Using Word Embeddings to Examine Gender Bias in Dutch Newspapers, 1950-1990

Melvin Wevers
DHLab KNAW Humanities Cluster
Oudezijds Achterburgwal 185
1012DK Amsterdam, the Netherlands
melvin.wevers@dh.huc.knaw.nl

Abstract

Contemporary debates on filter bubbles and polarization in public and social media raise the question to what extent news media of the past exhibited biases. This paper specifically examines bias related to gender in six Dutch national newspapers between 1950 and 1990. We measure bias related to gender by comparing local changes in word embedding models trained on newspapers with divergent ideological backgrounds. We demonstrate clear differences in gender bias and changes within and between newspapers over time. In relation to themes such as sexuality and leisure, we see the bias moving toward women, whereas, generally, the bias shifts in the direction of men, despite growing female employment number and feminist movements. Even though Dutch society became less stratified ideologically (depillarization), we found an increasing divergence in gender bias between religious and social-democratic on the one hand and liberal newspapers on the other. Methodologically, this paper illustrates how word embeddings can be used to examine historical language change. Future work will investigate how fine-tuning deep contextualized embedding models, such as ELMO, might be used for similar tasks with greater contextual information.

1 Introduction

In recent years, public and academic debates about the possible impact of filter bubbles and the role of polarization in public and social media have been widespread (Pariser, 2011; Flaxman et al., 2016). In these debates, news media have been described as belonging to particular political ideologies, producing skewed views on topics, such as climate change or immigration. These contemporary debates raise the question to what extent newspapers in the past operated in filter bubbles driven by their own ideological bias.

This paper examines gender bias in historical newspapers. By looking at differences in the strength of association between male and female dimensions of gender on the one hand, and words that represent occupations, psychological states, or social life, on the other, we examine the gender bias in and between several Dutch newspapers over time. Did certain newspapers exhibit a bias toward men or women in relationship to specific aspects of society, behavior, or culture?

Newspapers are an excellent source to study societal debates. They function as a transceiver; both the producer and the messenger of public discourse (Schudson, 1982). Margaret Marshall (1995) claims that researchers can uncover the "values, assumptions, and concerns, and ways of thinking that were a part of the public discourse of that time" by analyzing "the arguments, language, the discourse practices that inhabit the pages of public magazines, newspapers, and early professional journals."

The period 1950-1990 is of particular interest as Dutch society underwent clear industrialization and modernization as well as ideological shifts (Schot et al., 2010). After the Second World War, Dutch society was stratified according to ideological and religious "pillars", a phenomenon known as pillarization. These pillars can be categorized as Catholic, Protestant, socialist, and liberal (Wintle, 2000). Newspapers were often aligned to one of these pillars (Wijfjes, 2004; Rooij, 1974). The newspaper *Trouw*, for example, has a distinct Protestant origin, while *Volkskrant* and *De Telegraaf* can be characterized as, respectively, Catholic and neutral. In recent years, the latter transformed into a newspaper with clear conservative leanings. Newspaper historians have studied the ideological backgrounds of Dutch newspapers using traditional hermeneutic means to which this study adds a computational analysis of language

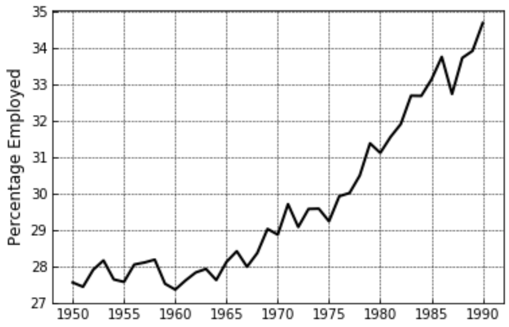

Figure 1: Female Employment Numbers

use related to gender.

The representation of gender in public discourse is related to ideological struggles over gender equality. Several feminist waves materialized in the Netherlands. The origins of the first feminist wave can be traced back to the mid-nineteenth century and lasted until the interwar period. It took until the 1960s for feminism to flare up again in the Netherlands. In between, confessional parties were vocal in their anti-feminist policies. During the 1960s, the second feminist wave, also known as 'new feminism', focused on gender equality in areas such as work, education, sexuality, marriage, and family (Ribberink, 1987).

The increasing equality between men and women is reflected in growing female employment numbers, which increased from 27.5 percent in 1950 to almost 35 percent in 1990 (Figure 1).[1] Apart from Scandinavia, the Netherlands has the highest levels of equality in Europe. Nonetheless, in terms of education and employment, women are still lagging behind and reports of gender discrimination are not uncommon in the Netherlands (Baali et al., 2018; Ministerie van Onderwijs, 2009).

2 Related Work

Word embedding models can be used for a wide range of lexical-semantic tasks (Baroni et al., 2014; Kulkarni et al., 2015). Hamilton et al. (2016) show how word embeddings can also be used to measure semantic shifts by comparing the contexts in which words are used to denote continuity and changes in language use. More recent work focused on the role of bias in word embeddings, specifically bias related to politics, gender, and ethnicity (Azarbonyad et al., 2017; Bolukbasi et al., 2016; Garg et al., 2018). Gonen et al. (2019) demonstrate that debiasing methods work, but argue that we should not remove them. Azarbonyad et al. (2017) compare semantic spaces related to political views in the UK parliament, effectively comparing biases between embeddings. Garg et al. (2018) turn to biases in embedding to study shifts related to gender and ethnicity.

