Universiteit Leiden
Leiden Institute of Advanced Computer Science

Exploring Relationships between Political Orientation and Language Use Online in The Netherlands

An Analysis of Comments on Political YouTube Videos

Pieke Heijmans

Graduation Thesis, October 2019

Supervised by Maarten H. Lamers & Suzan Verberne

Media Technology MSc program, Leiden University
piekeheijmans@gmail.com

Abstract. In this explorative research, relationships are examined between political orientation and language use online. This research aimed to expose a possible relationship between political orientation and language use online as well as to explore suitable research methods for analysis of similar cases where research on politics and aspects of language are combined. In this case study, YouTube comments on Dutch political videos were quantitatively and qualitatively analysed. These comments were taken from videos of four political parties, the Socialistische Partij, GroenLinks, Forum voor Democratie and Volkspartij voor Vrijheid en Democratie as they could be divided by quadrant categories left/right and populist/non-populist. Numerical data was gathered by taking comments of those videos and examining basic linguistic information such as number of unique words, average word length and spelling errors, both on the level of the messages and the sentences. The qualitative data consisted of an analysis of the psychological meaning of the used words using the Linguistic Inquiry and Word Count (LIWC) method. The results of this study showed an effect for some of the variables, indicating differences between populist and non-populist parties for the variables percentage of unique words, number of words used and the number of characters in the messages. No convincing evidence for any differences between the parties was found using the LIWC.

Keywords: language use, YouTube comments, populism, political orientation, LIWC, political content

Acknowledgements

I would like to thank some people who contributed to this thesis and helped me to be able to write and produce this thesis in its current form. First of all I would like to thank my first supervisor, Maarten H. Lamers, who supervised my thesis with enthusiasm and concern and always made the meetings fun rather than stressful. Second of all, I would like to thank my second supervisor, Suzan Verberne, who helped me to practically apply tools and theories of the field of computational linguistics and who supervised me entirely voluntary.

I would also like to thank Manolis Fragkiadakis and Jelena Prokic, who took on the role as presentation critics during the graduation presentation and added some critical notes to my thesis, also entirely voluntary.

Finally, I would like to thank all that personally supported me, either mentally or practically: thank you Jaël Poelen, Vera van de Seyp, Esmée Stouten, Sophie van Gennip and of course my parents Noëlle Koppers and Mart Heijmans.

- Pieke

Table of Contents

1 Introduction

In our current political climate, tension between right- and left-wing political parties is building up. Right-wing parties, that are considered to be conservative and traditional in their ideas are opposed to left-wing parties, that are considered to be progressive and egalitarian. This opposition has always been present in politics, but the tone of the public debate is changing with the current rise of right-wing populist parties and the rise of left-wing green and social parties. Both sides are at risk of extremism, which concerns ideologies that are different from the mainstream attitudes of society and can include morally unacceptable ideologies, which includes radicalism, reactionism, fundamentalism and fanaticism. This possible shift to extremism is a dangerous development as it poses risks to societies.

Although a shift to extremism based on just political parties having different ideologies is not at high risk, there is the risk of polarizing behaviour, both between political parties and between their supporters. First of all, the effect of polarization between political parties also increases polarization within the broader society (Layman, Carsey and Horowitz, 2006). One can speak of a culture war, in which "vastly different religious orientations, values, lifestyles and economies" stare each other down (2006). An example of such a culture war is the battle of the American blue Democrats versus the red Republicans. Within politics, polarization would increase the risk of "legislative gridlock and policy inaction" (Binder, 2003; Jones, 2001), making it harder to conduct policies. Another consequence is a "perceived decline in the civility of political debate" (Layman, Carsey and Horowitz, 2006), referring to an increased degree of political advertising that focuses on attacking their opponents (Sinclair, 2002) and an increase in uncivil speech during debates (Jamieson and Falk, 2000).

This polarizing tendency is often caused by miscommunication. Fundamental differences between supporters or politicians may influence the effectiveness of communication between different groups of individuals. Besides a difference in political preference between groups of people, these groups also tend to differ on other characteristics. For example, Bakker and Hopmann (2015) argue that political preference can be related to personality traits. Focusing on the *big five* personality traits of *openness to experience*, *conscientiousness*, *extraversion*, *agreeableness* and *neuroticism*, they found different levels of these traits in left- and right-wing supporters. More specifically, these differences consist of identification with left-wing parties being "characterised by higher levels of *openness* and lower levels of *conscientiousness*, whereas identification with the conservative parties is characterised by higher levels of *extraversion* but not *conscientiousness*" (Bakker and Hopmann, 2015).

Personality is one of many variables that cause differences between types of political supporters that are discussed by other researchers, such as differences in electoral geography and education level (De Voogd, 2013), degree of cultural participation (Achterberg and Houtman, 2006), differences in language use and proficiency (Brosius et al., 2017) and a lot of them connect to each other. Of these variables major differences in language use are chosen as research object as clear and unambiguous language use is needed to effectively communicate between groups of different backgrounds. Most importantly, differences between language use of political supporters and their political orientation has not been researched thoroughly, even though there appear to be differences in the language use of political leaders having different political orientations (Schoonvelde et al., 2019; Caprara and Zimbardo, 2004).

Language use is very much influenced by other previously mentioned factors, such as the closely related factors education level and language proficiency. According to research agency IPSOS that focuses on analysis voting statistics, there are large differences between education levels of voters between political parties, as depicted in Figure 1 (NOS, 2019). This figure shows the percentage of low-, middle-, and highly educated voters for the first Dutch *Provinciale Statenverkiezingen* in 2019 and it becomes apparent that percentages indicating education level of their voters differ vastly per party. As education level influences language proficiency, and language proficiency influences language use, a connection between language use and political orientation could be expected as well.

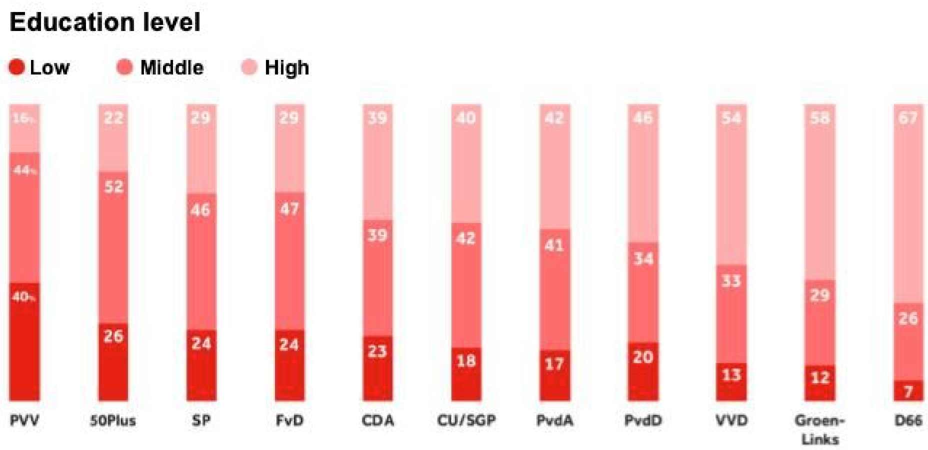

Figure 1. IPSOS research agency: percentage of education level of voters per political party, 2019

With regards to the possible consequences of a left-right division such as polarization and miscommunication and in prevention of ineffective policymaking, the need to explore this relationship between different types of political supporters becomes apparent. This research aims to explore this by clearing up relationships between political orientation and language use, looking at a case study of political parties in the Netherlands. A second aim of this research relates to the explorative approach of the research question and methods: when there is no clear direction for the answers available, to what extent are the chosen methods appropriate tools to find such directions? Therefore, the following research questions are addressed:

What are relationships between political orientation and language use online in the Netherlands?

- Main research question

To what extent is automatically extracting text features a suitable method for explorative research on language and politics?

- Sub research question

The research question of what relationships exist between political orientation in the Netherlands and language use was investigated by looking at user-generated content online (such as comments on *YouTube* videos posted by political parties) and collecting quantitative and qualitative information from these comments. This quantitative and qualitative information was used to find differences in language use. A large amount of data was readily available through online platforms as people inform themselves through online political content and participate in online debates about politics. For each political orientation, language use was expected to differ due to earlier discussed mediating variables such as language proficiency and education level. This paper continues to discuss theoretical background and related work in Section 2. Section 3 includes the method, Section 4 gives the results and Section 5 provides a discussion and conclusion. Section 6 notes references and Section 7 is the Appendix.

2 Background

In this section, background of the research and related work are discussed that touches upon the relationship between language use and political orientation. Discussed questions are: what are different political orientations in the Netherlands (Section 2.1.1) and in what ways is there a divide between people of these different political orientations (Section 2.1.2)? What are factors that can be expected to be of influence on this divide and therefore on language use (Section 2.1.3)? What are characteristics of language that indicate differences in language use between politicians or political supporters (Section 2.2.1) and what are methods used by other researchers in similar cases?

2.1 Theoretical Framework

2.1.1 Political Orientations in the Netherlands

A general approach to describe the current political spectrum in the Netherlands is *Kieskompas*, a website that independently compares views of voters with views of political parties. Krouwel (2006) developed this *Kieskompas* model, consisting of two-dimensional axises. On one axis there is the previously discussed left versus right distinction. On the second axis he distinguishes conservative versus progressive. In general, progressive parties are in favour of social change. On the other hand, conservatives tend to want to conserve traditional social institutions and generally are against social change (ProDemos, 2013). In addition, progressives tend to favour a more free approach allowing individuals to make their own decisions. Conservatives favour a state directed morality (ProDemos, 2013). *Kieskompas* uses this model to guide possible voters and indicate where on the scale these parties can be placed based on their political views. The result of this model is shown in Figure 2. The model depicts the Dutch political landscape and where each party could be placed in terms of leftness/rightness and progressiveness/conservativeness. Based on the model as depicted in Figure 2, it can be concluded that in general, political parties are either left and progressive or right and conservative.

Figure 2: Krouwel's Kieskompas, political orientation on the X-axis and conservative-progressive on the Y-axis, 2019

Besides the 'left and progressive' and 'right and conservative' spectrum, another important term to describe the current political spectrum is populism. As discussed, polarization within politics can lead to problems and both right-wing and left-wing populism are represented in the Dutch political climate. A populist party is generally considered a party of "the people" (Müller, 2017). Populism is "typically associated with the radical right" (Rooduijn and Akkerman, 2017), although contemporary radical-left parties have been labeled populist as well.

Right-wing populism is generally characterized by "its explicit or implicit sharp dichotomization of the social into an *Us identity* constructed along national, regional, religious and ethnic lines versus *Them* in various ways" (Wodak et al., 2013). Right-wing populism contains the idea that norms, cultures and traditions are endangered by these "Them" groups. On the other hand, rather than being socialist or communist, the left-wing populist parties "glorify a more general category: the good people" (Rooduijn and AKkerman, 2017). This means they do not reject the system of democracy, but instead criticize the economical and political elites of that system, leaving the ordinary people "detached of political decision-making" (Rooduijn and Akkerman, 2017). The Dutch socialist party *Socialistische Partij* is generally considered to be on the left spectrum of populism (Den Hollander, 2011; Rooduijn and Akkerman, 2017).

