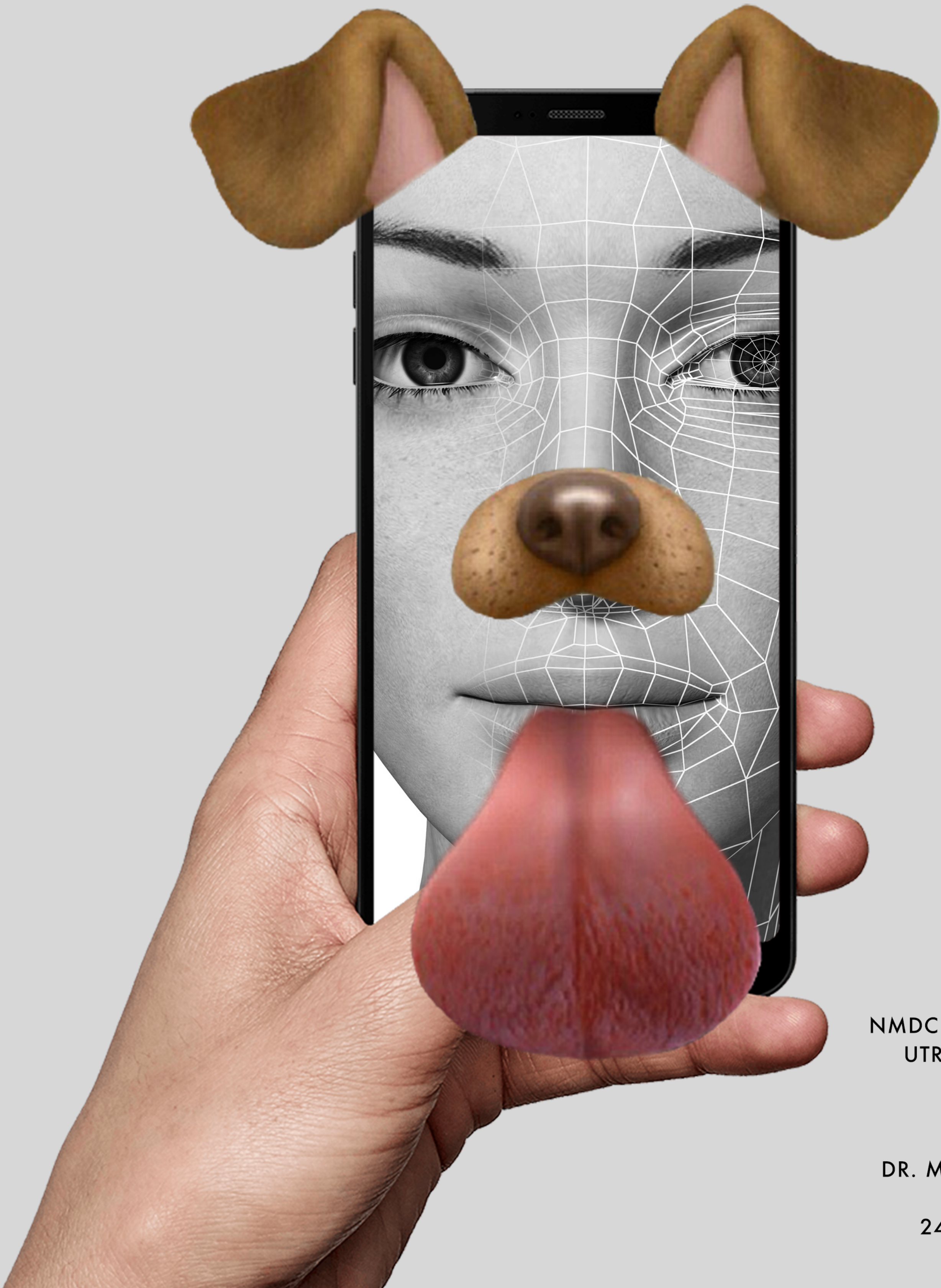
"A WHOLE NEW WAY TO SEE YOURSELF(IE)"