This study builds upon the work of Garg et al. (2018), and applies it to the context of the Netherlands—represented by Dutch newspapers. We extend their method further by distinguishing between sources, rather than using a comprehensive gold standard data set. We also incorporate external lexicons, such as the emotion lexicon from Cornetto, the *Nederlandse Voornamenbank* (database of Dutch first names), the Dutch translation of LIWC (Linguistic Inquiry and Word Count) and HISCO (Historical International Classification of Occupations) (Vossen et al., 2007; Tausczik and Pennebaker, 2010; Boot et al., 2017; Zijdeman et al., 2013; Bloothooft, 2010).

3 Data

The data set consists of six Dutch national newspapers: *NRC Handelsblad (NRC)*, *Het Vrije Volk (VV)*, *Parool*, *Telegraaf*, *Trouw*, and *Volkskrant (VK)*.[2] These newspapers can be characterized ideologically as liberal, social-democratic, liberal, neutral/conservative, Protestant, and Catholic.

For the analysis, we rely on the articles and not the advertisements in the newspapers. We preprocess the text by removing stopwords, punctuation, numerical characters, and words shorter than three and longer than fifteen characters. The quality of the digitized text varies throughout the corpus due to imperfections in the original material and limitations of the recognition software. Because of the variations in OCR quality, we only retain words that also appeared in a Dutch dictionary.

We use the Gensim implementation of Word2Vec to train four embedding models per newspaper, each representing one decade between 1950 and 1990.[3] The models were trained using C-BOW with hierarchical softmax, with a dimensionality of 300, a minimal word count

[1] https://opendata.cbs.nl/statline/#/CBS/nl/

[2] The digitized newspapers were provided by the National Library of the Netherlands. http://www.delpher.nl

[3] https://radimrehurek.com/gensim/

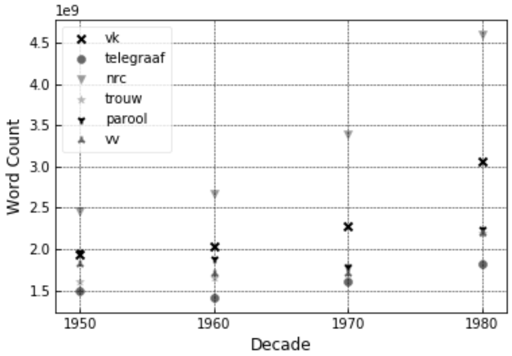

Figure 2: Total number of words per embedding model

and context of 5, and downsampling of 10^{-5}.[4] Figure 2 shows that the size of the vocabulary approximately doubles for some newspapers between 1950 and 1990. The variance of the targets words, however, was small ($\mu \approx 0.003$) and constant ($\sigma[1.3^{-9}, 2.9^{-9}]$), indicating model stability. Since we calculate bias relative to each model, these differences in vocabulary size will have little impact on shifts in bias.

To measure gender bias, we use three sets of targets words. First, we extract a list of approximately 12.5k job titles from the HISCO data set. Second, we select emotion words with a confidence score of 1.0, a positive polarity above 0.5 ($n = 476$) and a negative polarity below -0.5 ($n = 636$) from Cornetto. Third, we rely on the Dutch translation of LIWC2001, which contains lists of words to measure psychological and cognitive states (Pennebaker et al., 2001). We use the following LIWC (sub)categories: Affective and Emotional Processes; Cognitive Processes; Sensory and Perceptual Processes; Social Processes; Occupation; Leisure activity; Money and Financial Issues; Metaphysical Issues; and Physical states.

4 Methodology

For the calculation of gender bias, we construct two vectors representing the gender dimensions (male, female). We do this by creating an average vector that includes words referring to male (‘man’, ‘his’, ‘father’, etc.) or female as well as the most popular first names in the Netherlands

[4]Code can be found here: https://github.com/melvinwevers/historical_concepts and the models here: http://doi.org/10.5281/zenodo.3237380

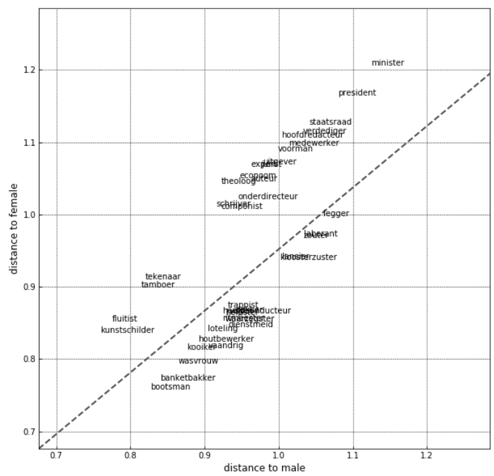

Figure 3: Job titles with strong bias towards men and women in *De Volkskrant*, 1980-1990

for the period 1950-1990.[5] Next, we calculate the distance between each gender vector and every word in a list of target words, for example, words that denote occupations: a greater distance indicates that a word is less closely associated with that dimension of gender. The difference between the distances for both gender vectors represents the gender bias: positive meaning a bias toward women and negative toward men. Figure 3 shows the biases related to forty job titles. Words above the diagonal are biased towards men, and those underneath the diagonal towards women.