2.1.2 Educational Division between Political Orientations

De Voogd (2013) discusses several factors that are possibly causing a divide within society when it comes to voting behaviour. Amongst these factors are generational differences, lifestyle, religion, social origin and educational level. Mapped statistics of voting behaviour in the Netherlands showed different layers of voting behaviour in 2012 (Figure 3). An important difference may concern differences in educational level. This study of electoral geography has examined differences in voting behaviour by linking them to geographical location. One of their findings is that people with lower educational levels[1] generally vote more for populist parties. On the other hand left parties are better represented in urbanized areas, where people with higher educational levels are present. One interesting observation is the presence of both higher educated people as foreigners in urbanized areas. Furthermore, De Voogd does not conclude that there is a strict division between higher and lower educated voters, instead he speaks of niches, fragmentation between groups of people causing political parties to struggle representing all of their voters. However, the maps in Figure 3 show a visible relationship between higher educational level and green, progressive parties such as *GroenLinks*, *D66* and *Partij voor de Dieren*.

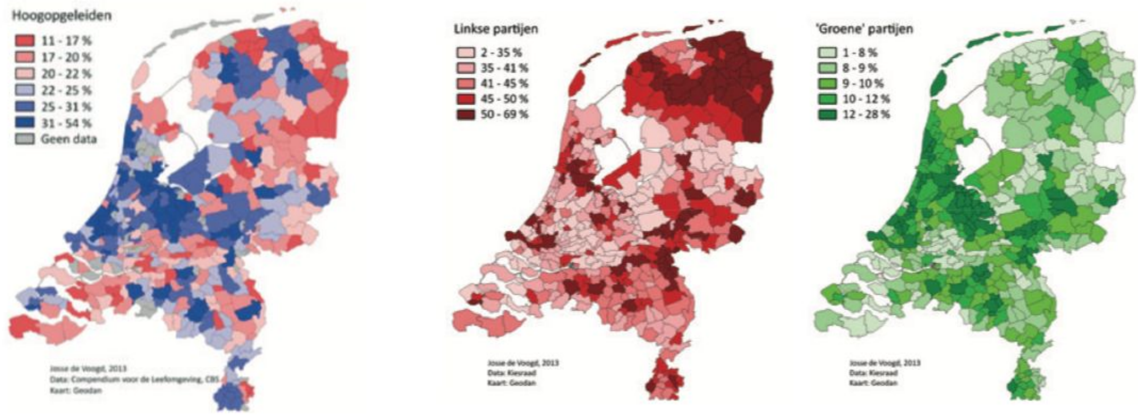

Figure 3: Total number of left parties per municipality during the elections of 2012 (PvdA, SP, D66, GL, PvdD), the green and progressive parties (D66, GL, PvdD), 'traditionally left' parties (PvdA and SP). Graph by De Voogd, 2013

The reason why this electoral division between supporters of different political parties is important for our study is because this connection between education level and different aspects of language use have been addressed by many researchers. Debrowska (1997) tested linguistic competence on adults and found that test scores increased dramatically with educational achievement. Least educated participants were also "the most likely to ignore syntactic cues and rely on non-linguistic strategies in interpreting test sentences". It is concluded that "cognitive routines for processing complex syntactic structures are of little use when dealing with normal everyday language, which tends to be very simple syntactically schooled language competence." Grammar judgements accuracy

[1] I am aware of the controversies around these terms such as *lower* and *higher education*, but for easiness of this research *higher education* will refer to having finished a higher education studies, such as university or a similar educational establishment. *Lower education* will refer to having finished secondary education only.

depends heavily on educational achievement as well (Mills and Hemsley, 1976). They concluded, different levels of education accompany different levels of linguistic competence. Chipere (2001) found similar results for school-going children versus non-school going children on grammatical judgement and comprehension tasks. Grammar judgements and comprehension or linguistic competence in general is strongly dependent on education level. Based on this strong correlation between language proficiency and education level and the existence of an electoral divide on educational background between supporters of political parties, it can be expected that language use of those political supporters may differ as well.

2.1.3 Cultural Participation

An explanation of this connection between green party supporters and educational level is offered by Achterberg and Houtman (2006), who argue that cultural participation is the mediating factor between the two. They argue that differences between two Dutch leftist parties, the *Socialistische Partij* and *GroenLinks* can be explained through their difference in cultural participation. People are more inclined to support the *Greens (*general term for green party's such as *GroenLinks*) when they participate culturally more actively, indicating cultural capital. Education would be a strong indicator of the amount of cultural participation, and therefore the amount of cultural participation of people indicates their preference for either *GroenLinks* or the *Socialistische Partij*. Burden (2009) found similar results investigating the relationship between education level and voter turnout, as "respondents with less than high school education were always less participatory than those with more education".

2.2 Related Work

2.2.1 Research on Language Use in Politics

Now that we know linguistic competence may differ amongst people supporting different political parties, what researches have been focusing on relationships between political preference and language use characteristics? First of all, looking at political leaders' language use may differ based on what party they belong to. For example, Schoonvelde et al. analysed language complexity in political speeches of both conservative and liberal politicians and found that liberal politicians use more complex language than conservative politicians (2019). The researchers investigated 'specific sets of speeches of US members of congress and UK members of Parliament'. However, besides a difference in language complexity between progressive and conservative politicians, an economic left-right difference was not systematically present. These differences could be attributed to politicians to learn to "speak the language of personality by identifying and conveying those individual characteristics that are most appealing at a certain time to a particular constituency' (Caprara and Zimbardo, 2004). Thus, a theory is that 'politicians persuasive messages should resonate with the receiver,' as they theorize that culturally-right individuals would be appealed more to short and clear sentences. On the other hand composed sentences with clauses with more ambiguities would be more appealing to culturally-left individuals as they would be more open to different and loose interpretations of statements (Schoonvelde et al., 2019).

As discussed, language of political leaders and parties may differ. But what do these differences consist of? A topic of interest for researchers is language use in populism. In the Netherlands, Geert Wilders is one of these populist party leaders and his language has been studied by Van Leeuwen (2012). He argues that use of complementation (a word in a sentence that can not be left out because it completes meaning by connecting words) of of his language in his speeches indicates the degree of room for discussion, in which his higher levels of complementation indicate a low degree of room for discussion. A similar analysis was done on Thierry Baudet's speeches (Hoogenband, 2019), another Dutch political leader that is considered populist, and concluded that his speeches contained language with short sentences with not many clauses. Not only political speeches were analysed, also campaign messages and manifestos were researched and support was found for "the conjecture about populist parties as they employ significantly less complex language in their manifestos" (Bischof and Senninger, 2018). However, Brosius et al. (2017) argue that "variation in complexity of political language regards personality differences: conservatives are thought to have a preference for less complex language than liberals". They add that for "ordinary people it is easier to connect with politicians keeping it simple and stupid." Therefore, politicians are generally advised to use simple language (Collins, 2012).

2.2.2 Methods on Language Use, Social Media Content and Politics

Now that indicated directions of the relationships between language use in politics are discussed, this section discusses methods used by other researchers to examine social media content, aspects of language and political issues. Oliveira et al. use sentiment analysis to extract data from social media to "reveal the political preferences of citizens" (2017). They analysed whether these results obtained by the sentiment analysis could correctly predict political preferences of citizens compared to prediction of traditional public opinion surveys (Oliveira et al., 2017). The comparison indicated that the sentiment analysis was more or less equally good in predicting the voter preferences as traditional research methods, meaning sentiment analysis is an appropriate tool for predicting political preferences based on social media data.

Other methods on political preference and social media include analysis of *Twitter* tweets. Pennacchiotti and Popescu (2011) tried to classify users on social media to "automatically infer the values of user attributes such as political orientation or ethnicity by leveraging observable information such as the user behavior, network structure and the linguistic content of the user's Twitter feed." To do this, they used a machine learning approach "which relies on a comprehensive set of features derived from such user information." These methods were successful in predicting user's political orientation with accuracy numbers of 0.8 or higher (Pennacchiotti and Popescu, 2011). Colleoni et al. (2014) used a similar method, a combination of machine learning and social network analysis to classify users as Democrats or Republicans based on *Twitter* content.

3 Method

This section discusses the methods chosen to answer the question of what the relationship is between political orientation in the Netherlands and Dutch language use online. First of all, an explanation is given for deciding what political parties were analysed (Section 3.1). Furthermore, the data is discussed in Section 3.2, including why this content was considered to be suitable for analysis and what the approach was to gathering and analysing the data. Section 3.3 and Section 3.4 discuss respectively the quantitative and the qualitative data that was gathered through analysis of the content from Section 3.2. In Section 3.5, implementation is discussed and Section 3.6 covers the analysis and how the research question was expected to be answered based on these results.

3.1 Political Parties

Looking at the political landscape described in Section 2.1, a number of different political orientations were taken into account. On the one hand, the division between left and right based on Krouwel's model (Figure 2) splits the political parties in two groups. For easiness of referring to the categories, left and progressive will be referred to as left and right and conservative will be referred to as right. Populism versus not-populism could be considered another factor that characterizes the Dutch political landscape and this led to a quadratic division of *left and populist*, *left and non-populist*, *right and populist* and *right and non-populist* (Table 1). Each quadrant was paired to a political party that would fit in that category and the to be analysed parties were chosen based on these quadrants. Therefore, each chosen party would differ with another party based on either their leftness/rightness or their populist character/non-populist character.

	Left	**Right**
Populist	*Socialistische Partij*	*Forum voor Democratie*
Non-Populist	*GroenLinks*	*Volkspartij voor Vrijheid en Democratie*

Table 1: Overview of the analysed parties

3.2 Data

To understand the relationship between political orientation and language use, ideally voters of political parties and their language use should have been taken into account. However, due to privacy issues (voters are anonymous) and the inability of reaching out to those voters directly, party identification had to be established in another way. Forums online could provide a rich source of online data and much politically oriented content is available. Political parties post this political content such as videos for several reasons, not only to persuade average voters but to gain support of elite party actors and therefore strengthening the relationship with their community (Ridout, Fowler, Brantstetter, 2010).

Salmond (2010) argues for the same two-fold attraction of posting YouTube videos: to reach out to new voters and retain existing ones. “There are a lot of politically engaged people who visit YouTube. They want not only to be informed about politics for themselves, but who also often want to learn political arguments so they can persuade less politically engaged people in their social network about which way to vote.” In addition, the second reasoning includes *YouTube* to be one of the “most efficient ways to communicate with voters without having the message filtered by journalists. The other two ways to broadcast to voters without the journalistic filter are direct mail and direct email – and neither of which have the same potential for rich content as a *YouTube* video.”

Therefore, people that respond to political content may not be voting for the political party posting this content, but with these goal of attracting new voters and retaining existing voters, it could be assumed that a general interest in this content was present. These replies could be either a positive or negative response to the content, but a general assumption that people are triggered by this content and that they for some reason are following and viewing this content could be made. A general interest in this content was sufficient enough for this research to explore the possibility that there would be a relationship between political orientation and online language use. However, with this method the political orientation of the people commenting on the videos can not be established with certainty.