EXPLORING HOW FACE FILTERS TRANSFORM THE PRACTICE OF SELFIE CREATION



NMDC MASTER'S THESIS
UTRECHT UNIVERSITY

MEIKE SCHIPPER
5944635
DR. MICHIEL DE LANGE

24 SEPTEMBER 2018

Abstract

In 2015, Snapchat launched the face filters feature and promoted it as "a whole new way to see yourself(ie)" (Snap Inc. 2015). Ever since, the feature has been copied by many platforms and the use of interactive face filters has rapidly become part of selfie culture. Face filters are known to convey stereotypical norms of beauty, femininity and self-presentation, but also instigate new ways of experimental selfie creation. However, academic research on pre-made figurative face filters and how they change the contemporary practice of selfie creation is lacking. This thesis fills this gap by exploring how face filters change the conventional practices of selfie creation, how gender-stereotypical selfie creation is confirmed or disrupted by those filters, and how this may lead to liberated or suppressed practices of selfie creation.

Qualitative and quantitative methods are combined to analyze the differences between two datasets of selfies, collected from the hashtags #selfie and #filterselfie on Instagram. Face detection software is used to measure the selfies, and manual categorization of the datasets is executed to gather data about gender and facial expressions.

As a result, this thesis offers an overview of the different ways in which face filters may be liberating or suppressing, and how it changes conventional gender display. It concludes that most practices of so-called liberation of conventions are caused by the filters' affordances rather than intentional subversion of conventions by users themselves. In line with Barnard's (2016) concept of the *(dis)empowerment paradox*, it also concludes that face filters may be liberating on an individual level, while they simultaneously reinforce the cultural conventions of gender display and self-portrayal. Additionally, the methodological reflection in this thesis offers insights and proposes enhancements for the use of computational methods as a means to analyze visual culture within the humanities.

Keywords: selfie, face filters, gender display, cultural analytics, digital humanities, Instagram.

Preface

The writing of this thesis has been a very experimental and dynamic process for me, during which I have constantly pushed my own boundaries and challenged my skills. I could not have done this without the support of others. First of all, I would like to express my gratefulness to my supervisor Michiel, who supported me throughout the experimental process and trusted me enough to let me continue. Thanks to Tim, who encouraged my enthusiasm for computational image analysis and gave me the freedom to pursue this interest during his course. Thanks to Mirko, who told me that failure could be interesting as well, and that all mistakes and errors provided me with new insights. I would like to thank Rob and Ishara for helping me when I struggled with MatLab and Excel, and solving my troubles in minutes. Thanks to Marjolein, who suggested and explained the use of Pythagoras to calculate the size of rotated bounding boxes, something I had been struggling with for days. And last but not least, Esther, Job, Robin, Gemma, Anouk, Kim, Koen, Robin, Vivette and Thom; I cannot thank you enough for assisting me with the time-consuming labor of manually categorizing 2000 images. I hope you all enjoy reading the outcomes.

Content

1. Introduction

Animal ears, virtual sunglasses, rainbows, face swaps, beautifying and disfiguring filters; the use of these interactive face filters has rapidly become part of selfie culture. Face filters are based on augmented reality, which means that face detection software recognizes a face in front of a mobile camera and adds a real-time virtual layer on top of it. The real-time feedback on the screen enables users to playfully interact with these filters and effects. Snapchat originally launched the face filters feature in September 2015 and promoted it as “a whole new way to see yourself(ie)” (Snap Inc. 2015). With 178 million daily Snapchat users in the third quarter of 2017, the use of these Snapchat filters is widespread (Snap Inc. 2017). In May 2017, Instagram launched a similar feature of face filters (Instagram 2017). Face filters and virtual make-overs are even the main functionality of other popular apps like Meitu and B612, and the app store is filled with apps that do roughly the same.

The animal ears and virtual sunglasses resemble playful masks that seem harmless. However, they have additional beautifying and stereotypical feminine effects on selfies, as they commonly make chins smaller, skin softer, eyes bigger and eyelashes longer. Columnist Aimee Simeon (2017) expressed her worries about face filters and calls them “problematic”. She states that face filters transform her “into a thinner, more refined version of myself . . . the more "socially desirable" me. (..) Instead of celebrating the traits that make us unique, we are constantly given new ways to hide them . . . and now one of those ways is through filters” (Simeon 2017). On the other side of the spectrum, columnist Katherine Timpf (2017) disagrees with Simeon and states that she experiences face filters as liberating because she does not have to wear real-life make up before she posts a selfie. Face filters give her the opportunity to take funny and cute selfies regardless of her real-life looks.