Finally, after standardizing and centering the bias values, we apply Bayesian linear regression to determine whether the bias changed over time. The linear model is formulated as:

$$\mu_i = \alpha + \beta * Y_i + \epsilon,$$

with μ_i the bias for each decade (i) and Y_i the coefficient related to each decade (i). The likelihood function is: $X \sim \mathcal{N}(\mu, \sigma)$ with priors defined: $\alpha \sim \mathcal{N}(0, 2)$, $\beta \sim \mathcal{N}(0, 2)$, and $\epsilon \sim \mathrm{HalfCauchy}(\beta = 1)$. For model training, we use a No-U-Turn-Sampler (NUTS) (5k draws, 1.5k tuning steps, Highest Posterior Density (HPD) of .95).[6] For the target words Job Titles, the proposed model (Model B) outperforms a model that only

[5]The word lists for both vectors can be found in Appendix A. The first names were harvested from https://www.meertens.knaw.nl/nvb/

[6]HPD is the Bayesian equivalent of the frequentists confidence interval in Frequentist credible interval. https://docs.pymc.io

	WAIC	pWAIC	dWAIC	weight	SE	dSE
Model B	64624.8	2.9	0	0.99	201.6	0
Model A	64682.1	1.88	57.28	0.01	201.36	15.2

Table 1: Model Comparison

	mean	sd	hpd_2.5	hpd_97.5	n_eff	Rhat
a	-0.164	0.010	-0.185	-0.145	1315.073	1.000
bY	0.046	0.006	0.033	0.055	1261.437	0.999
sigma	1.001	0.005	0.992	1.010	1035.282	1.003

Table 2: Model B Summary

includes the intercept (Model A), indicating that bias changes as a function of time (Table 1 & Table 2).

We compute a linear model that combines all newspapers for the target words Job Titles, Positive Emotions, Negative Emotions, and the selected LIWC columns. Then, for the same categories, we compute individual linear models for each newspaper. The resulting models are reported in Appendix B.

5 Results

The combined linear models, including all newspapers, generally display minimal shifts in bias. While the effects are weak, they fall within a .95 HPD. Partly, the weak trends are related to opposing shifts in the individual newspapers, cancelling each other out. Nonetheless, the bias associated with the categories 'TV', 'Music', 'Metaphysical issues', 'Sexuality' navigate toward women (0.22, 0.12, 0.15, 0.22), with all of them starting from a position that was clearly oriented toward men (-0.36, -0.20, -0.28, -0.39).[7] Conversely, 'Money', 'Grooming', and Negative Emotion words move toward men (-0.24, -0.17, -0.16), which in the 1950s were all more closely related to women (0.33, 0.20, 0.19). For the Job Titles, we see a slight move toward women (0.05), while words from the LIWC category Occupation move marginally in the direction of men (-0.05). This suggests that job titles might be more closely related to women, while the notion of working gravitates toward men.

The linear models for the individual newspapers demonstrate distinct differences between the newspapers. First, *Volkskrant* is the most stable newspapers with 56% of the categories not changing.[8] When bias changes in this newspaper, it

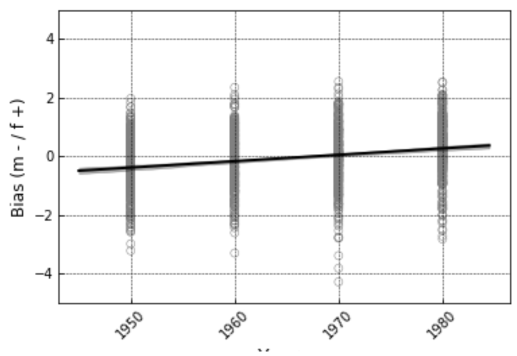

Figure 4: Combined model 'Sexuality'

moves toward women 9 out the 11 categories that change. *Telegraaf*, *NRC*, and *Parool* generally move toward men, respectively (84%, 92%, and 80%). The bias of *Trouw* and *Vrije Volk*, contrarily, move toward women (both 72%).

A noteworthy result is that in all newspapers the bias shifts toward men in the category 'money'. Moreover, they also all exhibit a move toward women for the category 'sexuality', with the clearest shift in *Volkskrant*, *Trouw*, and *Vrije Volk*.

6 Discussion

While the newspaper discourse as a whole is fairly stable, individual newspapers show clear divergences with regard to their bias and changes in this bias. We see that the newspapers with a social-democratic (*Vrije Volk*) and religious background, either Catholic (*Volkskrant*) and Protestant (*Trouw*) demonstrate the clearest shift in bias toward women. The liberal/conservative newspapers *Telegraaf*, *NRC Handelsblad*, and *Parool*, on the contrary, orient themselves more clearly toward men. Despite increasing female employment numbers in the Netherlands, the association with job titles moves only gradually toward women, while words associated with working move toward men. More detailed analysis of the individual trend within each decade is necessary to untangle what exactly is taking place. For example, which words show the biggest shift, and can we identify groups of associated words of which particular words show divergent behavior? Methodologically, this paper shows how word embedding models can be used to trace general shifts in language related to gender. Nevertheless, certain cultural expressions of gender are not captured by distributional semantics represented through word

[7] Numbers refer to the slope

[8] Lower confidence interval < 0 and upper > 0

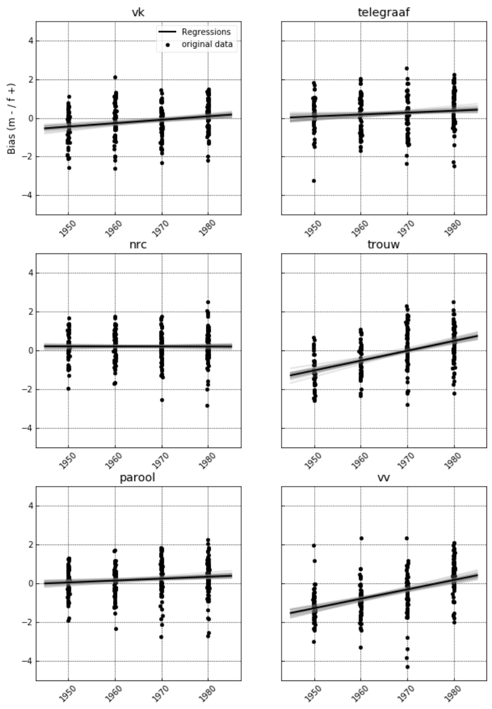

Figure 5: Individual newspaper model ‘Sexuality’

embeddings, but rather in syntax, for example, through the use of active of passive sentences. Future work will investigate how fine-tuning state-of-the-art embedding models, such as ELMO and BERT, can be leveraged to gain more contextual knowledge about words and their association with gender (Peters et al., 2018).

