

Politicians on Twitter: just like Angry
Birds? *A longitudinal study of content and
sentiment across left-wing and right-wing
representatives in the United States*

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Section 1 – Motivation and Context

Motivation and Problem

New media such as Twitter are used more often for political campaigning (Blumler & Gurevitch, 2001). Although previous research has shown that the number of tweets does have a positive effect on the number of seats, little is known about the "type" of messages representatives distribute (Kruikemeier, 2014; Warnick, Xenos, Endres, & Gastil, 2005). Even though the harmful effects of *micro-targeting*¹ after the elections in the US (2016) and Brazil (2018) are more often mentioned (Zuiderveen et al., 2018; Bayer, 2020; see 'Cambridge Analytica'²). To tackle this, I will use the following research question: *"To what extent does the content and sentiment of both left-wing and right-wing politicians change as elections get close?"*

On the one hand, I expect representatives to become more fierce (read "negative") as elections get close because the power struggle in politics is not physical, but verbal. The outcome is dichotomous: seats added or removed (Dang-Xuan, Stieglitz, Wladarsch, & Neuberger, 2013; Smailović et al., 2015; Zhelyazkova, 2019). On the other hand, I expect the content of tweets to shift from *policy* to *agreeableness* and *integrity* because personal attacks are (1) less complicated than policy issues, and (2) the 'reptilian brain'³ is activated during battles (Lascoumes & Le Gales, 2007; Vaillant, 2011).

High-level description

I collected 500 tweets from a left-wing politician (@SenSanders) and 500 tweets from a right-wing politician (@RepMattGaetz). I will calculate the posterior probability for each day. I will do this for both content and sentiment. Finally, the average sentiment and average content are examined based on the posterior probabilities.

Domain

A User Generative Content Study (UGC) of politicians on Twitter has been chosen. First of all because last year I studied the relationship between socioeconomic status (SES) and nationalism during COVID-19 in the Netherlands. No significant association was found, but respondents in the qualitative part indicated that "strong language" has a positive effect on their attitude towards a representative. Second because I consider a (Quantitative) Research Master in Sociology. And last but not least, I am

¹ A marketing strategy in which (voting) behavior based on metadata obtained from social media accounts, dating apps, navigation systems, and other (new) media is influenced – often without the user noticing it (Bayer, 2020).

² <https://www.opendemocracy.net/en/democraciaabierta/public-opinion-in-brazil-after-the-campaigns-of-trump-and-bolsonaro/>

³ A philosophical concept in social psychology which assumes that vital bodily functions, including survival instinct, are activated in case of danger (Vaillant, 2011).

concerned with the change in both content of political topics, and how campaigns are conducted in our (cyber) society (see Motivation and Problem).

Dimensions

I chose three dimensions, all based on definitions and papers in social psychology (see, among others, Caprara et al., 2003; Schneider & Bos, 2011), political science, and communication sciences (see, among others, Moody & Fournon, 2013; Lawrence, Molyneux, Coddington, & Holton, 2014). The first dimension consists of policy, the second of agreeableness, and the last deals with integrity. I choose them because (1) policy issues lie along ideological dividing lines, (2) ideas about the ideal society differ between left-wing and right-wing politicians, and (3) an integrity issue highlights deviance⁴ (Hague, Harrop, & McCormick, 2016; Kriesi et al., 2006; Mazzoleni, 2008).

Section 2 – Training texts

Content

I used two training texts for each dimension. Except for policy. Three have been selected for this based on scientific reasons (see Bekkers, Fenger, & Scholten, 2017), which have been shortened by the use of a random number generator.

Within policy, the first text was about migrants. It investigated the attitudes of people towards immigration in America (Fussell, 2014). Another article consisted of gray literature and dealt with healthcare in Europe (Mossialos, Dixon, Figueras, & Kutzin, 2002). The last paper was a chapter on economic policy (Garrett & Lange, 1996). To train the dimension agreeableness, I choose a paper by Meier and Robinson (2004) on the relationship between anger and agreement, and a chapter by Graziano and Eisenberg (1997) about the concept. Finally, the integrity dimension was trained using a paper that discusses corruption in the public sector (Lambsdorff, 2002) and an article on unethical records (Darden, 2008). A complete overview of the training text by dimension can be found in Appendix 8.

Sentiment

I trained the sentiment of my tweets by 500 negative and 500 positive sentences from imdb.com, amazon.com, and yelp.com (Kotzias et al., 2015⁵). I also choose a sentiment lexicon with 2,006 positive terms and 4,783 negative terms (Hu & Liu, 2004⁶). Both were published peer-reviewed articles, which benefits reliability and validity, as multiple authors have reviewed the lists (Babbie, 2009).

⁴ A frequently used concept in sociology to indicate that someone is not in line with the accepted behavior in a society or culture-shared group (Ballantine, Roberts, & Korgen, 2018).