After deciding that responses under videos of political content could possibly indicate political orientation (these people are following or viewing the political content) and because of a lack of better available options due to voters being anonymous, it was decided that *YouTube* would be a suitable platform to use for analysis. On *Twitter*, politicians post content in the form of *tweets* but their responses are *retweets* and not messages typed by other users, making it harder to collect suitable data. All chosen political parties owned a *YouTube* channel and actively posted content on their channels. Furthermore, a lot of data (responses from viewers) was available and accessible as *YouTube* does not prevent scraping of data by restraining privacy laws, as *Facebook* for example does. Video links were selected from the *YouTube* channel for each of the four parties. In selecting video’s, recency of video’s and the number of comments on that video: the most recent videos with a sufficient number of comments (50+) were selected for analysis. If these videos were unavailable, a video with a lower number of comments was selected. This was due to a large difference between the number of comments on the videos between the different parties: for example 2 *YouTube* videos posted by FvD were good for 945 comments, while 10 videos posted by VVD were good for 378 comments. It was aimed to gather 500+ comments for each party, depending on how many comments were available. The comments were gathered in june 2019.

After collecting the video links, a data scraper tool on a website (http://ytcomments.klostermann.ca) was used to gather the comments and output them in a table. In total comments of 32 video links were scraped resulting in 2157 comments divided over four groups of commenters. In total, 560 comments were gathered for the *SP* group, 274 for the *GL* group, 945 for the *FvD* group and 378 for the *VVD* group. A complete list of the analysed videos is presented in Section 6.3. A list with the video titles, associated parties, upload date and the number of comments that were gathered from each video can be found in Appendix 7.1.

3.3 Quantitative Aspects of Language Use

The internet allows for written language to be readily available in large quantities, therefore the focus point of this research was written language online. To find differences between the language use of the people commenting on content of political parties, there needed to be concrete characteristics about their online language use that could be easily measured and compared. However, in selecting these measurable variables it is the question which aspects of language use could produce meaningful information. What kind of output could actually say something useful about the language use of that specific group of political content-commenters? This section covers the measured variables that were expected to possibly differ across the different group of commenters. It was chosen to analyse these variables on both the level of messages and the level of sentences. This was due to the expectation that sentences could provide meaningful information about language use as well: it might be that sentences can be very short, even though a message can still be very long or sentences can be very long, even though the message is quite short. It was chosen to analyse on both levels so that this information would not be disregarded.

First of all, vocabulary is an indicator of language proficiency level. Although vocabulary could refer to both the size of someone's vocabulary in numbers of words known and depth of knowledge (Greidanus and Nienhuis, 2001), as in quality of their knowledge and correct usage of those words, both have been found to highly correlate (Schmitt and Meara, 1997). However, maintaining a large word stock and word knowledge specifically contributes to acquiring language proficiency (Hermann, 2003). One could not measure someone's complete vocabulary based on a single comment on a *YouTube* video, however looking at messages or sentences, it is possible to count the number of unique words in a message, which is also known as the *Type/Token Ratio*. This *TTR* "weights range of vocabulary for size of speech sample. The larger the resulting *TTR*, the less repetitive the vocabulary usage" (Richards, 1987). It takes the total number of unique words and divides it by the total number of words, for example 20 unique words out of 20 gives a ratio of 1 and a single word repeated 20 times gives a ratio of 1/20 or 0.05. Thus, this number is not a measurement of someone's vocabulary size, it is a playful way of indicating expected differences in language use based on the idea that people with a higher language proficiency generally have a larger vocabulary than people with a lower language proficiency and that this difference could become visible in the language use of their online posts.

Secondly, complexity of language was another factor that would be expected to differ amongst the different commenter groups as it relates to language proficiency levels (Brosius et al., 2017) and therefore possibly to language use. The *Flesch-Kincaid Readability Test (FKRT)* is an example of a test that addresses text complexity. This complexity is evaluated by the *FKRT* by taking "the number of words per sentence, and the length of the words in the sentences" (Brosius et al., 2017). The variables of this *FKRT*, such as *the number of words* per message or sentence and the *average length of the words* in the messages or sentences could indicate variety in text complexity. These *number of words* per message or sentence were easily calculated by counting how much words were present in each sentence. The length of the words in the messages or sentences or *average word length* were calculated by counting the number of characters for each word, adding them up and dividing them by the number of words in the message or sentence. Different values in *number of words* per message and sentence and differences in *average word length* possibly addressed different levels of text complexity. In addition, the *total number of characters* in each message and in each sentence were calculated.

A spelling check (*pyspellchecker*) was used as a general tool to check correct spelling of words. Spelling tests are often part of language proficiency test and people largely agree to correct spelling being important in learning new languages (Tanaka and Ellis, 2003). Existing spelling check tools checked the messages and sentences for *spelling errors* and calculated whether spelling errors were made. This is a dictionary based method, meaning that *spelling errors* were only counted as the selected words were not present in a dictionary. Therefore, grammar errors were not taken into account. The number of *spelling error*s made per message or sentence served as an indication of that person's spelling accuracy. Spelling accuracy would be expected to differ between groups of political content-commenters if differences in language use are present. In Table 2, an overview of all discussed factors is shown with their descriptions, measurements and an example.

Variable	**Description**	**Measurement**	**Example**
(1) Type/Token Ratio	Not someone's actual vocabulary, but merely an indication whether people used more or less unique words in their messages or sentences.	Number of unique words out of the total words in the message or sentence.	24 out of the 27 words in the message were unique words. In this case, 3 words were a repetition of one of the other 24 words. The

			Type/Token Ratio is 24/27 = 0.89.
(2) Total Number of Words	The number of words in a message or sentence indicates complexity of language. A higher number of words in a sentence indicates a higher complexity.	Numbers of words per message or per sentence.	There were 30 words in a message. There were 8 words in a sentence.
(3) Average Word Length	The average word length in a message or sentence indicates complexity of language. A higher average word length indicate higher complexity.	Average word length taken from al the words in the message or sentence.	There were 30 words in a message and on average each word consisted of 4,2 characters.
(4) Total Number of Characters	The total number of alphabetical characters in a message or sentence.	Counting all the alphabetical characters in the message or sentence.	A message contains 180 alphabetical characters. A sentence contains 30 alphabetical characters.
(4) Spelling Errors	The number of words that contain a spelling error made per message or sentence (using the *pyspellchecker* tool), indicating the spelling accuracy of that message or sentence. Dictionary-based method.	Number of words containing a spelling error based on prevalence in a given dictionary.	In a message or sentence, 2 words were found that were classified as misspelled as they were not present in the given dictionary.

Table 2: Factor, description, measurement and example of the measured aspects of language use

3.4 Qualitative Aspects of Language Use

Next to these rather numerical calculations with the data, a way of qualitatively looking at language use was needed and this was done using a *Linguistic Inquiry and Word Count* (*LIWC*) dictionary that operated through a method that counted the prevalence of words for each category. Using this method, differences in psychological types of words became visible. The *LIWC* is a text analysis program that examines underlying processes of text on a word-by-word basis (Pennebaker, Francis and Booth, 2001). It “counts words in psychologically meaningful categories” and it aims to “detect meaning in a wide variety of experimental settings, including to show attentional focus, emotionality, social relationships, thinking styles and individual differences” (Tausczik and Pennebaker, 2010). Its Dutch equivalent was made available through the translation of Zijlstra and colleagues (2004). The Dutch *LIWC* consists of five categories with 66 subcategories, namely linguistic dimensions, psychological processes, relativity, personal affairs and experimental dimensions. The *LIWC* categories, their most relevant subcategories and their corresponding numbers are shown in Table 3.

LIWC Categories				
I Linguistic Dimensions	**II Psychological Processes**	**III Relativity**	**IV Personal Affairs**	**V Experimental Dimensions**
1-11 pronoun, me, you, other, etc.	12 Emotional processes 20 Cognitive processes 27 Senses and perceptual processes 31 Social processes	37 Time 41 Space	47 Occupation 51 Leisure 56 Money 57 Religion 60 Physical state	66 Swearing

Table 3: Dutch LIWC categories

What the LIWC could reveal in terms of language use is for example complexity of words, as some words would indicate “multidimensional, differentiated thinking in a text” (Brosius et al., 2017). If a speaker or author gives several perspectives on a given topic, a text becomes conceptually more complex (Hermann, 2002; Pennebaker and King, 1999). An example of these type of words that signify differentiation between perspectives are exclusion words or conjunctions, such as ‘but’, ‘without’, ‘exclude’, ‘also’, ‘and’ or ‘although’ (Tausczik and Pennebaker 2010).

3.5 Implementation

The 2157 comments that were scraped from the *YouTube* videos were stored in a *.csv* file which was loaded into a *Python* script. The messages were stored in a 3D array, in which the first dimension contained the messages. The second dimension contained sentences that were created from the message using *NLTK’s sentence tokenizer*. This tokenizer divides a text into a list of sentences by using an unsupervised algorithm to “build a model for abbreviation words, collocations, and words that start sentences” (NLTK, n.d.). The third dimension contained the words for each sentence. They were obtained through separation of spaces. After creating this 3D array, all punctuation, symbols and non-alphabetical characters were removed and all words were set to lowercase, resulting in the arrays only containing lowercase alphabetical characters.

After collecting the raw data, for both the messages and sentences individually, some calculations were done for each of the variables discussed in Section 3.3 For the level of messages, that meant it was calculated how many sentences were in each message (output in *number of sentences*), the *Type/Token Ratio*, the *number of total words* in that messages, the total *number of characters* in that message, the *average word length* of the message, and the number of *spelling errors*. For each sentence, the same variables were calculated except the *number of sentences* in each sentence, as they all equaled 1. All variables were easily calculated by counting characters in each string, except the number of *spelling error*s which was calculated differently.

The number of *spelling errors* was calculated using the *pyspellchecker*, a plug-in for *Python* that checks words for correctness of spelling using words that are in some given dictionary. The used dictionaries were both the standard English one that came with the tool and a Dutch dictionary posted on their *Github* page (Github, 2017). The reason for keeping the English dictionary was to prevent the tool from misclassifying English words as spelling errors, due to some comments being posted in English. In addition, some other words that were not in the initial Dutch dictionary were added to the list as they would also risk incorrectly classifying words as words containing spelling errors. These words were specific to this research and were words that would be expected to be frequently used. Examples are the names of the chosen political parties and their abbreviations (such as 'fvd', 'gl', 'groenlinks', 'vvd', 'sp') and their current political leaders ('mark', 'rutte', 'jesse', 'klaver', 'thierry', 'baudet, 'lilian', 'marijnissen'). The variable *spelling error*s outputted the number of words not present in the dictionary.

For analysing the *LIWC* categories, a *Python* script was used that counts occurrences of words from each of the Dutch *LIWC* categories. Four different datafiles with *YouTube* comments were created, one for each political party. The files were analysed using the *LIWC* and it outputted how many words existed for each category (66 categories in total). It did so for all the comments of one party combined and gave a number per category that indicated how many percent of the total words of the whole data file fell in that specific category. These percentages were compared and differences in underlying processes and meaning of text for the different political parties became apparent.