Acknowledgments

I would like to thank Folgert Karsdorp for his feedback. This research was part the project “Digital Humanities Approaches to Reference Cultures: The Emergence of the United States in Public Discourse in the Netherlands, 1890-1990”, which was funded by the Dutch Research Council (NWO).

References

Hosein Azarbonyad, Mostafa Dehghani, Kaspar Beelen, Alexandra Arkut, Maarten Marx, and Jaap Kamps. 2017. Words are malleable: Computing semantic shifts in political and media discourse. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, pages 1509–1518. ACM.

Laila Ait Baali, Roos van Os, and Jantien Kingma. 2018. Overheid moet gendergelijkheid centraal stellen. https://www.volkskrant.nl/gs-b6023212.

Marco Baroni, Georgiana Dinu, and Germán Kruszewski. 2014. Don’t count, predict! a systematic comparison of context-counting vs. context-predicting semantic vectors. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, volume 1, pages 238–247.

Gerrit Bloothooft. 2010. Nederlandse Voornamenbank. https://www.meertens.knaw.nl/nvb/veelgesteldevragen.

Tolga Bolukbasi, Kai-Wei Chang, James Zou, Venkatesh Saligrama, and Adam Kalai. 2016. Quantifying and reducing stereotypes in word embeddings. *arXiv preprint arXiv:1606.06121*.

Peter Boot, Hanna Zijlstra, and Rinie Geenen. 2017. The Dutch translation of the Linguistic Inquiry and Word Count (LIWC) 2007 dictionary. *Dutch Journal of Applied Linguistics*, 6(1):65–76.

Seth Flaxman, Sharad Goel, and Justin Rao. 2016. Filter bubbles, echo chambers, and online news consumption. *Public opinion quarterly*, 80(S1):298–320.

Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16):3635–44.

Hila Gonen and Yoav Goldberg. 2019. Lipstick on a Pig: Debiasing Methods Cover up Systematic Gender Biases in Word Embeddings But do not Remove Them. *arXiv:1903.03862 [cs]*.

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Cultural shift or linguistic drift? comparing two computational measures of semantic change. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing*, volume 2016, page 2116. NIH Public Access.

Vivek Kulkarni, Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2015. Statistically significant detection of linguistic change. In *Proceedings of the 24th International Conference on World Wide Web*, pages 625–635. International World Wide Web Conferences Steering Committee.

Margaret Marshall. 1995. *Contesting Cultural Rhetorics: Public Discourse and Education, 1890-1900*. University of Michigan Press, Ann Arbor.

Cultuur en Wetenschap Ministerie van Onderwijs. 2009. Vrouwenemancipatie (gendergelijkheid). https://www.rijksoverheid.nl/onderwerpen/vrouwenemancipatie.

Eli Pariser. 2011. *The filter bubble: What the Internet is hiding from you*. Penguin, London.

James W. Pennebaker, Martha E. Francis, and Roger J. Booth. 2001. Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Associates*, 71(2001):2001.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. *arXiv preprint arXiv:1802.05365*.

Anneke Ribberink. 1987. *Feminisme*. Stichting Burgerschapskunde, Leiden.

Maarten Rooij. 1974. *Kranten: dagbladpers en maatschappij*. Wetenschappelijke Uitgeverij, Amsterdam.

Johan Schot, Arie Rip, and Harry Lintsen, editors. 2010. *Technology and the Making of the Netherlands: The Age of Contested Modernization, 1890-1970*. MIT Press, Cambridge.

Michael Schudson. 1982. *The Power of News*. Harvard University Press, Cambridge.

Yla R. Tausczik and James W. Pennebaker. 2010. The psychological meaning of words: Liwc and computerized text analysis methods. *Journal of language and social psychology*, 29(1):24–54.

P. Vossen, Katja Hofmann, M. de Rijke, E. Tjong Kim Sang, and Koen Deschacht. 2007. The Cornetto database: Architecture and user-scenarios.

Huub Wijfjes. 2004. *Journalistiek in Nederland, 1850-2000: beroep, cultuur en organisatie*. Boom, Amsterdam.

Michael Wintle. 2000. *An Economic and Social History of the Netherlands, 1800-1920: Demographic, Economic, and Social Transition*. Cambridge University Press, Cambridge.

Richard Zijdeman, Kees Mandemakers, Sanne Muurling, Ineke Maas, Bart Van de Putte, Paul Lambert, Marco Van Leeuwen, Frans Van Poppel, and Andrew Miles. 2013. HSN standardized, HISCO-coded and classified occupational titles.