These contradicting reflections of Simeon and Timpf exemplify the paradoxical implications that face filters have on selfie creation. Lichty (2017, 19) explored this paradox regarding the face-editing app Meitu, and argues that “programs like Meitu embed and reveal cultural stereotypes and normative positions that create odd mappings across cultures”. By using face filters, users subject themselves to the gaze of the technology of augmentation and the stereotypical norms of self-presentation. Thus, face filters convey stereotypical norms of self-presentation, but also instigate new ways of selfie creation that may be experienced as liberating. In order to explore these paradoxical practices of filtered selfies, I have phrased the following research question:
How do face filters transform the stereotypical practice of selfie creation? I phrased the following sub questions: How do face filters confirm or enlarge gender stereotypes and conventions of selfie creation? How do face filters disrupt or subvert gender stereotypes and conventions of selfie creation? And consequently, how do face filters offer possibilities for liberated or suppressed practices of selfie creation?

In order to get a grip on the diffuse and quite inaccessible phenomenon of face filters that is spread among a variety of apps and platforms, I adopt a mixed-method approach that is inspired by Cultural Analytics and the use of digital methods within the humanities. In this thesis, qualitative and quantitative methods are combined to analyze the differences between two datasets of 1000 images that are collected from Instagram by the hashtags #selfie and #filterselfie. MATLAB is used to detect faces, calculate the degree of head tilt and calculate the ratio of the face as part of the image size. Categorization of all images is executed manually to assess the amount of people portrayed in each selfie, the gender and facial expressions of the most prominent person. Finally, the findings are analyzed and interpreted by examining the statistical data and close reading the patterns that appear.

The academic study of selfies is scattered among the fields of the humanities and the social sciences and entails a large variety of viewpoints. Recently published books such as Selfie Citizenship (Kuntsman, 2017), Culture of the Selfie (Peraica, 2017) and Exploring the Selfie (Eckel, Ruchatz and Wirth, 2018) demonstrate the current necessity of the academic debate, which ranges from the history of self-portraits to the current mobile selfie culture. With this thesis, I aspire to add new insights to the specific debate about stereotypical selfies, selfie editing and cultural norms of selfie creation. Although the cultural implications of virtual make-up and retouched selfies have been researched thoroughly (for example Elias and Gill 2018; Chae 2017), research on figurative face filters is lacking and Snapchat and Instagram filters have not yet been investigated within this debate. Photographic color filters and biometrics have been studied by Rettberg (2014; 2017), who has recently been awarded a grant for her new research project on machine vision in everyday life, which will include the use of face filters. However, as Leclercq (2016) states, the field of filtered selfies has generally not yet been assigned a “worth-to-study status in the academic scene” and is therefore a quite untouched but urgent field to explore.

Aside from researching the practice of selfie creation with the use of face filters, this thesis additionally explores *how* to research this phenomenon with large-scale computational analysis. Data-based analysis of filtered selfies is obstructed by the ephemeral character and limited transparency of Snapchat, the most dominant app in the field of modified selfies. By using Instagram as an alternative entryway into the phenomenon, this study provides an initial examination of the relatively new and unexplored role of figurative face filters in the practice of selfies. The mixed-method approach that is adopted in this thesis is experimental and learnt-by-doing. It is an attempt to test and enhance the operationalization of the frequently criticized Cultural Analytics approach, the general use of computational methods within the digital humanities and the large-scale analysis of online visual culture. Throughout this thesis I critically reflect on the possibilities and limitations of the methodology to enable further development of this quickly expanding field.

In the next chapter, I will theoretically conceptualize the selfie, explore the liberating and suppressing powers of selfies, define stereotypical characteristics of selfies, and will finally clarify the different aspects of face filters and how they may change the general practice of the selfie. The third chapter contextualizes the chosen methods, and reports on the steps taken. The fourth chapter exposes the findings of the analysis and discusses the possible liberating and suppressing powers of face filters. The fifth chapter focuses on rethinking the large-scale analysis of online visual culture within the Humanities, and builds upon methodological reflections of the analysis. The sixth and final chapter concludes by summarizing the findings and suggests directions for further research.