3.6 Analysis

How did the findings answer the research question of what relationships exist between political orientation and language use in the Netherlands? The analysis of the data was split in two: a quantitative and a qualitative analysis. The quantitative analysis obtained 44 means with their standard deviations (6 variables for the messages, 5 variables for the sentences and 4 political parties, thus 11 * 4) and the *LIWC* outputted percentages which indicated how prevalent a certain category of words was in comparison with the total words. How could these numerical values and prevalence percentages be interpreted?

Due to the explorative nature of this research, specific hypotheses such as 'comments on videos of parties that are considered more left and populist are expected to have more characters than comments under videos of parties that are considered more right and non-populist' were not theorized. This study explored different possibilities without theorizing on beforehand what these possibilities would be. This meant that the numerical values found for the *total number of sentences*, *Type/Token Ratio*, *total number of word*s, *average word length* and *spelling error*s were compared for each category and conclusions were made on finding significant differences between the groups. Through performing multiple *One-Way Anova's* the groups were tested for significant differences.

However, for the qualitative analysis this open interpretation approach was harder as the *LIWC* consisted of 66 categories and not all categories were relevant for this study. Therefore, 5 hypotheses were set up based on previously discussed literature about language use of politicians and general characteristics of the party. These hypotheses take general ideas about left/right, conservative/progressive and populism/non-populism into account.

1. Comments on videos posted by populist parties contain more *negative emotions* (category 16, 17, 18 and 19) than comments of non-populist parties.
2. Comments on videos posted by populist parties contain more words referring to *the other* (category 6).
3. Comments on videos posted by progressive parties contain more *future-referencing words* (category 40) and comments on videos posted by conservative parties contain more *past-referencing words* (category 38).
4. Comments on videos posted by progressive left parties contain more *inclusion words* (category 44) and comments on videos posted by conservative right parties contain more *exclusion words* (category 45).
5. Comments on videos posted by populist parties contain more *curse words* (category 66).

4. Results

The results Section consists of three parts, the first part (Section 4.1) discusses the results of the analysis of the comments. Section 4.2 discusses the results for all sentences of those comments. Note that therefore the same comments were used but they were split in sentences, so although the same comments were analysed, the splitting of the data in sentences made up for different data and therefore different results. Section 4.3 discusses the psychological categories of the words using the *LIWC*. Section 4.4 summarizes the findings.

4.1 Messages

The final dataset consisted of 2157 messages, out of which 2132 messages were used for analysis (n = 2132). Some messages were left out due to them being considered *spam* and therefore negatively influencing the data. *Spam* was defined as messages with sentences that consisted of more than 50 words or messages with words that consisted of more than 30 characters. The number of messages were 555 for *SP*, 271 for *GL*, 933 for *FvD* and 373 for *VVD* (Table 4). For each of the comments the in Section 3.3 discussed variables were calculated and the results are discussed consecutively below.

A *One-Way Anova* was performed for each variable and a *Tukey* test was performed to indicate where the differences were between the parties. The data was tested for normality and in the case of non-normally distributed data it was chosen to perform a logarithmic transformation and test the data for normality again. However, if a logarithmic transformation did not result in normally distributed values, it was chosen to perform the *One-Way Anova* with the original data anyway, due to robustness of the method (Laerd Statistics, N.d.). The significance level was set at 0.01 for all *t*-tests instead of the more conventional 0.05 due to the large number of *t*-tests conducted in this study increasing the risk of a *type II error* (false positives). An overview of all results is shown in Appendix 7.3.

	SP	GL	FvD	VVD	Total
N	555	271	933	373	2132

Table 4: n-values for all messages on the political videos per party

4.1.1 Number of Sentences

The data was not normally distributed and a logarithmic transformation did not result in normally distributed data either. Therefore, the data was kept as it was and a *One-way Anova* was performed. An overview of the different means for each group is shown in Table 5. The found *p*-value for the *One-Way Anova* was 0.583, indicating no statistically significant difference between any of the groups. A more elaborate overview of differences between the groups is shown in Appendix 7.3. Concluding, the number of sentences for each message did not differ significantly, regardless what political party posted the *YouTube* content.

Number of Sentences *not normally distributed*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	2.88	2.49	2.79	2.87
SD	0.11	0.19	0.12	0.31

Table 5: Descriptives for variable Number of Sentences in each message

4.1.2 Type/Token Ratio

The data was not normally distributed, however a *One-Way Anova* was performed and found a *p*-value of 0.002. A post-hoc *Tukey* test showed that the difference was significant between *GL* and *SP* (p = 0.002), as shown in Table 6. This means that the comments on *GL* content had a statistically significant higher *Type/Token Ratio* per message compared to the comments on videos posted by the *SP*. Thus, comments under videos posted by the *SP* consisted of more words that were similar to each other. However, after testing this effect for populist (*SP* and *FvD*) versus non-populist (*GL* and *VVD*), a *p*-value of 0.001 (Table 15) indicated a significant difference between the two, meaning that comments posted under videos of parties with a populist character generally contained less unique words than those of parties that did not have a populist character. An overview of the descriptives of this variable is presented in Table 6 and Table 15 (Section 4.4).

Type/Token Ratio *not normally distributed*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	0.89	0.92	0.90	0.90
SD	0.005	0.007	0.004	0.006
***p*-value < 0.01**	* 0.002	* 0.002		

Table 6: Descriptives for variable Type/Token Ratio of the messages

4.1.3 Total Number of Words

As the data was not normally distributed, a logarithmic transformation of the data was needed. After logarithmic transformation, the data turned out to be normally distributed. A *One-Way Anova* resulted in a *p*-value of 0.000. A post-hoc *Tukey* analysis was performed to find between what groups the significant difference(s) existed. There were three significant differences found. *GL* comments generally had less words in them than *FvD* comments (p = 0.001) and *SP* comments (p = 0.000). Also, *VVD* comments generally had less words than *SP* comments (p = 0.001). This effect was even stronger if the variable was tested for populist versus non-populist as the independent factor (p = 0.000; Table 15). Therefore, it can be concluded that comments on *YouTube* videos of parties that could be considered populist contain a larger *number of words* compared to their non-populist counterparts. An overview of the descriptives is shown in Table 7 and Table 15.

Total Number of Words *normally distributed after logarithmic transformation*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	37.6	29.8	37.9	37.7
SD	1.71	2.97	2.34	4.60
***p*-value < 0.01**	* 0.000 * 0.001	* 0.000 * 0.001	* 0.001	* 0.001

Table 7: Descriptives for variable Total Number of Words of the messages

4.1.4 Average Word Length

After testing the data for normality, the data turned out to be normally distributed. None of the groups were significantly different from each other, according to a *One-Way Anova* test with a p-value of 0.030. This means the *average word length* of the comments on the political videos were not statistically different for each party. In Table 8 and Table 15, descriptives for the variable *average word length* are summarized.

Average Word Length *normally distributed*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	4.81	5.05	4.95	4.77
SD	0.04	0.10	0.05	0.06

Table 8: Descriptives for variable Average Word Length of the words in the messages

4.1.5 Number of Characters

As the data was not normally distributed, a logarithmic transformation of the data was needed. After logarithmic transformation, the data turned out to be normally distributed. *A One-Way Anova* resulted in a p-value of 0.000. A post-hoc *Tukey* analysis was performed to find between what groups the significant difference(s) existed. There were four significant differences found, as in the messages of *GL* and VVD generally a lower total num*ber of* *characters* was present compared to *SP* and *FvD*, whose messages generally consisted of a higher *number of characters*. Therefore, a significant difference between *GL* and *FvD* was present with *p* = 0.001 and a difference between *GL* and *SP* with *p* = 0.000. *VVD* and *FvD* (*p* = 0.010) and *VVD* and *SP* (*p* = 0.00). Therefore, the comments on videos of more populist parties (*SP* and *FvD*) generally contained more characters compared to their non-populist counterparts (*VVD* and *GL*). This effect was even stronger if the groups were tested for populist versus non-populist parties as the independent factor (*p* = 0.000; Table 15). Table 9 and Table 15 show descriptives of the variable.

Total Number of Characters *normally distributed after logarithmic transformation*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	177.6	144.8	183.1	179.2
SD	8.3	14.5	12.4	22.6
***p*-value < 0.01**	* 0.000 * 0.000	* 0.000 * 0.001	 * 0.001 * 0.010	 * 0.000 * 0.010

Table 9: Descriptives for variable Total Number of Characters in the messages

4.1.6 Spelling Errors

The variables were not normally distributed and not successfully transformed. A *One-Way Anova* found a *p*-value of 0.003, indicating a statistical difference between the groups. However, a post-hoc *Tukey* analysis could not find between what groups this difference existed. Therefore, it was decided to do another *t-test* with left-rightness as independent factor which found a significant *p*-value of 0.000 (Table 15). This means that the comments under videos that were posted by left-wing political parties contained statistically significant less *spelling errors* than messages posted under videos of their right-wing counterparts. In Table 10 and Table 15, descriptives of the variable *spelling errors* are summarized.

Spelling Errors *not normally distributed*	**SP**	**GL**	**FvD**	**VVD**
N (2132)	555	271	933	373
Mean	0.45	0.43	0.67	0.74
SD	0.04	0.06	0.05	0.12

Table 10: Descriptives for variable Spelling Errors in the messages

4.2 Sentences

The final dataset consisted of 5937 sentences. The number of total sentences for each party were 1594 for *SP*, 672 for *GL*, 2604 for *FvD* and 1067 for *VVD* (Table 11). For each of the sentences the *Type/Token Ratio*, *total number of words*, *average word length*, *total number of characters* and the *number of spelling errors* in that sentence were calculated and the results are discussed consecutively below. A *One-Way Anova* was performed for each variable and a *Tukey* test indicated where the differences were between the parties. The significance level was set at 0.01 for all *t*-tests. An overview of all *p*-values can be found in Appendix 7.3

	SP	GL	FvD	VVD	Total
N	1594	672	2604	1067	5937

Table 11: n-values for all sentences on the political videos per party

After testing for normality, the same transformations were performed for the variables of the sentences as for the variables of the messages. For the variable *Type/Token Ratio*, a *p*-value of 0.145 between the groups was found, meaning there was no statistically significant difference between any of the groups. Thus, sentences in the comments posted on videos with different political backgrounds did not differ on *Type/Token Ratio.* For the variable *total number of words*, a *p*-value of 0.005 was found and a post-hoc *Tukey's* test indicated that the difference existed between the groups *GL* and *FvD* (*p* = 0.005; Table 9). Sentences of the comments posted on videos of *GL* contained significantly less words than the sentences of the comments posted on videos of *FvD*. The distribution of the means and standard deviations did not indicate left-rightness or populism-non populism making up for this difference, as *SP* and *VVD* had a similar mean of 13.0 (Table 12).

The factor *average word length* showed no significant difference between the groups (*p* = 0.042), meaning the *average word length* of the sentences in the comments on political videos did not differ based on what party posted the video. The same was true for the *number of characters* of the sentences. Although a *One-Way Anova* found a *p*-value of 0.004, a post-hoc *Tukey*'s analysis could not account for specific differences between the parties, meaning the *number of characters* of the sentences of the comments did not differ based on what political party posted the content.