⁵ <https://archive.ics.uci.edu/ml/datasets/Sentiment+Labelled+Sentences#>

⁶ <http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html>

Word count, likelihoods

I used Naive Bayes to calculate the likelihoods (see Equation 1; Zacharaski, 2015). $p(w_k|h_i)$ stated the probability of a word (w_k) given each hypothesis (h_i). In this case, there were three. Consecutively: $p(w_k|h = agreeableness)$, $p(w_k|h = integrity)$ en $p(w_k|h = policy)$. Also, n_k stood for the number of times each word occurs, given h_i . Finally, $|Vocabulary|$ denoted the number of unique words and n the total number of words.

$$p(w_k|h_i) = \frac{n_k + 1}{n + |Vocabulary|} \quad (1)$$

In the content lexicon, "social" was one of the most common terms (see Appendix 1, Table 4). I obtained the numbers by matching all words per dimension and counting how often each word was present (see Appendix, Module_1.xlsx). For example, social appeared 39 times in the training texts of agreeableness, 14 times in the training texts of integrity, and 94 times in the training texts of policy (see Appendix 1, Table 4).

I established the likelihood (given the policy dimension) as follows. First of all, the term appeared 94 times within the dimension policy ($n_k = 94$). Also, there were 5,841 unique words ($|Vocabulary|$). And a total of 28,975 words (n). Eventually, this resulted in a likelihood of $\approx .00273$ (see Equation 2). A summary of the likelihoods and counts given each dimension for the 14 other most common words, can be found in Table 4 in Appendix 1.

$$p(social|policy) .00273 \approx \frac{(94 + 1)}{(28,975 + 5,841)} \quad (2)$$

"Excellent" turned out to be one of the most common terms (see Appendix 1, Table 5). This word appeared once in a negative training text and 24 times in a positive text (see Appendix 1, Table 4). I calculated the $p(excellent | positive)$ as follows. First of all, there were 330 unique words ($|Vocabulary|$). Also, a total of 1,226 words (n). And finally, the term appeared 24 times in a positive text (n_k). The probability of excellent given positive is therefore $\approx .01607$ (see Equation 3; Appendix 1, Table 5). A summary of the likelihoods and counts given each dimension for the 14 other most common words, can be found in Table 5 in Appendix 1.

$$p(excellent|positive) .01607 \approx \frac{(24 + 1)}{(1,226 + 330)} \quad (3)$$

Section 3 – Classification of Reviews

Website with the tweets

<https://twitter.com/SenSanders>

I use Twitter because it is relevant to my research question. Also, it is a social network where the goal is to post ideas, resulting in mutual interaction. I find this interesting because sociology pays a lot of attention to the negative consequences of Twitter (e.g. *echo chamber effect*⁷), but little to the possibility of engaging in power-free debates (see Habermas, 1929). Finally, between the ages of twelve and fourteen, I often looked at other people's tweets. I noticed that messages were about the things that bothered classmates, or what they wanted to do. The number of followers determined your status, but both tweets and profiles were not parallel to social reality. Even though, in the meantime, elections can be gain by the use of social media (Kruikemeier, 2014; see Cambridge Analytica).

One review or post from the website

<https://twitter.com/SenSanders/status/1300834090959228928>

Posterior probability of the tweet discussing each dimension

To calculate the posterior probability, I first decided to tokenize all words. Afterward, stop words, capitalizations, and punctuation marks have been removed (Bowler & Datar, 2018; see Appendix, Module_1.xlsx). The result was as follow: | Disgusting | Jeff | Bezos | Became | Richest | Man | Earth | Spying | Underpaying | Mistreating | Workers | Must | Build | Powerful | Trade | Union | Movement | Stand | Billionaire | Class | Finally | Say | Enough |

Second, I built on the Naive model from the previous section (see Equation 4; Zacharaski, 2015). Here, h denoted the hypothesis by category, and indicated $p(h)$ the prior – in this case, one divided by the number of dimensions, or one third (Zacharaski, 2015). After all, there were three expectations, the chance that the tweet is part of the dimension agreeableness (1), integrity (2), or policy (3). Finally, $p(D)$ noted the probability of a word and $p(D|h)$ was equal to $p(w_k|h_i)$ (see Equation 1; Zacharaski, 2015).

$$p(h|D) = \frac{p(D|h) \times p(h)}{p(D)} \quad (4)$$

Subsequently, I searched for the likelihood of each token given the relevant category. In other words $p(w_k|h = agreeableness)$, $p(w_k|h = integrity)$ and $p(w_k|h = policy)$. Table 1 gives a truncated overview, and Table 6 in Appendix 1 A complete diagram.

⁷ A situation in which someone only receives information through social media without any discomfort (Garimella, Gionis, Morales, & Mathioudakis, 2018).