A Gender Vectors

Male vector: hij (he), vader (father), opa (grandpa), zoon (son), man (man), mannen (men), & heer (sir)

Female vector: zij (she), moeder (mother), oma (grandma), dochter (daughter), vrouw (woman), vrouwen (women), & dame (madam)

B Linear Models

		mean	sd	hpd_2.5	hpd_97.5
positive_words	a	-0.009	0.018	-0.042	0.026
	bY	-0.023	0.010	-0.042	-0.004
negative_words	a	0.193	0.017	0.158	0.224
	bY	-0.157	0.009	-0.175	-0.141
job_titles	a	-0.164	0.011	-0.185	-0.142
	bY	0.046	0.006	0.035	0.059
Affect	a	0.198	0.023	0.156	0.241
	bY	-0.162	0.012	-0.185	-0.139
Posemo	a	0.104	0.022	0.064	0.147
	bY	-0.098	0.012	-0.121	-0.076
Negemo	a	0.251	0.024	0.203	0.296
	bY	-0.194	0.012	-0.218	-0.171
Anx	a	0.309	0.027	0.256	0.357
	bY	-0.232	0.015	-0.261	-0.203
Anger	a	0.184	0.027	0.130	0.236
	bY	-0.150	0.014	-0.174	-0.121
Sad	a	0.209	0.026	0.156	0.254
	bY	-0.171	0.013	-0.198	-0.147
Senses	a	0.134	0.023	0.090	0.183
	bY	-0.112	0.012	-0.137	-0.089
Social	a	0.033	0.023	-0.011	0.080
	bY	-0.042	0.012	-0.066	-0.018
Occup	a	0.035	0.022	-0.010	0.076
	bY	-0.053	0.012	-0.074	-0.030
Leisure	a	-0.066	0.025	-0.114	-0.022
	bY	0.031	0.013	0.007	0.055
Home	a	-0.027	0.043	-0.105	0.062
	bY	-0.001	0.023	-0.046	0.043
Sports	a	0.045	0.038	-0.038	0.105
	bY	-0.042	0.020	-0.080	-0.002
TV	a	-0.364	0.088	-0.526	-0.195
	bY	0.217	0.045	0.130	0.302
Music	a	-0.200	0.049	-0.292	-0.102
	bY	0.122	0.025	0.076	0.168
Money	a	0.335	0.028	0.284	0.390
	bY	-0.243	0.015	-0.272	-0.215
Metaph	a	-0.281	0.030	-0.341	-0.225
	bY	0.146	0.015	0.119	0.180
Physcal	a	-0.008	0.027	-0.063	0.041
	bY	-0.020	0.014	-0.044	0.007
Body	a	0.043	0.025	-0.010	0.087
	bY	-0.059	0.013	-0.084	-0.034
Sexual	a	-0.382	0.046	-0.471	-0.289
	bY	0.216	0.023	0.167	0.255
Eating	a	-0.007	0.034	-0.069	0.055
	bY	-0.015	0.018	-0.046	0.023
Sleep	a	0.134	0.049	0.041	0.230
	bY	-0.110	0.027	-0.160	-0.054
Groom	a	0.204	0.055	0.088	0.300
	bY	-0.166	0.031	-0.224	-0.105