Finally, the variable *spelling error* was found to differ significantly between the groups (*p* = 0.000). The differences existed between the groups *SP* and *FvD* (*p* = 0.000), *SP* and *VVD* (*p* = 0.000) and *GL* and *VVD* (*p* = 0.006). Performing a *One-Way Anova* with left-rightness as independent variable found a *p*-value of 0.000. Thus, it can be concluded that sentences of the comments on videos posted by left-wing parties contained significantly less spelling errors than sentences of the comments under videos posted by their right-wing counterparts. The descriptives and significant results of all variables are shown in Table 12.

Sentences	Total	SP	GL	FvD	VVD	Significance
N	5937	1594	672	2604	1067	
Type/Token R.	**Mean**	0.96	0.96	0.95	0.96	
not normally distributed	**SD**	0.002	0.003	0.002	0.002	
Total Nr of Words	**Mean**	13.0	11.7	13.4	13.0	GL-FvD *p = 0.005
norm. distr. after log transf.	**SD**	0.26	0.35	0.20	0.35	
Average Wordl.	**Mean**	4.89	5.02	4.93	4.84	
normally distributed	**SD**	0.03	0.05	0.03	0.04	
Total Nr of Chars	**Mean**	61.1	57.0	64.5	62.0	
norm. distr. after log transf.	**SD**	1.23	1.79	1.04	1.75	
Spelling Errors	**Mean**	0.15	0.17	0.24	0.26	SP-VVD *p = 0.000 SP-FvD *p = 0.000 GL-FvD *p = 0.006 Left-Right *p = 0.000
not normally distributed	**SD**	0.01	0.02	0.02	0.02	

Table 12: Descriptives and significant results for all variables on the sentence level

4.3 LIWC

All comments for each party were collected and analysed using the Dutch *LIWC*. For each party, the number of words in the total sample, the number of unique words in the sample and the number of unique words in the *LIWC* were collected (Table 13). Numbers were expressed as fraction of the total words in the sample, but for easiness of reading (due to the numbers being very small) they are shown as percentage of the total in the results below (Table 14). Only the categories are shown that are discussed in Section 3.6. Although these numbers are quantitative, they are treated as qualitative data: no analysis was conducted with the numbers due to no appropriate method for analysis being available. This resulted in the numbers being inspected visually and the conclusions were drawn based on these visual inspections.

	SP	GL	FvD	VVD
Nr of words in sample	11371	4853	29559	8563
Nr of unique words in sample	2905	1646	5714	2377
Nr of unique words in LIWC	872	536	1306	761

Table 13: LIWC output: total number of words in sample, number of unique words in sample and the number of uinque words in LIWC for each political party

LIWC Category	LIWC Cat. Number	SP	GL	FvD	VVD
Neg. emotions **Anxiety** **Anger** **Sadness**	16 17 18 19	1.93% 0.15% 0.53% 0.50%	1.52% 0.12% 0.45% 0.49%	1.44% 0.13% 0.40% 0.37%	1.66% 0.11% 0.47% 0.41%
Other	6	0.95%	1.23%	1.29%	1.42%
Future **Past**	40 38	0.67% 2.35%	0.89% 1.36%	0.66% 1.51%	0.68% 2.19%
Inclusion **Exclusion**	44 45	7.17% 4.05%	6.61% 3.52%	6.82% 4.10%	7.18% 4.32%
Curse words	66	0.09%	0.20%	0.10%	0.17%

Table 14: LIWC results for categories 16, 17, 18, 19, 6, 40, 38, 44, 45 and 66 for each political party.

The data is displayed in the histograms below (Figure 4 and Figure 5). None of the categories *negative emotions*, *anxiety*, *anger* or *sadness* showed any large deviations between the different parties (Figure 4). Therefore, the expectation that comments on videos posted by populist parties contain more *negative emotions* than comments of non-populist parties (LIWC hypothesis 1) can not be supported with this *LIWC* analysis.

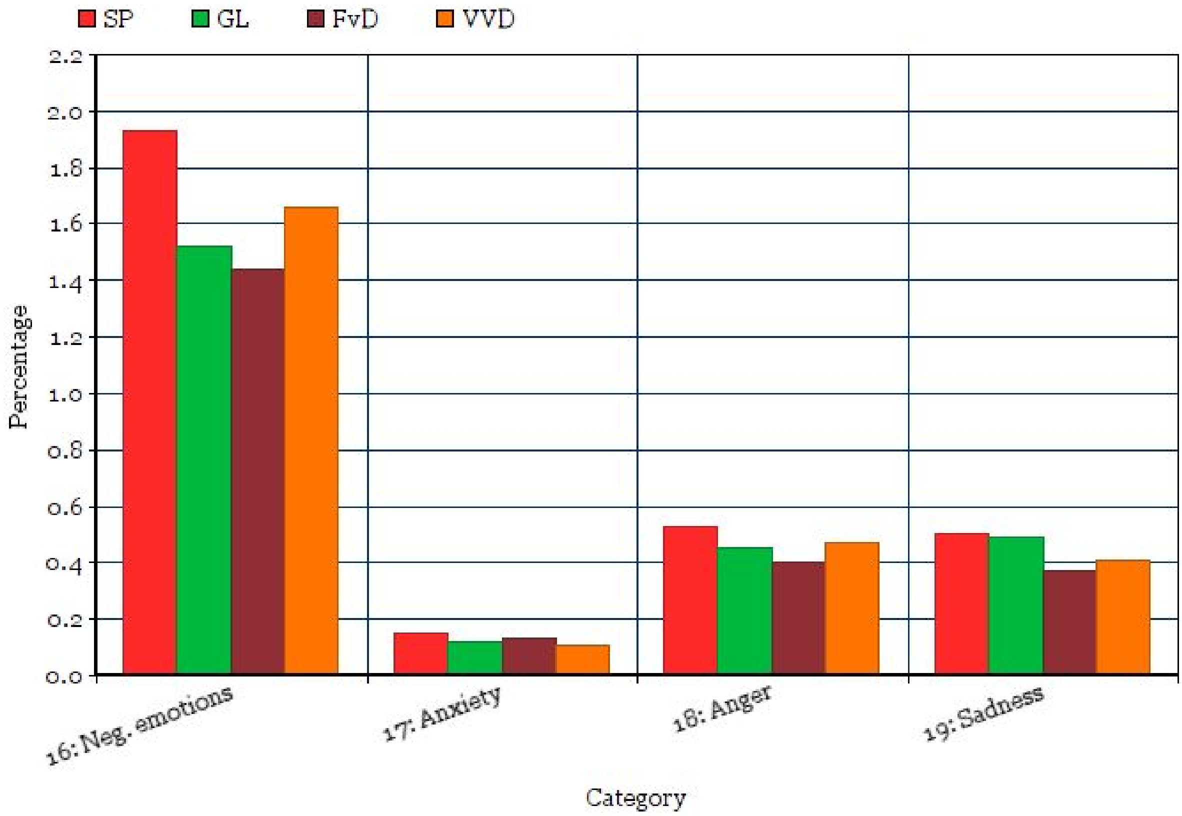

Figure 4: Histogram of LIWC categories negative emotions, anxiety, anger and sadness

Figure 5 shows the remaining categories. Although small variations exist between the parties, none of the variations are notably large and therefore none of the remaining hypotheses can be supported either. These included the expectation that comments on videos posted by populist parties would contain more words referring to *the other* (LIWC hypothesis 2), comments on videos posted by progressive parties would contain more *future*-referencing words and comments on conservative videos would contain more *past*-referencing words (LIWC hypothesis 3). Furthermore, the results did not indicate that comments on videos posted by progressive left parties contain more *inclusion words*, that comments on videos by conservative right parties contained more *exclusion words* (LIWC hypothesis 4) or that videos posted by populist parties would contain more *curse words* (LIWC hypothesis 5).

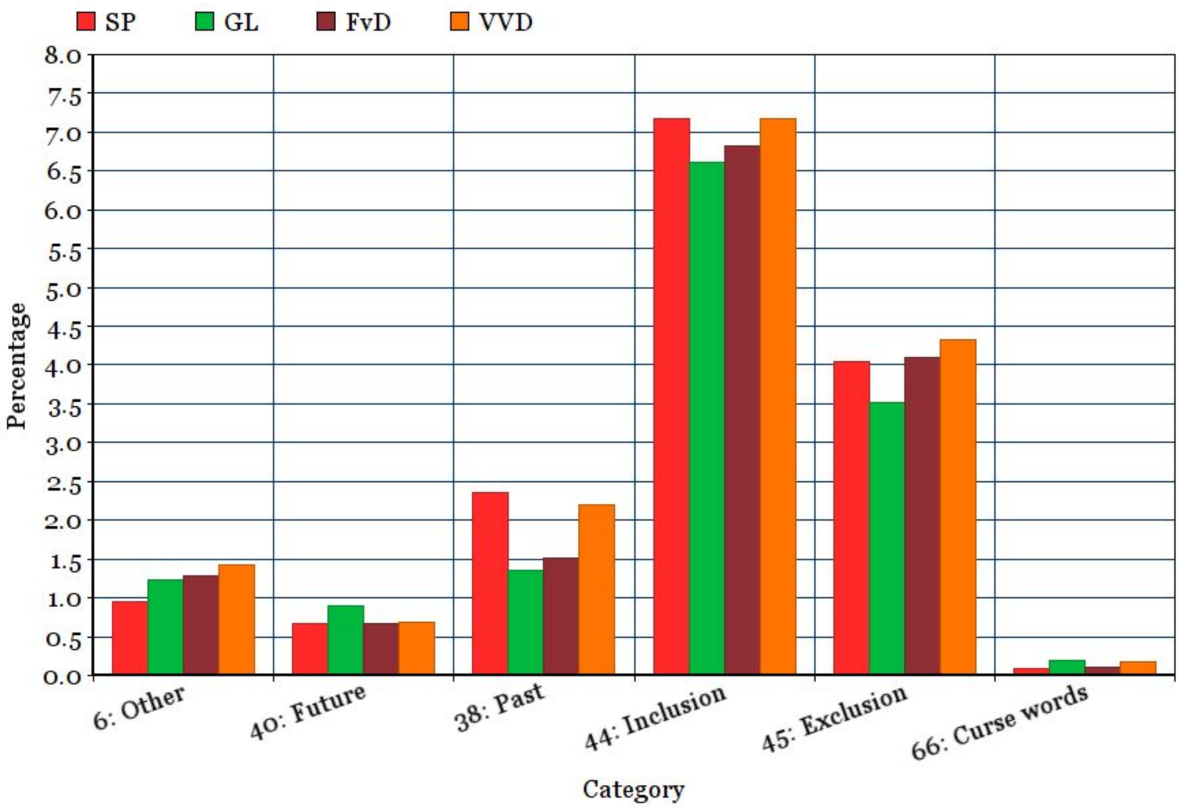

Figure 5: Histogram of LIWC other, future, past, inclusion, exclusion and curse words

4.4 Summary

Due to the large number of individual *t*-tests, this section contains an overview of the results that were found to be statistically significant. Comments on *YouTube* videos of parties that could be considered populist contain *less unique words* (*Type/Token Ratio*; *p* = 0.001; Table 15), a *larger number of words* (*p* = 0.000; Table 15) and contained *more characters* (*p* = 0.000; Table 15)) than comments on videos of parties that are not considered populist parties. On the other hand, both the comments on videos (*p* = 0.000; Table 15)) and the individual sentences in those comments (*p* = 0.000; Table 12)) contained less *spelling errors* if they were posted by a left-wing party compared to when they were posted to a right-wing party. None of the *LIWC* hypotheses were supported by the data.