Table 1

Overview of counts (in training texts) and likelihoods of @SenSanders' tweet by dimension

All words	agreeableness		integrity		policy	
	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>
Disgusting	0	.0000287	0	.0000287	0	.0000287
Jeff	0	.0000287	0	.0000287	0	.0000287
Bezos	0	.0000287	0	.0000287	0	.0000287
Became	0	.0000287	2	.0000862	1	.0000574
...
Say	0	.0000287	1	.0000574	0	.0000287
Enough	1	.0000574	1	.0000574	1	.0000574

After finding the likelihoods, I calculated the posterior for the entire tweet by "updating" the independent posteriors for each additional word. I did this by making use of Equation 5.

$$p(h|X_1 \dots X_n) = \frac{p(h) \prod_{i=1}^n p(X_i|h)}{\sum_y p(X_i|h) \times p(h)} \quad (5)$$

In this equation $p(h|X_1 \dots X_n)$ stated the posterior probability of a category given any word from a tweet, $\prod_{i=1}^n p(X_i|h)$ indicated a multiplication of all $p(X_i|h)$ – which was interchangeable with the likelihood obtained from Equation 1 ($p(w_k|h_i)$) – and $\sum_y p(X_i|h) \times p(h)$ calculated a normalization constant (Zacharaski, 2015; Liberali, 2020). For example, by investigation of @SenSanders' tweet, it was found that the posterior probability of the dimension agreeableness given the terms "disgusting" and "trade" equals $\approx .00917^8$ (see Equation 6). And the entire tweet was found to have a posterior probability of $\approx .000000181$ for the category agreeableness, $\approx .000097523$ for integrity and $\approx .999902296$ for policy (see Table 2; Appendix 2, Table 8). A complete overview including formulas can be found in Appendix 2.

$$(agreeableness|disgusting \cap trade) = \frac{p(agreeableness) \times p(disgusting|agreeableness) \times (trade|agreeableness)}{(p(agreeableness) \times p(disgusting|agreeableness) \times (trade|agreeableness)) + (p(integrity) \times p(disgusting|integrity) \times (trade|integrity)) + (p(policy) \times p(disgusting|policy) \times (trade|policy))} \quad (6)$$

Table 2

Overview of the posterior probability of @SenSanders' tweet by dimension

All words	agreeableness	integrity	policy
{Disgusting}	.333333333	.333333333	.333333333
{Disgusting, Jeff}	.333333333	.333333333	.333333333
{Disgusting, Jeff, Bezos}	.333333333	.333333333	.333333333
...
{Disgusting, Jeff, Bezos, Became, ..., Say, Enough}	.000000181	.000097523	.999902296

⁸ $(1/3 \times 0,0000287 \times 0,0000287)/[(1/3 \times 0,0000287 \times 0,0000287) + (1/3 \times 0,0000287 \times 0,0000287) + (1/3 \times 0,0000287 \times 0,0030733)]$

Finally, I classified @SenSanders' tweet by making use of the maximum a posterior rule (see Equation 7). Here, $\arg \max_{h \in H}$ indicated that after calculating the posterior for each hypothesis, my model should return the highest value (Zacharaski, 2015). In this case .999902296, which means that the tweet is about policy (see Table 2).

$$h_{MAP} = \arg \max_{h \in H} p(D|h) \times p(h) \quad (7)$$

Posterior probability of the tweet being positive

To determine whether the tweet from @SenSanders is positive or negative, I built upon the Naïve model from section 2 and Bayes Theorem (see Equation 1; see Equation 4; see Equation 5). For example, the likelihood of enough given negative was $\approx .007069^9$, and enough given positive $\approx .002571^{10}$ (see Appendix 1, Table 7). Since there are two dimensions – positive and negative – the prior is 0.5 (Zacharaski, 2015). Computing Equation 5 yielded the following:

$$p(h|X_1 \dots X_n) = \frac{p(h) \prod_{i=1}^n p(X_i|h)}{\sum_y p(X_i|h) \times p(h)} \quad ; \quad p(\text{positive}|\text{enough}) = \frac{p(\text{positive}) \times p(\text{enough}|\text{positive})}{[p(\text{positive}) \times p(\text{enough}|\text{positive})] + [p(\text{negative}) \times p(\text{enough}|\text{negative})]} \quad ;$$

$$,294096 \approx \frac{\frac{1}{2} \times .002571}{\left[\frac{1}{2} \times .002571 + \frac{1}{2} \times .007069 \right]}$$

I repeated this process for the entire tweet. First of all, I searched the likelihood for each token given a certain sentiment. In other words, $p(w_k|h = \text{positive})$ and $p(w_k|h = \text{negative})$. A complete overview can be found in Table 7 in Appendix 1. After computing the equations (see Appendix 3), the posterior for negative was found to be greater than for positive, specifically $\approx .846153846$, and $\approx .153846154$ (see Appendix 3, Table 9). Finally, I classified the tweet as negative, by use of the maximum a posterior rule (h_{MAP}).

