Conditional language models for linguistic variation and change

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Conditional language models

A language model estimates the probability of a sequence by predicting the next word, given the sequence so far.

$$P(w_1, ...w_n) = \prod_{i=1}^{n} P(w_i \mid w_1, ...w_{i-1}) \tag{1}$$

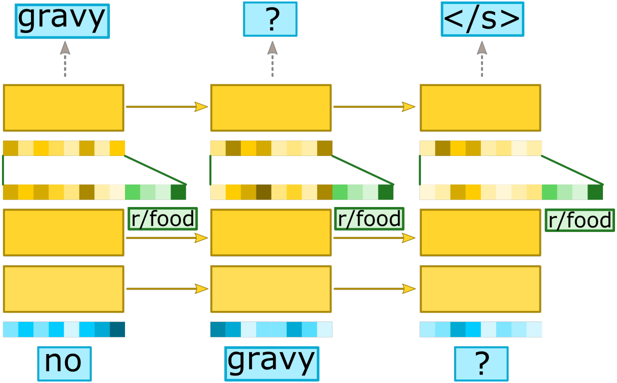
A *conditioned* language model takes additional context, c, into account.

$$P(w_1, ...w_n \mid c) = \prod_{i=1}^{n} P(w_i \mid w_1, ...w_{i-1}; c) \tag{2}$$

Conditional multi-layer neural language models

- Common neural language modelling technique: Concatenate a vector representation of c to the input
- This is commonly used in generative models to get the model to generate text that's relevant to some context, c.
  - Image captioning: concatenate image representation (e.g., Vinyals et al., 2015)
  - Machine translation: concatenate source sentence representation (e.g., Kalchbrenner and Blunsom, 2013)
- In a multi-layer model, we can also inject c between layers by concatenating it to the hidden layer

Community-conditioned language models[1]



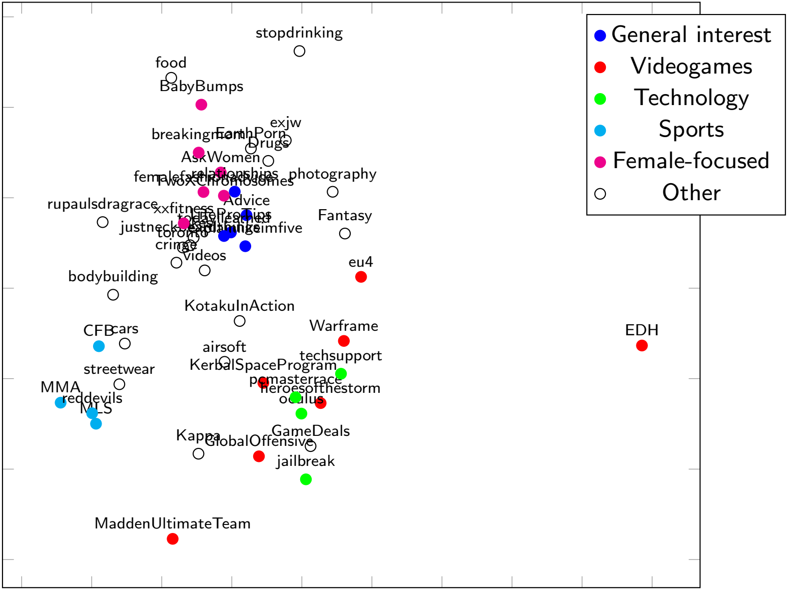
By conditioning on community, we can account for community-level linguistic variation.

[1] Joint work with Jean-Philippe Bernardy.

Conditioning on community improves LM performance

	l_c	test epoch	Perplexity	Info. gain
LSTM	-	21	51.99	-
	0	17	50.83	1.023
	1	34	49.66	1.047
	2	11	50.23	1.035
	3	16	**49.60**	**1.048**
Transformer	-	20	61.43	-
	0	7	58.71	1.046
	1	12	61.69	0.992
	2	7	78.76	0.780
	3	10	**52.28**	**1.054**

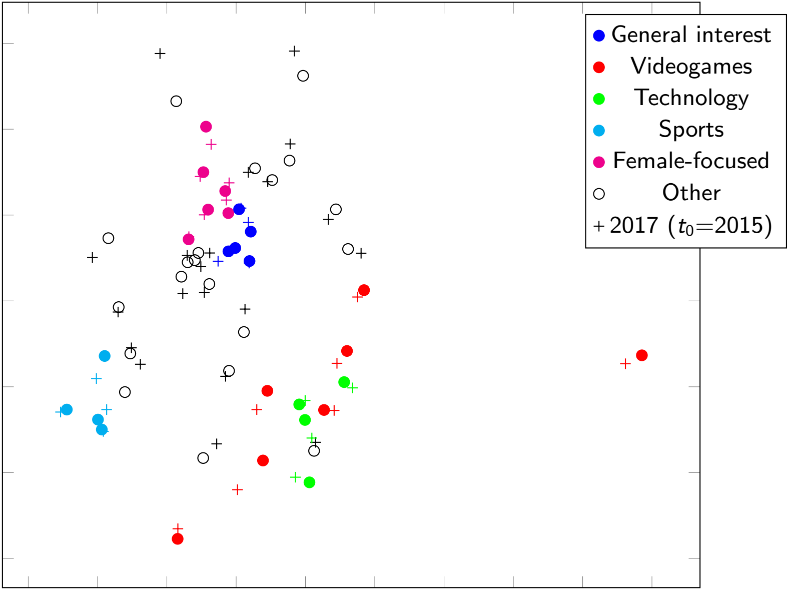
The community embedding (PCA)