Table 3: Combined Linear Model

		mean	sd	hpd_2.5	hpd_97.5	category
nrc	a	0.649	0.049	0.567	0.758	Affect
	a	0.572	0.049	0.482	0.667	Posemo
	a	0.701	0.050	0.605	0.800	Negemo
	a	0.797	0.054	0.684	0.901	Anx
	a	0.687	0.050	0.592	0.787	Anger
	a	0.648	0.055	0.553	0.761	Sad
	a	0.631	0.044	0.545	0.711	Senses
	a	0.474	0.050	0.379	0.567	Social
	a	0.480	0.045	0.386	0.561	Occup
	a	0.485	0.047	0.401	0.577	Leisure
	a	0.465	0.095	0.288	0.653	Home
	a	0.487	0.075	0.325	0.621	Sports
	a	0.290	0.158	-0.018	0.585	TV
	a	0.645	0.093	0.478	0.829	Music
	a	0.719	0.051	0.622	0.810	Money
	a	0.159	0.060	0.049	0.278	Metaph
	a	0.559	0.055	0.441	0.657	Physcal
	a	0.571	0.051	0.476	0.666	Body
	a	0.184	0.094	-0.015	0.343	Sexual
	a	0.661	0.067	0.526	0.784	Eating
	a	0.799	0.088	0.639	0.966	Sleep
	a	0.461	0.116	0.184	0.653	Groom
	a	0.451	0.035	0.376	0.515	positive_words
	a	0.662	0.032	0.604	0.720	negative_words
	a	0.181	0.022	0.134	0.222	job_titles
	bY	-0.384	0.026	-0.431	-0.331	Affect
	bY	-0.308	0.026	-0.359	-0.258	Posemo
	bY	-0.413	0.027	-0.462	-0.359	Negemo
	bY	-0.486	0.029	-0.543	-0.431	Anx
	bY	-0.395	0.027	-0.446	-0.343	Anger
	bY	-0.369	0.027	-0.420	-0.315	Sad
	bY	-0.356	0.023	-0.397	-0.306	Senses
	bY	-0.275	0.025	-0.327	-0.226	Social
	bY	-0.271	0.024	-0.316	-0.220	Occup
	bY	-0.207	0.026	-0.255	-0.159	Leisure
	bY	-0.345	0.051	-0.439	-0.250	Home
	bY	-0.171	0.037	-0.247	-0.101	Sports
	bY	-0.090	0.084	-0.240	0.074	TV
	bY	-0.219	0.050	-0.304	-0.115	Music
	bY	-0.487	0.026	-0.536	-0.436	Money
	bY	-0.125	0.032	-0.189	-0.066	Metaph
	bY	-0.303	0.027	-0.351	-0.248	Physcal
	bY	-0.308	0.027	-0.360	-0.261	Body
	bY	0.012	0.046	-0.073	0.098	Sexual
	bY	-0.409	0.037	-0.476	-0.336	Eating
	bY	-0.461	0.047	-0.558	-0.375	Sleep
	bY	-0.283	0.063	-0.413	-0.162	Groom
	bY	-0.244	0.018	-0.277	-0.204	positive_words
	bY	-0.384	0.017	-0.415	-0.348	negative_words
	bY	-0.131	0.012	-0.154	-0.106	job_titles
parool	a	0.602	0.051	0.515	0.701	Affect
	a	0.594	0.049	0.496	0.686	Posemo
	a	0.648	0.053	0.552	0.755	Negemo
	a	0.763	0.060	0.648	0.883	Anx
	a	0.604	0.055	0.487	0.706	Anger
	a	0.627	0.059	0.525	0.749	Sad
	a	0.544	0.052	0.438	0.648	Senses
	a	0.322	0.056	0.214	0.424	Social
	a	0.434	0.059	0.316	0.545	Occup
	a	0.296	0.057	0.191	0.413	Leisure
	a	0.196	0.106	-0.016	0.374	Home
	a	0.387	0.093	0.207	0.556	Sports
	a	0.211	0.188	-0.113	0.584	TV
	a	0.310	0.106	0.114	0.529	Music
	a	0.759	0.060	0.641	0.878	Money
	a	0.026	0.067	-0.106	0.154	Metaph
	a	0.349	0.058	0.249	0.473	Physcal
	a	0.400	0.056	0.303	0.512	Body
	a	0.049	0.103	-0.124	0.259	Sexual
	a	0.361	0.074	0.206	0.485	Eating
	a	0.515	0.104	0.320	0.714	Sleep
	a	0.418	0.136	0.184	0.679	Groom
	a	0.479	0.041	0.401	0.554	positive_words
	a	0.638	0.038	0.563	0.716	negative_words
	a	-0.053	0.025	-0.097	-0.001	job_titles
	bY	-0.341	0.027	-0.390	-0.290	Affect
	bY	-0.335	0.027	-0.387	-0.283	Posemo
	bY	-0.377	0.028	-0.429	-0.324	Negemo
	bY	-0.463	0.033	-0.524	-0.398	Anx
	bY	-0.341	0.030	-0.400	-0.284	Anger
	bY	-0.388	0.031	-0.451	-0.330	Sad
	bY	-0.310	0.028	-0.367	-0.260	Senses
	bY	-0.159	0.030	-0.216	-0.107	Social
	bY	-0.254	0.032	-0.319	-0.195	Occup
	bY	-0.145	0.030	-0.200	-0.083	Leisure
	bY	-0.141	0.056	-0.256	-0.035	Home
	bY	-0.245	0.048	-0.332	-0.150	Sports
	bY	0.001	0.097	-0.172	0.208	TV
	bY	-0.063	0.057	-0.160	0.056	Music
	bY	-0.490	0.031	-0.549	-0.424	Money
	bY	0.109	0.034	0.047	0.177	Metaph
	bY	-0.159	0.031	-0.214	-0.100	Physcal
	bY	-0.214	0.029	-0.278	-0.161	Body
	bY	0.091	0.054	-0.004	0.194	Sexual
	bY	-0.213	0.039	-0.285	-0.139	Eating
	bY	-0.276	0.058	-0.380	-0.154	Sleep