Section 4 – Analysis

To answer the question *"To what extent does the content and sentiment of both left-wing and right-wing politicians change as elections get close?"* I used Natural Language Processing (NLP) and supervised learning¹¹ to classify tweets from politicians along dimension and sentiment (see Section 5 for accuracy and validation).

First of all, @SenSanders turned out to be predominantly more negative than @RepMattGaetz. This was true both in the period before the elections and nearby (see Figure 1). For example, between May 19 and April 27, Sanders was a lot more positive with an average posterior of

⁹ $(10+1)/(1,226+330)$

¹⁰ $(4+1)/(1,226+330)$

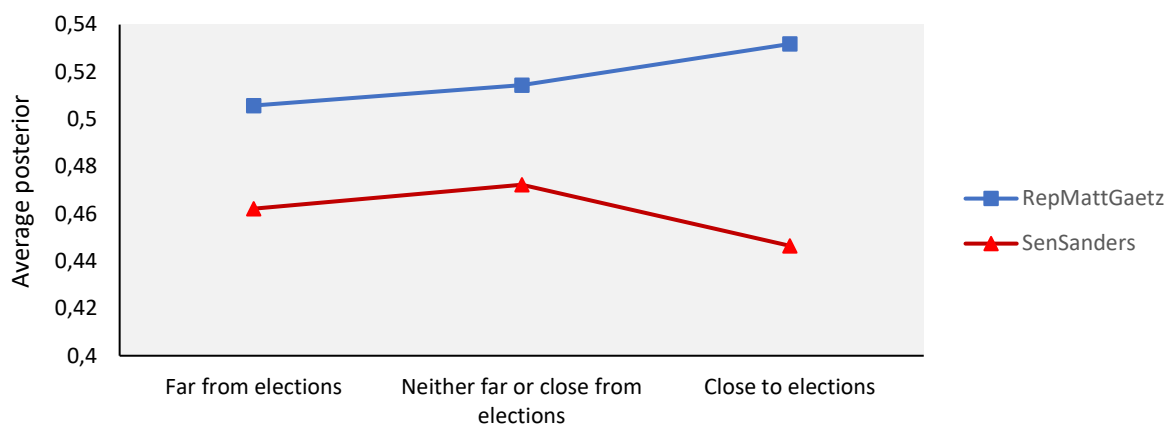
¹¹ A form of Machine Learning (ML) in which categories have been composed in advance (Zhou, 2018; Liberali, 2020).

.460 than between July 9 and September 1 (.447). The opposite was true for Gaetz. His positivity increased from .506 to .532 (see Figure 1).

To test whether this difference is significant, I conducted a two-way ANOVA. In advance, I tested three conditions: (1) no outliers, (2) no homogeneity of variance, and (3) the presence of a normal distribution (Field, 2009; see Appendix 7). The independent variable was the categorical data, and the dependent variable was the mean of sentiment (see Figure 1). I found no significant difference for date ($F(2)=.165$, $P=.848$, $\eta^2=.000$). However, a significant difference in Twitter ID has been found ($F(1)=18,120$, $P<.050$, $\eta^2=.018$), which explained 1.8 percent of the variance in sentiment.

Figure 1

Average posterior of positive sentiment by datum and representative

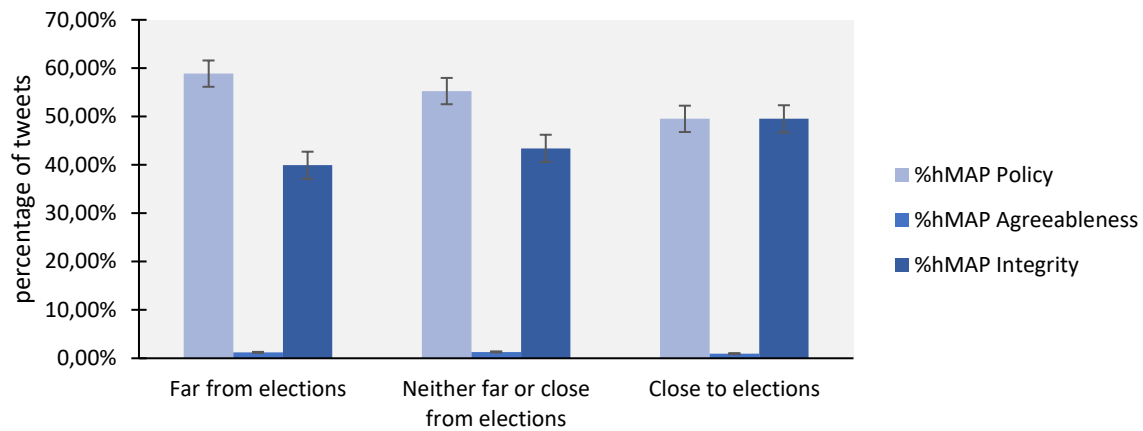


Second, my model did not classify any tweet from @RepMattGaetz as policy or agreeableness (see Appendix 5). I also found no clear trends for @SenSanders (see Appendix 5). However, the average posterior (over time) stated .533037 for negative given policy and .44693 for positive given policy. The posteriors for the sentiment of agreeableness were .388407 and .611593. It can, therefore, be said that Bernie Sanders is predominantly negative within the dimension policy, but positive about the things he agrees or disagrees.