Messages	**μ Left (SP + GL)**	**μ Right (FvD + VVD)**	**μ Populist (SP + FvD)**	**μ Non-pop. (GL + VVD)**	***p* Left vs. Right**	***p* Pop. vs. non-pop.**
N	826	1306	1488	644	2132	2132
Number of Sentences	2.75	2.81	2.82	2.71	0.718	0.538
Type/Token Ratio	0.90	0.90	0.89	0.91	0.848	* 0.001

Total Nr of Words	35.03	37.86	37.81	34.35	0.594	* 0.000
Average Wordl.	4.89	4.90	4.90	4.89	0.886	0.825
Total Nr of Chars	166.8	182.0	181.0	164.7	0.576	* 0.000
Spelling Errors	0.44	0.69	0.58	0.61	* 0.000	0.721

Table 15: Significance levels for the left vs. right and populist vs. non-populist parties for the messages

5. Discussion

In this section, the explanation of the results will be discussed, both within context of this study and in relation to related research. First, the findings are discussed as well as shortcomings and limitations.

5.1 Review of Results

For some variable comparisons, strong *p*-values were found, however for some other variables the evidence that there was a difference in language use in the comments between the party was not convincing. This may be due to various reasons, including shortcomings in the set up assumptions, the gathering of data, the statistical analysis or that a difference just does not exist. All of these are discussed in further detail.

5.1.1 Internal Methodology

In selecting target audiences, an assumption was made that these audiences would be representative of people interested in the political party that posted the political videos. There are multiple problems with this assumption, possibly causing noise in the target groups. First of all, there is no guarantee that the comments posted on the videos can be positively associated with the party posting that video. This also became clear during analysis, as *hate-comments* (comments of dislike or aversion) were posted on most of the videos. Now, this would not even be that much of a problem if the ratios of *hate-comments* were expected to be the same for each political party. However, this was not the case as for example *VVD* received much more hate comments due to them being a coalition partner within the current government. On the other hand, *GroenLinks* received a lot of *hate-comments* as well due to environmental topics currently being hot items with both strong proponents and opponents. A sentiment-analysis of comments would be able to filter these comments on positive or negative sentiment with more precision, however due to the time and scope of this research such a sentiment analysis was not conducted.

In addition to this skewed distribution of *hate-comments*, another shortcoming is the assumption that people posting comments on *YouTube* represent a random population sample. However, this is not the case. To illustrate this point, demographics of *YouTube* visitors are shown in Figure 6 and demographics of people that voted during the Dutch 2017 elections in Figure 7. *YouTube's* largest demographic group is users between the ages of 25-34. On the other hand, looking at Figure 7, the largest population group of voters is people between the ages of 35-64, meaning that the the largest group of voters is not necessarily the group most active on social media websites such as *YouTube* and might have therefore been left out in the analysis of comments. This graph does not log the kind of activity of age groups either: demographics of YouTube comment-posters might be skewed even further towards young age than YouTube visitors that only watch videos. These graphs do not even include the idea that older people in general have less access to internet (Zickuhr and Madden, 2012), even though "one quarter of the people entitled to vote are over 65 years of age" (CBS, 2017). Also, this paragraph only discusses age as a factor why the *YouTube* sample does not represent a random population sample, but many more factors could be considered, such as gender (Weiser, 2000), differences in involvement on social media (Hargittai, 2007) and psychological well-being (Sanders et al., 2000).

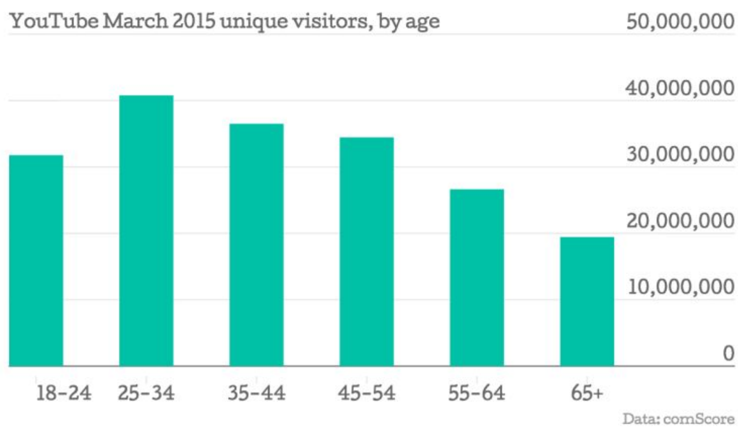

Figure 6: Age of unique YouTube visitors in 20

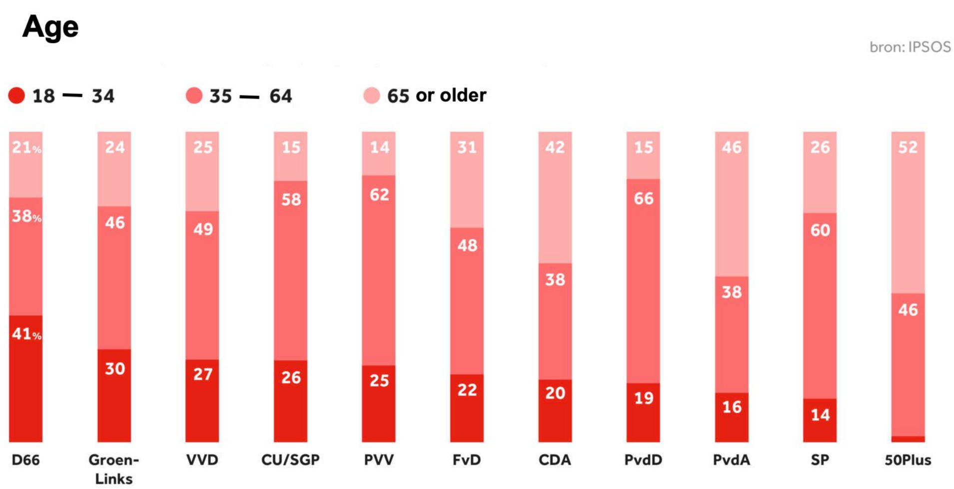

Figure 7: IPSOS research: percentages of age group of voters per political party, 2019.

5.1.2 Statistical Analysis

Besides limitations to the internal methodology, some shortcomings on the chosen statistical method may have negatively influenced the results. First of all, most of the variables were not normally distributed. The chosen method, a *one-way anova* is generally robust against violations of normality, however it was chosen to transform some variables to achieve more accurate results but not others. This may have led to some of the results being more accurate than others, while their *p*-values were treated the same when drawing conclusions. Another limitation was the sample size. Some *p*-values were very significant, indicating that the sample size *n* was large enough to achieve significant results. However, due to convincing evidence for some variables, a larger sample size would possibly have found significant results for other variables as well. Unfortunately, the number of total comments on the political party's *YouTube* channel were finite and therefore a much larger sample size was not possible for some groups. It was possible to gather data of more political parties, however, due to constraints of a thesis project, such as time and duration, more extensive data collection was beyond the scope of this project.

Another limitation concerns how some of the variables were handled. Mostly the outcome of the *spelling errors* variable was the result of some decisions that were made. First of all, it was dictionary based, meaning that if the words were existent in a dictionary, they were not counted as errors and if they were not they were counted as a spelling error. This method does not account for *spelling errors* that were made for certain words, but were present in the dictionary either way. An example is the Dutch word 'park' (meaning 'park'), that if it would be spelled as 'prak' (meaning 'mash' or 'crash') would still be occuring in the dictionary and therefore not counted as a spelling error, even if the word was supposed to mean 'park'. Another problem with the dictionary method is the inability of the dictionary to pick up on names of people and organizations. The most important ones such as party leaders and party abbreviations were manually added, but a lot of other relevant names, organizations and terms that were not added to the dictionary might have been misclassified as s*pelling errors* because the words were not captured in the dictionary. Not only does this problem apply for politically related words, it also misclassifies *internet slang* such as abbreviations like 'lmao', 'omg', 'jwz', etcetera as misspelled.

5.2 Framing the Results

Even though no specific hypotheses were set up, some of the findings were surprising. It does appear to be the case that there is a difference in language use between the people commenting on populist and non-populist videos. The use of less unique words in a sentence might partly be explained by the populist use of slogans, resulting in people using more similar words This possible explanation is based on the data, as it seemed that populist parties contained much slogans, such as "stem FvD" (vote for FvD), "FvD is de partij" (FvD is the party) and "go Thierry". However, use of slogans was not part of the research so whether populist parties used more slogans than non-populist parties can not be concluded based on these empirical observations. Another explanation that relates to previously mentioned research, is the idea that there is less variety in the comments due to ordinary people (Collins, 2012) connecting easier "with politicians keeping it simple and stupid" (Brosius et al,, 2017). If these same words are used by people associating with these populist parties, it might be true that they themselves use "simple and stupid" (Collins, 2012) language, meaning there would be less of a variety in the used vocabulary.

The surprising results were that comments on YouTube videos of populist parties would use a larger number of words and contained more characters. If people speak the language of their favoured politicians as the politicians "persuasive messages should resonate with the receiver" (Schoonvelde et al., 2019), they would be expected to form clear and short sentences. This preference for short and clear sentences would also be expected for the left-right division as it is theorized that "composed sentences with clauses with more ambiguities would be more appealing to culturally-left individuals as they would be more open to different and loose interpretations of statements" (Schoonvelde et al., 2019). The results do not contradict earlier research as those researchers did not focus on language use of individuals, merely they focused on what kind of language use these individuals preferred in politicians. However, in light of these results and the related theory, it is possible that the fact that people prefer certain language in politicians does not say anything about the language use of those people themselves.

Another finding is that comments on left-wing videos contained less *spelling errors* than comments posted on right-wing videos. As discussed, this might be the result of flaws in the method: that the dictionary did not include certain words that could have been more prevalent on the right-wing comments. For example, if there would be a large scandal around a right-wing politician and his or her name would be mentioned a lot in the comments, this would be classified as a spelling error for each message, increasing the number of *spelling errors* for the right-wing party comments. A clarifying explanation as to why this result was found and existed can not be related to literature.

5.3 External Contextualization

What do these findings contribute to research on language use or politics, or in general, to research? As discussed, not much research had been done on language use of certain groups of people that can be associated to political parties. These are the first steps into researching such differences between people interested in different political orientations. However, the connection between the target groups and their political orientation could have been more stronger to find more conclusive results: ideally, language use of voters should have been researched directly with the guarantee that these voters actually vote for a specific party and that their language use is accessible and analysable. In this research this was not the case due to the chosen method to look for online language use only has not been able to guarantee these conditions. Therefore, although analysis of online comments has been a rich source of gathering data, the value of this data in relation to whether it actually says anything about the aimed target group could have been questioned more. If there is another method available to gather data that directly represent target groups, the use of quantitative methods and programmed scripts can definitely help to find differences between these target groups, as the research did find significant differences between groups.