Diachronic community-conditioned models: Naive approach

- Idea: Use an embedding for each community × time period
    - With 46 communities and 2 time periods (2015, 2017) we now have 92 conditional vectors.
- Concatenate the community embedding at layer 0 (i.e., directly to the word embedding)

Diachronic community embedding



Word-level change

We have:

- W : $[\texttt{vocab\_size}, \texttt{word\_emsize}]$ – word embeddings
- C : $[\texttt{n\_comms} \times \texttt{n\_time\_periods}, \texttt{cond\_emsize}]$ – conditional embedding
- A : $[\texttt{cond\_emsize} + \texttt{word\_emsize}, \texttt{word\_emsize}]$ – linear layer (before input to the LSTM)

This gives us:

- $W'_{i,j,t} = (W_i \oplus C_{(j \cdot t)}) \cdot A$ – word i “contextualized” by community j in time period t
- $\hat{W}_{i,j} = cos\ dist(W'_{i,j,1}, W'_{i,j,2})$ – community-specific lexical change

Most changed words

We consider words that changed the most in a given community, relative to the same word in other communities. In particular, we consider:

$$\frac{\hat{W}_{i,j} - \sigma_i}{\mu_i}$$

where $\mu_i = \sum_j \hat{W}_{i,j}/|C|$ and σ_i is the associated standard deviation.

Words with the highest relative change

	Advice	AskWomen	BabyBumps	CFB	Drugs
0	méxico	stock	nicks	bloatware	navy
1	rally	nicks	simulation	os	shovelware
2	stock	rally	tsunami	mbr	camo
3	name	core	rebranding	touchscreen	platinum
4	puck	xbmc	rendering	soundcard	attire

	EDH	EarthPorn	Fantasy	GameDeals	GlobalOffensive
0	suburb	scarring	forklift	mouth	crest
1	county	bravado	throttling	yak	ingenuity
2	diets	prowess	cyclone	telepathy	caviar
3	york	medic	liquid	testicle	paints
4	suburbs	rng	boop	cigar	vegemite

	Jokes	Kappa	KerbalSpaceProgram	KotakuInAction	LifeProTips
0	ovr	panhandle	prom	mush	nicks
1	5.0.1	keto	knit	shotty	finishes
2	gear	supplement	bodycon	forma	name
3	jailbreak	ingestion	jean	progress	garbage
4	blueprint	bulking	chiffon	gallium	legends

	MLS	MMA	MaddenUltimateTeam	TwoXChromosomes	Warframe
0	headspace	kit	agnosticism	shotty	lansing
1	os	magnification	doctrine	stock	crest
2	introspection	coloring	famine	xbmc	ogden
3	bloatware	bokeh	gypsies	méxico	photoshopped
4	prescription	liberation	inventions	finishes	shaven

	airsoft	bodybuilding	breakingmom	cars	cringe
0	coulter	vocabulary	ao	sylvanas	blueprint
1	deman	symbolism	rendering	blanche	base
2	intervention	libya	nicks	asd	dmr
3	intervening	croft	gear	tyrande	tek
4	pakman	fiction	leg	arthas	forma

Words with the highest relative change

	eu4	exjw	explainlikeimfive	femalefashionadvice	food
0	posture	stock	chica	relativity	untether
1	hammy	shotty	xbmc	wallbang	firmware
2	competitiveedh	gear	legends	bomb	5.0.1
3	curls	tek	willson	mal	cortana
4	biceps	sport	date	foul	ota

	heroesofthestorm	jailbreak	justneckbeardthings	oculus	pcmasterrace
0	crest	panhandle	forma	yak	hooligan
1	photoshopped	meat	progress	needles	hubris
2	rfk	sushi	stock	fisting	taboo
3	waldo	condiment	home	fatass	yak
4	seagull	pasta	wip	chirp	grade

	photography	reddevils	relationships	rupaulsdragrace	stopdrinking
0	untether	passthrough	eps	throttling	tsunami
1	ow	lightbulbs	hz	output	sr-71
2	medic	png	ftl	hz	clout
3	intervention	flac	toothpicks	polarity	glider
4	cr7	lobina	meu	500fps	divas

	streetwear	techsupport	todayilearned	toronto	videos
0	intoxication	draper	5.0.1	potatoe	ace
1	burdens	theo	ovr	classicfolders	experimentation
2	intervention	goats	playfire	voodoo	wip
3	manoeuvre	peppers	comp	vanilla	progress
4	immunity	savannah	mp	nostalgia	ovr

	xxfitness
0	nicks
1	riches
2	rally
3	swag
4	yahweh

Questions & continuations

- The community/time period embeddings seem to work, but the highest change lists don't look too good. Why?
  - H1: The model doesn't have enough parameters to adjust the word meanings, given community information.
  - H2: The community/time contextualzation operates on word *vectors*, but it should be parametrized by word *tokens*
- What (less naive) conditional architecture would better fit cognitive/interactional theories of language change?
- How does this proposal relate to prior work using language models for semantic change detection?

References I

Kalchbrenner, N. and Blunsom, P. (2013). Recurrent Continuous Translation Models. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, page 10, Seattle, Washington.

Vinyals, O., Toshev, A., Bengio, S., and Erhan, D. (2015). Show and Tell: A Neural Image Caption Generator. *arXiv:1411.4555 [cs]*.