Finally, On the one hand, I found that @RepMattGaetz was on average positive about issues related to integrity (.517345). On the other hand, @SanSanders stated a negative posterior given integrity (.525574). I conducted a two-way ANOVA to test whether these differences were significant. The ANOVA resulted in a significant difference for Twitter ID ($F(1)=7,204$, $P<.050$, $\eta^2=.010$). Hence, Sanders was not only a lot more negative about integrity but started to tweet more about this topic as elections get close, at the expense of policy (see Figure 2; see Appendix 5).

Figure 2

Percentage of tweets from @SenSanders by dimension, based on classification of the maximum a posterior rule



In line with the expectations, I found that politicians are more personal and fierce on Twitter as elections get close (Blumler & Gurevitch, 2001). Integrity is an important issue, especially for right-wing politicians. It deviates from, for example, television debates, where representatives mainly talk about policy (Druckman, 2005).

Finally, people can use the results from this paper to build upon the debate about the influence of social media in politics and the decision-making process. A specific recommendation is more attention to reflection: Do we want a society where politics – and, therefore, policy – is driven by emotions, or based on the best argument? I propose a radical solution: ban online campaigns and social media use for all politicians.

Section 5 – Validation

I validated my model by using a measure of inter-reliability agreement, Cohen's Kappa (κ) (Babbie, 2009). At the sentence level, I analyzed ten percent of the tweets ($n = 173$). To find the accuracy and recall, I used a confusion matrix (Garreta & Moncecchi, 2013). This did not include non-classified sentences (invalid cases = 71%).

Cohens Kappa

I calculated the Kappa by dividing the observed agreement (p_o) minus the expected agreement (p_e) by one minus the expected agreement (p_e) (Babbie, 2009; see Appendix 10). The result was a Kappa (κ) of .95282443. In other words, an almost perfect match (Babbie, 2009; Appendix, 10).

Confusion matrix

The overall accuracy is calculated by adding up all correctly predicted values (true positives) in table 3 and dividing them by the total number of values (Garreta & Moncecchi, 2013; see Appendix 11). Finally, this resulted in an accuracy of 63 percent.

Table 3*Confusion matrix by ML-prediction and actual dimension*

		Actual		
		Policy	Agreeableness	Integrity
Predicted	Policy	11	1	3
	Agreeableness	1	0	1
	Integrity	1	0	1

I calculated the recall by dividing the true positives (TP) per dimension by the TP plus all errors in the row (Garreta & Moncecchi, 2013). A sensitivity of 73 percent applied for policy, 0 percent for agreeableness, and 50 percent for integrity (see Appendix 11)

Limitations

This study has some limitations. First of all, the sample size is small (Babbie, 2009). Second, I analyzed only the twitter accounts of @SenSanders and @RepMattGaetz. It is, therefore, not possible to generalize. Third, I did not take into account the controlling effect of the opposition, including Bernie Sanders. Fourth, the data did not succeed in conditions (1) and (2) of the two-way ANOVA. Fifth, following the validation section, I have not trained my model properly yet on the dimensions agreeableness and integrity. Finally, I limited myself to the United States.

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Appendix 1

Table 4

The 15 most frequent words (in the training texts) by dimension, including likelihood

Unique words	agreeableness		integrity		Policy		total	
	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>
Agreeableness	175	.00506	0	.00003	0	.00003	175	.005055
Health	3	.00011	1	.00006	147	.00425	151	.004366
Social	39	.00115	14	.00043	94	.00273	147	.004251
Corrupt	0	.00003	143	.00414	0	.00003	143	.004136
Capital	0	.00003	0	.00003	139	.00402	139	.004021
State	1	.00006	121	.00350	5	.00017	127	.003676
Behavior	81	.00236	27	.00080	1	.00006	109	.003159
Group	44	.00129	5	.00017	57	.00167	106	.003073
Economic	0	.00003	24	.00072	82	.00238	106	.003073
Trade	0	.00003	0	.00003	106	.00307	106	.003073
Immigrants	0	.00003	0	.00003	105	.00304	105	.003045
Public	1	.00006	59	.00172	40	.00118	100	.002901
Blame	94	.00273	2	.00009	1	.00006	97	.002815
Immigration	0	.00003	0	.00003	97	.00281	97	.002815
Prosocial	96	.00279	0	.00003	0	.00003	96	.002786