	bY	-0.283	0.074	-0.417	-0.136	Groom
	bY	-0.273	0.022	-0.313	-0.229	positive_words
	bY	-0.378	0.019	-0.417	-0.346	negative_words
	bY	-0.009	0.014	-0.032	0.022	job_titles
telegraaf	a	0.606	0.062	0.496	0.729	Affect
	a	0.502	0.061	0.388	0.622	Posemo
	a	0.649	0.067	0.527	0.784	Negemo
	a	0.847	0.076	0.704	1.013	Anx
	a	0.479	0.066	0.344	0.594	Anger
	a	0.575	0.068	0.452	0.709	Sad
	a	0.609	0.057	0.492	0.710	Senses
	a	0.487	0.063	0.363	0.606	Social
	a	0.086	0.063	-0.037	0.205	Occup
	a	0.178	0.075	0.021	0.307	Leisure
	a	0.685	0.127	0.412	0.933	Home
	a	0.112	0.112	-0.107	0.341	Sports
	a	0.047	0.182	-0.310	0.404	TV
	a	-0.062	0.127	-0.289	0.188	Music
	a	0.487	0.075	0.342	0.642	Money
	a	0.289	0.072	0.150	0.428	Metaph
	a	0.398	0.067	0.261	0.526	Physcal
	a	0.369	0.066	0.227	0.482	Body
	a	0.116	0.122	-0.121	0.355	Sexual
	a	0.547	0.089	0.367	0.712	Eating
	a	0.877	0.112	0.669	1.097	Sleep
	a	0.584	0.144	0.295	0.855	Groom
	a	0.335	0.048	0.252	0.435	positive_words
	a	0.631	0.046	0.542	0.717	negative_words
	a	-0.020	0.030	-0.079	0.039	job_titles
	bY	-0.298	0.032	-0.358	-0.231	Affect
	bY	-0.190	0.033	-0.248	-0.124	Posemo
	bY	-0.337	0.037	-0.409	-0.265	Negemo
	bY	-0.384	0.040	-0.462	-0.313	Anx
	bY	-0.278	0.036	-0.344	-0.207	Anger
	bY	-0.260	0.035	-0.329	-0.194	Sad
	bY	-0.272	0.028	-0.329	-0.219	Senses
	bY	-0.147	0.034	-0.207	-0.079	Social
	bY	-0.120	0.033	-0.193	-0.065	Occup
	bY	-0.080	0.038	-0.149	-0.002	Leisure
	bY	-0.195	0.067	-0.333	-0.058	Home
	bY	-0.176	0.059	-0.291	-0.059	Sports
	bY	0.131	0.096	-0.049	0.340	TV
	bY	0.085	0.066	-0.031	0.205	Music
	bY	-0.254	0.039	-0.344	-0.181	Money
	bY	0.004	0.039	-0.072	0.081	Metaph
	bY	-0.165	0.035	-0.233	-0.098	Physcal
	bY	-0.223	0.036	-0.287	-0.150	Body
	bY	0.080	0.065	-0.039	0.203	Sexual
	bY	-0.200	0.045	-0.280	-0.103	Eating
	bY	-0.275	0.061	-0.373	-0.140	Sleep
	bY	-0.365	0.079	-0.532	-0.224	Groom
	bY	-0.140	0.026	-0.194	-0.093	positive_words
	bY	-0.317	0.024	-0.362	-0.273	negative_words
	bY	-0.049	0.016	-0.077	-0.017	job_titles
trouw	a	-0.089	0.059	-0.192	0.032	Affect
	a	-0.234	0.048	-0.331	-0.149	Posemo
	a	-0.025	0.061	-0.138	0.103	Negemo
	a	0.009	0.062	-0.102	0.125	Anx
	a	-0.158	0.066	-0.270	-0.024	Anger
	a	-0.038	0.064	-0.152	0.086	Sad
	a	-0.295	0.055	-0.400	-0.189	Senses
	a	-0.273	0.052	-0.366	-0.163	Social
	a	-0.068	0.054	-0.172	0.040	Occup
	a	-0.273	0.058	-0.379	-0.170	Leisure
	a	-0.429	0.125	-0.665	-0.183	Home
	a	0.131	0.101	-0.069	0.316	Sports
	a	-0.865	0.159	-1.184	-0.549	TV
	a	-0.640	0.107	-0.853	-0.441	Music
	a	0.092	0.057	-0.018	0.203	Money
	a	-0.795	0.064	-0.915	-0.671	Metaph
	a	-0.406	0.061	-0.519	-0.292	Physcal
	a	-0.250	0.070	-0.386	-0.110	Body
	a	-1.038	0.126	-1.272	-0.808	Sexual
	a	-0.576	0.090	-0.756	-0.411	Eating
	a	-0.319	0.112	-0.532	-0.091	Sleep
	a	-0.103	0.153	-0.438	0.172	Groom
	a	-0.279	0.043	-0.361	-0.192	positive_words
	a	-0.150	0.042	-0.246	-0.084	negative_words
	a	-0.404	0.028	-0.460	-0.354	job_titles
	bY	0.051	0.030	-0.010	0.107	Affect
	bY	0.113	0.026	0.067	0.163	Posemo
	bY	0.036	0.033	-0.029	0.097	Negemo
	bY	0.047	0.033	-0.017	0.109	Anx
	bY	0.115	0.034	0.056	0.184	Anger
	bY	0.021	0.034	-0.043	0.087	Sad
	bY	0.191	0.028	0.144	0.250	Senses
	bY	0.142	0.027	0.089	0.198	Social
	bY	0.074	0.030	0.017	0.131	Occup
	bY	0.229	0.030	0.171	0.281	Leisure
	bY	0.326	0.066	0.203	0.453	Home
	bY	0.060	0.054	-0.039	0.171	Sports
	bY	0.544	0.078	0.386	0.689	TV
	bY	0.350	0.055	0.240	0.463	Music
	bY	0.006	0.031	-0.050	0.062	Money
	bY	0.343	0.034	0.283	0.410	Metaph
	bY	0.301	0.033	0.235	0.366	Physcal
	bY	0.221	0.036	0.152	0.297	Body
	bY	0.503	0.061	0.375	0.604	Sexual
	bY	0.434	0.046	0.346	0.519	Eating

