3166	0.0360
neg concord	0.1521	0.2332	0.4006	0.9070	0.3443	0.2408
zero copula	0.2752	0.1747	0.4426	0.5825	0.3542	0.1149
neg auxiliary in	-0.0516	0.1626	0.2494	0.7225	0.2157	0.3290
finna	-0.1312	-0.4150	0.1726	0.4601	0.2367	0.0843
wh-question	0.2261	-0.0630	0.3553	0.5149	0.2656	0.2713
resultant done	-0.1833	-0.1396	0.4136	1.3690	-0.0110	0.1419
zero poss	0.0711	0.1473	0.1567	0.1426	0.2557	-0.1064
zero 3rd sing p	0.0958	0.2481	0.3339	0.4650	0.3459	0.1912
is/was generali	0.3176	0.2561	0.0603	-0.0704	0.3116	-0.0739
double object	0.0699	-0.0598	0.2240	0.5305	0.0262	0.2569
steady	-0.0113	0.2866	0.1222	0.2339	0.0891	-0.0156
be done	-0.0338	-0.0338	0.0702	0.1345	-0.0238	-0.0338
single neg	-0.1313	0.2987	0.1576	0.7323	0.2247	0.5612
overt copula	-0.3507	0.1147	-0.4100	-0.5465	-0.0588	0.1049
overt poss	-0.0321	-0.3068	-0.2734	-0.6178	-0.1879	-0.4589