Note. $N=5,841$; $|Vocabulary|=28,975$

Table 5*The 15 most frequent words (in the training texts) by sentiment including likelihood*

Unique words	negative		positive		total	
	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>
Great	5	.00386	84	.05463	89	.05784
Good	13	.00900	62	.04049	75	.04884
Works	1	.00129	45	.02956	46	.03021
Well	7	.00514	33	.02185	40	.02635
Work	25	.01671	9	.00643	34	.02249
Like	12	.00835	18	.01221	30	.01992
Excellent	1	.00129	24	.01607	25	.01671
Recommend	6	.00450	19	.01285	25	.01671
Best	2	.00193	20	.01350	22	.01478
Nice	0	.00064	22	.01478	22	.01478
Love	0	.00064	20	.01350	20	.01350
Worked	10	.00707	10	.00707	20	.01350
Better	7	.00514	12	.00835	19	.01285
Easy	3	.00257	15	.01028	18	.01221
Comfortable	3	.00257	14	.00964	17	.01157

Note. N=1,226; |Vocabulary|=330

Table 6

Overview of the counts (in the training texts) and likelihoods of @SenSanders' tweet by dimension

All words	agreeableness		integrity		policy	
	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>
Disgusting	0	0,0000287	0	0,0000287	0	0,0000287
Jeff	0	0,0000287	0	0,0000287	0	0,0000287
Bezos	0	0,0000287	0	0,0000287	0	0,0000287
Became	0	0,0000287	2	0,0000862	1	0,0000574
Richest	0	0,0000287	0	0,0000287	0	0,0000287
Man	0	0,0000287	1	0,0000574	0	0,0000287
Earth	0	0,0000287	0	0,0000287	0	0,0000287
Spying	0	0,0000287	0	0,0000287	0	0,0000287
Underpaying	0	0,0000287	0	0,0000287	0	0,0000287
Mistreating	0	0,0000287	0	0,0000287	0	0,0000287
Workers	0	0,0000287	2	0,0000862	20	0,0006032
Must	0	0,0000287	0	0,0000287	0	0,0000287
Build	0	0,0000287	2	0,0000862	0	0,0000287
Powerful	0	0,0000287	1	0,0000574	15	0,0004596
Trade	0	0,0000287	0	0,0000287	106	0,0030733
Union	2	0,0000862	0	0,0000287	10	0,0003159
Movement	0	0,0000287	2	0,0000862	0	0,0000287
Stand	0	0,0000287	0	0,0000287	0	0,0000287
Billionaire	0	0,0000287	0	0,0000287	0	0,0000287
Class	0	0,0000287	0	0,0000287	2	0,0000862
Finally	1	0,0000574	4	0,0001436	13	0,0004021
Say	0	0,0000287	1	0,0000574	0	0,0000287
Enough	1	0,0000574	1	0,0000574	1	0,0000574
\prod^a		1,38E-104		7,47E-102		7,66E-98

Note. $N=5,841$; $|Vocabulary|=28,975$

^a The final product is multiplied with a prior of one third.

Table 7

Overview of the counts (in the training texts) and likelihoods of @SenSanders' tweet by sentiment

All words	positive		negative	
	<i>n</i>	<i>likelihood</i>	<i>n</i>	<i>likelihood</i>
Disgusting	0	.000643	1	.001285
Jeff	0	.000643	0	.000643
Bezos	0	.000643	0	.000643
Became	0	.000643	0	.000643
Richest	0	.000643	0	.000643
Man	0	.000643	0	.000643
Earth	0	.000643	0	.000643
Spying	0	.000643	0	.000643
Underpaying	0	.000643	0	.000643
Mistreating	0	.000643	0	.000643
Workers	0	.000643	0	.000643
Must	0	.000643	0	.000643
Build	0	.000643	0	.000643
Powerful	0	.000643	0	.000643
Trade	0	.000643	0	.000643
Union	0	.000643	0	.000643
Movement	0	.000643	0	.000643
Stand	0	.000643	0	.000643
Billionaire	0	.000643	0	.000643
Class	0	.000643	0	.000643
Finally	0	.000643	0	.000643
Say	0	.000643	0	.000643
Enough	3	.002571	10	.007069
\prod^a		7,67025E-74		4,21864E-73

Note. $N=1,226$; $|Vocabulary|=330$

^a The final product is multiplied with a prior of one third.