	bY	0.252	0.059	0.132	0.363	Sleep
	bY	0.125	0.080	-0.048	0.273	Groom
	bY	0.206	0.022	0.164	0.250	positive_words
	bY	0.115	0.021	0.074	0.153	negative_words
	bY	0.207	0.015	0.180	0.236	job_titles
vk	a	-0.136	0.049	-0.224	-0.040	Affect
	a	-0.211	0.047	-0.312	-0.128	Posemo
	a	-0.098	0.055	-0.202	0.014	Negemo
	a	-0.070	0.063	-0.183	0.053	Anx
	a	-0.033	0.052	-0.130	0.071	Anger
	a	-0.080	0.051	-0.170	0.027	Sad
	a	-0.075	0.049	-0.168	0.021	Senses
	a	-0.190	0.055	-0.293	-0.086	Social
	a	-0.176	0.054	-0.277	-0.062	Occup
	a	-0.100	0.057	-0.206	0.015	Leisure
	a	-0.137	0.105	-0.326	0.086	Home
	a	-0.053	0.097	-0.246	0.128	Sports
	a	-0.539	0.179	-0.852	-0.197	TV
	a	-0.063	0.109	-0.272	0.146	Music
	a	0.103	0.059	-0.011	0.219	Money
	a	-0.483	0.064	-0.612	-0.364	Metaph
	a	-0.100	0.056	-0.194	0.031	Physcal
	a	-0.066	0.058	-0.166	0.052	Body
	a	-0.454	0.099	-0.630	-0.266	Sexual
	a	-0.118	0.074	-0.255	0.018	Eating
	a	-0.120	0.095	-0.301	0.064	Sleep
	a	0.371	0.132	0.127	0.617	Groom
	a	-0.218	0.038	-0.284	-0.139	positive_words
	a	-0.066	0.035	-0.134	-0.003	negative_words
	a	-0.030	0.026	-0.082	0.020	job_titles
	bY	0.016	0.025	-0.029	0.064	Affect
	bY	0.067	0.027	0.011	0.115	Posemo
	bY	-0.015	0.029	-0.066	0.045	Negemo
	bY	-0.058	0.033	-0.121	0.011	Anx
	bY	-0.028	0.028	-0.075	0.032	Anger
	bY	0.011	0.026	-0.036	0.070	Sad
	bY	0.019	0.027	-0.032	0.071	Senses
	bY	0.047	0.029	-0.006	0.105	Social
	bY	0.114	0.028	0.058	0.169	Occup
	bY	0.110	0.031	0.049	0.168	Leisure
	bY	0.090	0.056	-0.014	0.197	Home
	bY	0.124	0.051	0.027	0.223	Sports
	bY	0.256	0.093	0.077	0.421	TV
	bY	0.101	0.056	-0.003	0.219	Music
	bY	-0.087	0.032	-0.153	-0.027	Money
	bY	0.190	0.033	0.123	0.249	Metaph
	bY	0.026	0.029	-0.029	0.083	Physcal
	bY	0.039	0.029	-0.015	0.096	Body
	bY	0.177	0.049	0.070	0.256	Sexual
	bY	0.023	0.039	-0.046	0.102	Eating
	bY	-0.004	0.053	-0.107	0.102	Sleep
	bY	-0.196	0.070	-0.326	-0.060	Groom
	bY	0.118	0.020	0.081	0.157	positive_words
	bY	-0.018	0.018	-0.049	0.019	negative_words
	bY	0.028	0.013	0.003	0.053	job_titles
vv	a	-0.480	0.057	-0.589	-0.370	Affect
	a	-0.640	0.055	-0.752	-0.531	Posemo
	a	-0.381	0.064	-0.503	-0.261	Negemo
	a	-0.479	0.065	-0.600	-0.345	Anx
	a	-0.503	0.061	-0.618	-0.382	Anger
	a	-0.500	0.063	-0.615	-0.372	Sad
	a	-0.616	0.052	-0.724	-0.521	Senses
	a	-0.633	0.056	-0.750	-0.527	Social
	a	-0.575	0.059	-0.699	-0.478	Occup
	a	-0.987	0.068	-1.107	-0.850	Leisure
	a	-0.939	0.108	-1.145	-0.722	Home
	a	-0.756	0.102	-0.942	-0.555	Sports
	a	-1.403	0.226	-1.836	-0.950	TV
	a	-1.427	0.102	-1.625	-1.234	Music
	a	-0.172	0.065	-0.294	-0.053	Money
	a	-0.919	0.068	-1.046	-0.781	Metaph
	a	-0.880	0.066	-1.003	-0.752	Physcal
	a	-0.779	0.067	-0.917	-0.668	Body
	a	-1.326	0.111	-1.532	-1.107	Sexual
	a	-0.921	0.077	-1.048	-0.730	Eating
	a	-0.992	0.107	-1.184	-0.764	Sleep
	a	-0.549	0.151	-0.828	-0.255	Groom
	a	-0.867	0.044	-0.950	-0.781	positive_words
	a	-0.633	0.039	-0.704	-0.558	negative_words
	a	-0.667	0.023	-0.707	-0.617	job_titles
	bY	0.006	0.031	-0.051	0.065	Affect
	bY	0.085	0.029	0.026	0.139	Posemo
	bY	-0.049	0.034	-0.113	0.010	Negemo
	bY	-0.050	0.034	-0.118	0.016	Anx
	bY	0.030	0.032	-0.034	0.090	Anger
	bY	-0.027	0.034	-0.093	0.041	Sad
	bY	0.063	0.028	0.007	0.116	Senses
	bY	0.152	0.030	0.090	0.208	Social
	bY	0.146	0.030	0.090	0.205	Occup
	bY	0.280	0.035	0.209	0.342	Leisure
	bY	0.266	0.059	0.154	0.372	Home
	bY	0.136	0.054	0.030	0.241	Sports
	bY	0.475	0.114	0.274	0.724	TV
	bY	0.494	0.055	0.394	0.604	Music
	bY	-0.123	0.035	-0.188	-0.053	Money
	bY	0.388	0.035	0.319	0.459	Metaph
	bY	0.204	0.034	0.133	0.274	Physcal
	bY	0.145	0.036	0.083	0.220	Body
	bY	0.507	0.056	0.410	0.615	Sexual

bY	0.295	0.041	0.221	0.384	Eating
bY	0.143	0.057	0.039	0.267	Sleep
bY	0.023	0.083	-0.127	0.203	Groom
bY	0.217	0.023	0.179	0.266	positive_words
bY	0.069	0.021	0.029	0.109	negative_words
bY	0.242	0.013	0.218	0.269	job_titles

Table 4: Individual Linear Model