The method of using the *LIWC*, however, has not been able to find significant results. The analysing of all comments for each party simultaneously resulted in one value for each category, which made it hard to analyse the data. A separate LIWC analysis for each comment would provide more information, but was practically less feasible. Also, the visual exploration of differences between the LIWC categories for each party did not result in any meaningful findings. Therefore, the way the *LIWC* was handled in this case, caused the question whether the *LIWC* was the most suitable method to find relevant psychological meaning in the comments. If the LIWC was used to analyse each comment individually, this would possibly lead to a different conclusion.

When it comes to relationships between language use and political orientation, populism or non-populism is a variable that might be of influence on language use, as indicated by the small p-values. More research is needed on people and their favoured political orientation and their language use, on the condition that the groups are directly represented and not through possible associations such as posting comments on political YouTube videos. This may result in finding more unexpected relationships between language and political orientation that vastly differ from language used by politicians.

5.4 Conclusion

This research has opened up the way to investigate language use of people with different political orientations with the goal of becoming aware of differences between people that possibly contribute to a political divide. By exploring all possible relationships and not hypothesizing what relationships could be expected, it has been a research open to unexpected relationships, which is indeed what had been found. The question of what are relationships between political orientation and language use online in the Netherlands has been answered by first describing the political landscape as left versus right and populist versus non-populist. Next, differences in language use between people that can be associated with these parties were explored. Mostly differences existed between language use of comments on populist videos and language use of non-populist videos, meaning that language use is in some way related to political orientation. However, the reasons for this relationship and why these differences exist have yet to be discovered. Possibly other case studies that transcend the Dutch political landscape can tell us more about how language use relates to people supporting populist or non-populist parties.

The explorative nature of this research has made it possible to reflect on the suitability of certain research methods for similar research cases. By reflecting on what worked well for and what limited this research, the possibilities of these methods became more contained. The method of automatically extracting text features proved to be a suitable method for numerical and quantitative analysis. However, it was harder to draw conclusions for the extracted text features that aimed to find qualitative information. For this specific research, a sentiment analysis might have been a more suitable option. Based on this study, doing more research on the relationships between language use and political orientation would be expected to bring forward positive results, depending on what methods are used and how theories are framed and connected.

6. References

6.1 Bibliography

Achterberg, P., & Houtman, D. (2006). Why do so many people vote ‘unnaturally’? A cultural explanation for voting behaviour. *European Journal of Political Research*, *45*(1), 75-92.

Bakker, B. N., Hopmann, D. N., & Persson, M. (2015). Personality traits and party identification over time. *European Journal of Political Research*, *54*(2), 197-215.

Binder, S. A. (2003). Stalemate: Causes and Consequences of Legislative Gridlock (Washington: Brookings).

Bischof, D., & Senninger, R. (2018). Simple politics for the people? Complexity in campaign messages and political knowledge. *European Journal of Political Research*, *57*(2), 473-495.

Burden, B. C. (2009). The dynamic effects of education on voter turnout. *Electoral Studies*, *28*(4), 540-549.

Brosius, A., Bakker, B., Schoonvelde, M., & Schumacher, G. (2017). Evaluating Complexity in Political Speech. *University of Amsterdam: The Euengage Working Paper Series.*

Caprara, G. V., & Zimbardo, P. G. (2004). Personalizing politics: a congruency model of political preference. *American psychologist*, *59*(7), 581.

Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data. *Journal of communication*, *64*(2), 317-332.

Collins, P. (2012). *The art of speeches and presentations: The secrets of making people remember what you say*. John Wiley & Sons.

Dąbrowska, E. (1997). The LAD goes to school: A cautionary tale for nativists. *An Interdisciplinary Journal of the Language Sciences* 35(2), 735-766.

Greidanus, T., & Nienhuis, L. (2001). Testing the quality of word knowledge in a second language by means of word associations: Types of distractors and types of associations.*Modern Language Journal, 85*, 567-577.

Hargittai, E. (2007). Whose space? Differences among users and non-users of social network sites. *Journal of computer-mediated communication*, 13(1), 276-297.

Hermann, F. (2003). Differential effects of reading and memorization of paired associates on vocabulary acquisition in adult learners of English as a second language. *TESL-EJ*, 7(1), 1-16.

Hermann, Margaret G. 2002. Assessing leadership style: A trait analysis in the psychological assessment of political leaders. Ann Arbor: University of Michigan Press.

Hoogenband, F. V. D. (2019). *Baudet gaat voor iets Wilders: Hoe grammaticale kenmerken van speeches van Baudet laten zien dat hij toch echt een man van het volk is*.

Jamieson, K. H., & Falk, E. (2000). Continuity and Change in Civility in the House. In *Polarized politics: Congress and the president in a partisan era.*. Washington, DC: CQ Press. 96-108

Jones, D. R. (2001). Party polarization and legislative gridlock. *Political Research Quarterly*, *54*(1), 125-141.

Layman, G. C., Carsey, T. M., & Horowitz, J. M. (2006). Party polarization in American politics: Characteristics, causes, and consequences. *Annu. Rev. Polit. Sci.*, *9*, 83-110.

van Leeuwen, M. (2012). Stijl en grammatica-Complementatie in politieke speeches. *Tijdschrift voor Taalbeheersing*, *34*(1), 54-73.

Müller, J. W. (2017). What is populism?. Penguin UK.

Oliveira, D. J. S., Bermejo, P. H. D. S., & dos Santos, P. A. (2017). Can social media reveal the preferences of voters? A comparison between sentiment analysis and traditional opinion polls. Journal of Information Technology & Politics, 14(1), 34-45.

Pennacchiotti, M., & Popescu, A. M. (2011). A machine learning approach to twitter user classification. In *Fifth International AAAI Conference on Weblogs and Social Media*.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). Linguistic inquiry and word count: LIWC 2001. *Mahway: Lawrence Erlbaum Associates*, 71(2001), 2001.

Pennebaker, J W and L King. 1999. "Linguistic styles: language use as an individual difference." Journal of personality and social psychology 77(6), 1296–1312.

Politics in the Netherlands. (2013). The Hague: ProDemos.

Richards, B. (1987). Type/token ratios: What do they really tell us?. *Journal of child language*, *14*(2), 201-209.

Ridout, T. N., Franklin Fowler, E., & Branstetter, J. (2010). Political advertising in the 21st century: The rise of the YouTube ad. In *APSA 2010 Annual Meeting Paper*.

Rooduijn, M., & Akkerman, T. (2017). Flank attacks: Populism and left-right radicalism in Western Europe. Party Politics, 23(3), 193-204.

Salmond, R. (2011). MeTube: Politicians, YouTube, and election campaigns in longstanding democracies. *Youtube, and Election Campaigns in Longstanding Democracies.*

Sanders, C. E., Field, T. M., Diego, M., & Kaplan, M. (2000). The relationship of Internet use to depression and social isolation among adolescents. *Adolescence*, *35*(138), 237-237.

Schoonvelde, M., Brosius, A., Schumacher, G., & Bakker, B. N. (2019). Liberals lecture, conservatives communicate: Analyzing complexity and ideology in 381,609 political speeches. *PloS one*, *14*(2).

Schmitt, N. & Meara, P. (1997). Researching vocabulary through word knowledge framework: Word associations and verbal suffixes. *Studies in Second Language Acquisition,* 19, 17-36.

Sinclair, B. (2002). The dream fulfilled? Party development in Congress, 1950-2000. *Responsible partisanship*, 121-140.

Tanaka, K., & Ellis, R. (2003). Study abroad, language proficiency, and learner beliefs about language learning. *JALT journal*, *25*(1), 63-85.

Tausczik, Y. R. and J. W. Pennebaker. 2010. “The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods.” Journal of Language and Social Psychology 29(1), 24-54.

de Voogd, J. (2013). *Nieuwe scheidslijnen op de kaart*. Ministerie van Binnenlandse Zaken en Koninkrijksrelaties DGBK-Bureau Verkenning en Onderzoek.

Weiser, E. B. (2000). Gender differences in Internet use patterns and Internet application preferences: A two-sample comparison. *Cyberpsychology and behavior*, 3(2), 167-178.

Wodak, R., Khosravinik, M., & Mral, B. (Eds.). (2013). Right-wing populism in Europe: Politics and discourse. A&C Black.

Zickuhr, K., & Madden, M. (2012). Older adults and internet use. *Pew Internet & American Life Project*, 6.

Zijlstra, H., Van Meerveld, T., Van Middendorp, H., Pennebaker, J. W., & Geenen, R. D. (2004). De Nederlandse versie van de ‘linguistic inquiry and word count’(LIWC). *Gedrag Gezond*, 32, 271-281.

6.2 Website Links

Bijna een kwart stemgerechtigden 65 jaar of ouder. (2017). Retrieved from https://www.cbs.nl/nl-nl/nieuws/2017/08/bijna-een-kwart-stemgerechtigden-65-jaar-of-ouder

Dit is de forum kiezer en zo ziet de rest van de stemmers eruit. (2019). Retrieved from https://nos.nl/artikel/2277050-dit-is-de-forum-kiezer-en-zo-ziet-de-rest-van-de-stemmers-eruit.html

GitHub - OpenTaal/dutch. (2017). Retrieved from https://github.com/OpenTaal/dutch

One-way ANOVA (cont...). (n.d.). Retrieved from https://statistics.laerd.com/statistical-guides/one-way-anova-statistical-guide-3.php

nltk.tokenize package. Retrieved from https://www.nltk.org/api/nltk.tokenize.html

6.3 Videos

18 vragen aan Mark Rutte [Video file]. (2017, March 12). Retrieved from https://www.youtube.com/watch?v=xVg3mDu6gc8

Baudet vs Jetten: Klimaatakkoord langste zelfmoordbrief uit de geschiedenis [Video file]. (2019, July 3). Retrieved from https://www.youtube.com/watch?v=UDPPvkuZrOI

Complete speech Jesse Klaver in AFAS Live "Stem voor verandering" [Video file]. (2017,