Equations

$$\left(\text{agreeableness} \left| \begin{array}{l} \text{disgusting, jeff,} \\ \text{bezos, became,} \\ \text{... , say,} \\ \text{enough} \end{array} \right. \right) = \frac{p(\text{agreeableness}) \times p(\text{disgusting}|\text{agreeableness}) \times p(\text{jeff}|\text{agreeableness}) \times p(\text{bezos}|\text{agreeableness}) \times p(\text{became}|\text{agreeableness}) \times \dots \times p(\text{say}|\text{agreeableness}) \times p(\text{enough}|\text{agreeableness})}{p((\text{agreeableness}) \times p(\text{disgusting}|\text{agreeableness}) \times p(\text{jeff}|\text{agreeableness}) \times p(\text{bezos}|\text{agreeableness}) \times p(\text{became}|\text{agreeableness}) \times \dots \times p(\text{say}|\text{agreeableness}) \times p(\text{enough}|\text{agreeableness})) + p((\text{integrity}) \times p(\text{disgusting}|\text{integrity}) \times p(\text{jeff}|\text{integrity}) \times p(\text{bezos}|\text{integrity}) \times p(\text{became}|\text{integrity}) \times \dots \times p(\text{say}|\text{integrity}) \times p(\text{enough}|\text{integrity})) + p((\text{policy}) \times p(\text{disgusting}|\text{policy}) \times p(\text{jeff}|\text{policy}) \times p(\text{bezos}|\text{policy}) \times p(\text{became}|\text{policy}) \times \dots \times p(\text{say}|\text{policy}) \times p(\text{enough}|\text{policy}))}$$

$$\left(\text{integrity} \middle| \begin{matrix} \text{disgusting, jeff,} \\ \text{bezos, became,} \\ \dots, \text{say,} \\ \text{enough} \end{matrix} \right) = \frac{p(\text{integrity}) \times p(\text{disgusting}|\text{integrity}) \times p(\text{jeff}|\text{integrity}) \times p(\text{bezos}|\text{integrity}) \times p(\text{became}|\text{integrity}) \times \dots \times p(\text{say}|\text{integrity}) \times p(\text{enough}|\text{integrity})}{p((\text{agreeableness}) \times p(\text{disgusting}|\text{agreeableness}) \times p(\text{jeff}|\text{agreeableness}) \times p(\text{bezos}|\text{agreeableness}) \times p(\text{became}|\text{agreeableness}) \times \dots \times p(\text{say}|\text{agreeableness}) \times p(\text{enough}|\text{agreeableness})) + p((\text{integrity}) \times p(\text{disgusting}|\text{integrity}) \times p(\text{jeff}|\text{integrity}) \times p(\text{bezos}|\text{integrity}) \times p(\text{became}|\text{integrity}) \times \dots \times p(\text{say}|\text{integrity}) \times p(\text{enough}|\text{integrity})) + p((\text{policy}) \times p(\text{disgusting}|\text{policy}) \times p(\text{jeff}|\text{policy}) \times p(\text{bezos}|\text{policy}) \times p(\text{became}|\text{policy}) \times \dots \times p(\text{say}|\text{policy}) \times p(\text{enough}|\text{policy}))}$$

$$\left(\text{policy} \middle| \begin{matrix} \text{disgusting, jeff,} \\ \text{bezos, became,} \\ \text{... , say,} \\ \text{enough} \end{matrix} \right) = \frac{p(\text{policy}) \times p(\text{disgusting}|\text{policy}) \times p(\text{jeff}|\text{integrity}) \times p(\text{bezos}|\text{policy}) \times p(\text{became}|\text{policy}) \times \dots \times p(\text{say}|\text{policy}) \times p(\text{enough}|\text{policy})}{p((\text{agreeableness}) \times p(\text{disgusting}|\text{agreeableness}) \times p(\text{jeff}|\text{agreeableness}) \times p(\text{bezos}|\text{agreeableness}) \times p(\text{became}|\text{agreeableness}) \times \dots \times p(\text{say}|\text{agreeableness}) \times p(\text{enough}|\text{agreeableness})) + p((\text{integrity}) \times p(\text{disgusting}|\text{integrity}) \times p(\text{jeff}|\text{integrity}) \times p(\text{bezos}|\text{integrity}) \times p(\text{became}|\text{integrity}) \times \dots \times p(\text{say}|\text{integrity}) \times p(\text{enough}|\text{integrity})) + p((\text{policy}) \times p(\text{disgusting}|\text{policy}) \times p(\text{jeff}|\text{policy}) \times p(\text{bezos}|\text{policy}) \times p(\text{became}|\text{policy}) \times \dots \times p(\text{say}|\text{policy}) \times p(\text{enough}|\text{policy}))}$$