March 10). Retrieved from https://www.youtube.com/watch?v=QyBJ7y9k9MA
De economie groeit en de lonen blijven nog steeds achter? [Video file]. (2019, June 14). Retrieved from https://www.youtube.com/watch?v=GL2qNK8_2gA&t=1s
De gevolgen van arbeidsmigratie voor Polen [Video file]. (2019, May 21). Retrieved from https://www.youtube.com/watch?v=24xph2t47Eo
De lonen moeten omhoog! [Video file]. (2019, July 4). Retrieved from https://www.youtube.com/watch?v=FYFq3BsWHEQ
Dit is Europa (1/5) [Video file]. (2019, April 22). Retrieved from https://www.youtube.com/watch?v=nrjf_VqwCBs
De VVD Campagne [Video file]. (2012, August 26). Retrieved from https://www.youtube.com/watch?v=2fHR-XBwiVY
Doe mee met de verandering [Video file]. (2016, December 19). Retrieved from https://www.youtube.com/watch?v=hfRKfh7wnTQ
Een bericht van Hans Brusselmans [Video file]. (2019, May 10). Retrieved from https://www.youtube.com/watch?v=aA4jUU-ntHs
Een gesprek tussen Johnny en Jesse [Video file]. (2017, February 23). Retrieved from https://www.youtube.com/watch?v=v6dk6eI1qFQ
Een gesprek tussen links en rechts met Jesse Klaver [Video file]. (2017, January 9). Retrieved from https://www.youtube.com/watch?v=G6tbaYBx7O0
Fragment Roemer, Wilders, Rutte over 'islamitisch stemvee' [Video file]. (2011, May 19). Retrieved from https://www.youtube.com/watch?v=f3I5UDMmPLE
GroenLinks wil Nederland veranderen [Video file]. (2015, September 13). Retrieved from https://www.youtube.com/watch?v=a3puFITDlbw
Het SP-MilieuAlarmteam in actie [Video file]. (2019, July 9). Retrieved from https://www.youtube.com/watch?v=kf6OVqAbMx8
Ivo Opstelten verrast het 2750ste nieuwe VVD-lid van 2017! [Video file]. (2017, September 18). Retrieved from https://www.youtube.com/watch?v=zVeykVePMr0
Jesse Klaver vs. Buma: stop Lelystad Airport | Pauw en Jinek 15-03-2019 [Video file]. (2019, March 16). Retrieved from https://www.youtube.com/watch?v=-TNWUVxzSnY
Jesse Klaver: "Nu werken aan een sociaal Europa." [Video file]. (2016, June 27). Retrieved from https://www.youtube.com/watch?v=33xIHtf29Hg
Klaas Dijkhoff over De Luizenmoeder, een opgestapte burgemeester en Groningen #2 [Video file].
(2018, February 5). Retrieved from https://www.youtube.com/watch?v=5zKLOLWmuiY
Klaver vs. Wilders: "Wees eerlijk over de consequenties." [Video file]. (2016, June 27). Retrieved from https://www.youtube.com/watch?v=MJB1p9OKh_A

Mark Rutte neemt de staatsschuldbarometer in gebruik [Video file]. (2009, September 16). Retrieved from https://www.youtube.com/watch?v=xLH5PV-bTd8

Nederland is van iedereen [Video file]. (2017, February 2). Retrieved from https://www.youtube.com/watch?v=gtGQIliGElQ

Pessimist of optimist? [Video file]. (2017, February 24). Retrieved from https://www.youtube.com/watch?v=8nr1AZsLzz8

Podcast: Mark Rutte in gesprek met Youstoub - Deel 1 [Video file]. (2017, January 8). Retrieved from https://www.youtube.com/watch?v=tvhLC_FHTy4

Speech Mark Rutte VVD-Congres mei 2015 [Video file]. (2015, June 2). Retrieved from https://www.youtube.com/watch?v=RzIim4SMrd4

SP: Nieuw Vertrouwen [Video file]. (2012, June 30). Retrieved from https://www.youtube.com/watch?v=djdqDsDco68

Spreek je uit | GroenLinks campagnevideo | Europese verkiezingen 2019 [Video file]. (2019, May 22). Retrieved from https://www.youtube.com/watch?v=zLLAiwkTMk4

Succes! De ambulancezorg wordt geen markt [Video file]. (2019, June 26). Retrieved from https://www.youtube.com/watch?v=HnJdXm1vBUI

Trucjes! Kamer stemt tegen doorrekening 1000 miljard! [Video file]. (2019, July 4). Retrieved from https://www.youtube.com/watch?v=WdCE3zyG13U&t=29s

Uniek: De SP ging undercover! [Video file]. (2019, May 6). Retrieved from https://www.youtube.com/watch?v=3FHLgqB8fbY&t=113s

Vandaag stemt Mark Rutte voor doen! [Video file]. (2018, March 21). Retrieved from https://www.youtube.com/watch?v=yaph1f2lQ5g

VVD Zendtijd Politieke Partijen [Video file]. (2018, March 12). Retrieved from https://www.youtube.com/watch?v=K010wh8e3y4

7. Appendix

7.1 Video Descriptions

Party	Video Title	Date	Nr of Comments
SP	De gevolgen van arbeidsmigratie voor Polen	May 21, 2019	11
SP	Het SP-MilieuAlarmteam in actie	July 9, 2019	1
SP	De lonen moeten omhoog!	July 4, 2019	2
SP	De economie groeit en de lonen blijven nog steeds achter?	June 14, 2019	5
SP	Succes! De ambulancezorg wordt geen markt	June 26, 2019	11
SP	Uniek: De SP ging undercover!	May 6, 2019	34
SP	SP: Nieuw Vertrouwen	June 30, 2012	104
SP	Een bericht van Hans Brusselmans	May 10, 2019	283
SP	Fragment Roemer, Wilders, Rutte over 'islamitisch stemvee'	May 19, 2011	107
GL	Complete speech Jesse Klaver in AFAS Live "Stem voor verandering"	March 10, 2017	34
GL	Een gesprek tussen Johnny en Jesse	February 23, 2017	11
GL	Een gesprek tussen links en rechts met Jesse Klaver	January 9, 2017	21
GL	GroenLinks wil Nederland veranderen.	September 13, 2015	93
GL	Klaver vs. Wilders: "Wees eerlijk over de consequenties."	June 27, 2016	21
GL	Jesse Klaver: "Nu werken aan een sociaal Europa."	June 27, 2016	9
GL	Doe mee met de verandering	December 19, 2016	7
GL	Nederland is van iedereen	February 2, 2017	12
GL	Spreek je uit | GroenLinks campagnevideo | Europese verkiezingen 2024	May 22, 2019	34
GL	Dit is Europa (1/5)	April 22, 2019	2
GL	Jesse Klaver vs. Buma: stop Lelystad Airport | Pauw en Jinek 15-03-2027	March 16, 2019	29
VVD	Klaas Dijkhoff over De Luizenmoeder, een opgestapte burgemeester en Groningen #3	February 5, 2018	72
VVD	Ivo Opstelten verrast het 2750ste nieuwe VVD-lid van 2017!	September 18, 2017	20
VVD	Pessimist of optimist?	February 24, 2017	22

VVD	Vandaag stemt Mark Rutte voor doen!	March 21, 2018	39
VVD	18 vragen aan Mark Rutte.	March 17, 2017	36
VVD	Podcast: Mark Rutte in gesprek met Youstoub - Deel 12	January 8, 2017	26
VVD	Speech Mark Rutte VVD-Congres mei 2022	June 2, 2015	18
VVD	De VVD Campagne	August 26, 2012	41
VVD	Mark Rutte neemt de staatsschuldbarometer in gebruik	September 16, 2009	68
VVD	VVD Zendtijd Politieke Partijen	March 12, 2018	35
FvD	Trucjes! Kamer stemt tegen doorrekening 1000 miljard!	July 4, 2019	421
FvD	Baudet vs Jetten: Klimaatakkoord langste zelfmoordbrief uit de geschiedenis	July 3, 2019	524

7.2 Statistical Testing of Messages

Messages	**Party 1**	**Party 2**	***p*-value**
4.1.1 Number of Sentences	SP *(+)*	GL *(-)*	0.555
not normally distributed	SP *(+)*	FvD *(-)*	0.979
	SP *(+)*	VVD *(-)*	1.000
	GL *(-)*	FvD *(+)*	0.688
	GL *(-)*	VVD *(+)*	0.634
	FvD *(-)*	VVD *(+)*	0.990
4.1.2 Type/Token Ratio	SP*(-)*	GL *(+)*	**0.002***
not normally distributed	SP *(-)*	FvD *(+)*	0.505
	SP *(-)*	VVD *(+)*	0.113
	GL *(+)*	FvD *(-)*	0.027
	GL *(+)*	VVD *(-)*	0.459
	FvD*(-)*	VVD *(+)*	0.607
4.1.3 Total Number of Words	SP *(+)*	GL *(-)*	**0.000***
normally distributed after logarithmic transformation	SP *(+)*	FvD *(-)*	0.254
	SP *(+)*	VVD *(-)*	**0.001***
	GL *(-)*	FvD *(+)*	**0.001***
	GL *(-)*	VVD *(+)*	0.519
	FvD *(+)*	VVD *(-)*	0.053

4.1.4 Average Word Length	SP (-)	GL (+)	0.136
normally distributed	SP (-)	FvD (+)	0.287
	SP (+)	VVD (-)	0.966
	GL (+)	FvD(-)	0.783
	GL (+)	VVD (-)	0.078
	FvD (+)	VVD (-)	0.166
4.1.5 Number of Characters	SP (+)	GL (-)	**0.000***
normally distributed after logarithmic transformation	SP (+)	FvD (-)	0.410
	SP (+)	VVD (-)	**0.000***
	GL (-)	FvD (+)	**0.001***
	GL (-)	VVD (+)	0.826
	FvD (+)	VVD (-)	**0.010***
4.1.6 Spelling Errors	SP (-)	GL (+)	0.998
not normally distributed	SP (-)	FvD (+)	0.038
	SP (-)	VVD (+)	0.020
	GL (-)	FvD(+)	0.105
	GL (-)	VVD (+)	0.046
	FvD (-)	VVD (+)	0.840
** notes* 1. *when comparing 2 parties (+) indicates a higher value, (-) indicates a lower value* 2. *alpha = 0.001*			

7.3 Statistical Testing of Sentences

Sentences	**party 1**	**party 2**	***p*-value**
Type/Token Ratio	SP(-)	GL (+)	0.456
not normally distributed	SP (+)	FvD (-)	0.758
	SP (+)	VVD (-)	1.000
	GL (+)	FvD (-)	0.101
	GL (+)	VVD (-)	0.511
	FvD(-)	VVD (+)	0.830
Total Number of Words	SP (+)	GL (-)	0.161
normally distributed after logarithmic transformation	SP (-)	FvD (+)	0.427

	SP (+)	VVD (-)	0.885
	GL (-)	FvD (+)	**0.005***
	GL (-)	VVD (+)	0.530
	FvD (+)	VVD (-)	0.146
Average Word Length	SP (-)	GL (+)	0.143
normally distributed	SP (-)	FvD (+)	0.701
	SP (+)	VVD (-)	0.844
	GL (+)	FvD(-)	0.455
	GL (+)	VVD (-)	0.040
	FvD (+)	VVD (-)	0.255
Number of Characters	SP (+)	GL (-)	0.551
normally distributed after logarithmic transformation	SP (+)	FvD (-)	0.205
	SP (+)	VVD (-)	0.738
	GL (-)	FvD (+)	0.023
	GL (-)	VVD (+)	0.976
	FvD (+)	VVD (-)	0.025
Spelling Errors	SP (-)	GL (+)	0.894
not normally distributed	SP (-)	FvD (+)	**0.000***
	SP (-)	VVD (+)	**0.000***
	GL (-)	FvD(+)	0.026
	GL (-)	VVD (+)	**0.006***
	FvD (-)	VVD (+)	0.700
** notes* *1. when comparing 2 parties (+) indicates a higher value, (-) indicates a lower value* *2. alpha = 0.001*			