Table 8*Posterior probabilities of @SenSanders' tweet by dimension*

All words	agreeableness	integrity	policy
{ Disgusting }	.333333333	.333333333	.333333333
{Disgusting, Jeff }	.333333333	.333333333	.333333333
{Disgusting, Jeff, Bezos }	.333333333	.333333333	.333333333
{Disgusting, Jeff, Bezos, Became }	.166666667	.500000000	.333333333
{Disgusting, Jeff, Bezos, Became, Richest }	.166666667	.500000000	.333333333
{Disgusting, Jeff, Bezos, Became, Richest, Man }	.111111111	.666666667	.222222222
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth }	.111111111	.666666667	.222222222
{Disgusting, Jeff, Bezos, Became, ... , Earth, Spying }	.111111111	.666666667	.222222222
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Underpaying }	.111111111	.666666667	.222222222
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Mistreating }	.111111111	.666666667	.222222222
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Workers }	.016393443	.295081967	.688524590
{Disgusting, Jeff, Bezos, Became, ... , Must }	.016393443	.295081967	.688524590
{Disgusting, Jeff, Bezos, Became, ... , Build }	.010309278	.556701031	.432989691
{Disgusting, Jeff, Bezos, Became, ... , Powerful }	.001280410	.138284251	.860435339
{Disgusting, Jeff, Bezos, Became, ... , Trade }	.000013886	.001499729	.998486384
{Disgusting, Jeff, Bezos, Became, ... , Union }	.000003792	.000136527	.999859681
{Disgusting, Jeff, Bezos, Became, ... , Movement }	.000003791	.000409468	.999586741
{Disgusting, Jeff, Bezos, Became, ... , Stand }	.000003791	.000409468	.999586741
{Disgusting, Jeff, Bezos, Became, ... , Billionaire }	.000003791	.000409468	.999586741
{Disgusting, Jeff, Bezos, Became, ... , Class }	.000001264	.000136527	.999862209
{Disgusting, Jeff, Bezos, Became, ..., Finally }	.000000181	.000048764	.999951055
{Disgusting, Jeff, Bezos, Became, ... , Say }	.000000181	.000097523	.999902296
{Disgusting, Jeff, Bezos, Became, ... , Say, Enough }	.000000181	.000097523	.999902296

Appendix 3

Equations

$$\left(\begin{array}{c|c} \text{positive} & \begin{array}{l} \text{disgusting, jeff,} \\ \text{bezos, became,} \\ \dots, \text{ say,} \\ \text{enough} \end{array} \end{array} \right) = \frac{p(\text{positive}) \times p(\text{disgusting}|\text{positive}) \times p(\text{jeff}|\text{positive}) \times p(\text{bezos}|\text{positive}) \times p(\text{became}|\text{positive}) \times \dots \times p(\text{say}|\text{positive}) \times p(\text{enough}|\text{positive})}{\left[\begin{array}{l} (p(\text{positive}) \times p(\text{disgusting}|\text{positive}) \times p(\text{jeff}|\text{positive}) \times p(\text{bezos}|\text{positive}) \times p(\text{became}|\text{positive}) \times \dots \times p(\text{say}|\text{positive}) \times p(\text{enough}|\text{positive})) + \\ (p(\text{negative}) \times p(\text{disgusting}|\text{negative}) \times p(\text{jeff}|\text{negative}) \times p(\text{bezos}|\text{negative}) \times p(\text{became}|\text{negative}) \times \dots \times p(\text{say}|\text{negative}) \times p(\text{enough}|\text{negative})) + \end{array} \right]}$$

$$\left(\begin{array}{c|c} \text{negative} & \begin{array}{l} \text{disgusting, jeff,} \\ \text{bezos, became,} \\ \dots, \text{ say,} \\ \text{enough} \end{array} \end{array} \right) = \frac{p(\text{negative}) \times p(\text{disgusting}|\text{negative}) \times p(\text{jeff}|\text{negative}) \times p(\text{bezos}|\text{negative}) \times p(\text{became}|\text{negative}) \times \dots \times p(\text{say}|\text{negative}) \times p(\text{enough}|\text{negative})}{\left[\begin{array}{l} (p(\text{positive}) \times p(\text{disgusting}|\text{positive}) \times p(\text{jeff}|\text{positive}) \times p(\text{bezos}|\text{positive}) \times p(\text{became}|\text{positive}) \times \dots \times p(\text{say}|\text{positive}) \times p(\text{enough}|\text{positive})) + \\ (p(\text{negative}) \times p(\text{disgusting}|\text{negative}) \times p(\text{jeff}|\text{negative}) \times p(\text{bezos}|\text{negative}) \times p(\text{became}|\text{negative}) \times \dots \times p(\text{say}|\text{negative}) \times p(\text{enough}|\text{negative})) + \end{array} \right]}$$

Table 9

Posterior probabilities of @SenSanders' tweet by sentiment

All words	positive	negative
{ Disgusting }	.333333333	.666666667
{Disgusting, Jeff }	.333333333	.666666667
{Disgusting, Jeff, Bezos }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest, Man }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Earth, Spying }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Underpaying }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Mistreating }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, Richest, Man, Earth, ... , Workers }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Must }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Build }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Powerful }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Trade }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Union }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Movement }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Stand }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Billionaire }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Class }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ..., Finally }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Say }	.333333333	.666666667
{Disgusting, Jeff, Bezos, Became, ... , Say, Enough }	.153846154	.846153846