2. The paradoxical practice of (filtered) selfies

2.1 The selfie paradox

In earlier times, we used convex mirrors to see ourselves and paint our self-portrait; nowadays, we use cameras, smartphones and social media to create and control our ways of self-expression (Rettberg 2014, 2). The development of the smartphone, that comes with a front-facing camera and internet connection, has rapidly changed the culture of analogue self-portraiture into the digital culture of the *selfie*. Oxford Dictionaries has published a widely used definition of the selfie: "a photograph that one has taken of oneself, typically one taken with a smartphone or webcam and uploaded to a social media website." Due to the interplay between the affordances of photographic technologies, the users and the conventions of self-presentation, the selfie cannot be considered a simple visual artifact. The image of the selfie is intrinsically intertwined with smartphone photography and the social practice of visual communication on social media platforms (Eckel, Ruchatz and Wirth 2018, 7). Schreiber (2017, 144) similarly states that the practices of visual communication on social media platforms can be considered to be an interplay between *affordances* (characteristics of the photographic and social media technologies), *audiences* (the communicative aspects) and *aesthetics* (the image itself). In other words, the communicative, social and aesthetic aspects all intersect in the practice of the selfie. In line with Eckel, Ruchatz and Wirth (2018, 14-15), I therefore approach the selfie as "an *image practice*—understood literally as image *and* practice at the same time."

The academic debate on selfies has been dominated by two opposing perspectives (Kedzior and Allen 2016, 1894). On the one hand, scholars state that smartphone photography and social media platforms have given us a way to largely control our impression on others. Rettberg (2014, 12) exemplifies this by stating that "the ease and inexpense of deleting digital images and taking new ones allows us to control the way we are represented to a far greater degree than in a photobooth or holding an analogue camera up to a mirror." The increased control over our self-presentation implies that selfies liberate self-portrayal from societal norms and conventions. Döring, Reif and Poeschl (2015, 957) state that "selfies as user-generated content provide the opportunity to experiment with various gender-related self-representations (..) and thereby are a chance to overcome traditional gender self-representation.” Taking selfies is a way to control the camera and to some extent control the gaze of the audience. In some online communities, selfies are even experienced as a tool of empowerment, such as the body-positive and queer movements (Vivienne 2017, 126) and self-shooting NSFW (Not Safe For Work) tumblr blogs (Tiidenberg and Cruz 2015, 77). Tiidenberg and Cruz (2015, 79) effectively describe empowerment as “personal sense of power and control, which carries potential for social impact through its influence on existing discourses and ways of looking.” Consequently, posting selfies that subvert and reject conventions of self-presentation may be understood as “everyday activism” (Vivienne 2017, 128).

On the other hand, critics have designated this hope for liberation and empowerment the *emancipation thesis*, which “tends to confuse the eye with the gaze, assuming that since the eye behind the camera belongs to the photographed person him- or herself, photography is no longer subject to any external scopic regime” (Schwarz, 2010, 164). In contrast to the notion of the selfie as everyday activism, selfies can also be considered a suppressed practice and are often linked to Foucault’s theories of governmentality and control (Kedzior and Allen 2018, 1897). The disempowering and suppressive potential of the selfie practice may by caused by different forms of control, such as the male gaze or hegemonic conventions of beauty (Kedzior and Allen 2016, 1896). Leary (on OUP blog, 2013) similarly states that “through the clothes one wears, one’s expression, staging of the physical setting, and the style of the photo, people can convey a particular public image of themselves, presumably one that they think will garner social rewards.” When people create a specific image based on expected social rewards and perceived likeability, selfies are subject to cultural norms of self-presentation. This is where the affordances, audiences and aesthetics of selfies blend together. From ethnographic research, Warfield (2014, 4) reports that “when looking at themselves in the camera lens, many young women enact and use photographic tropes and conventions to present themselves in what they deem to be favorable ways.” Additionally, the participants specifically mentioned that they looked at magazines and celebrity photos for conventions of beauty and posing (Warfield 2014, 4). And even from examining the allegedly subversive practice of #nomakeupselfies, Hampton (2015) concluded that “despite pro-selfie claims of agency, the internalization and replication of dominant social norms is evident in the majority of online selfie images” (11). It becomes clear that the enlarged control of self-portrayal does not necessarily lead towards a liberated practice.

Barnard (2016) effectively pinpoints the tension of the debate and proposes the term *(dis)empowerment paradox*. This means that the practice of selfie creation may be experienced as empowerment by the individual taker, while the selfie itself may simultaneously reinforce the stereotypical visual discourse on a societal level. Even when the selfie itself conforms to norms of self-portrayal and the expectations of the audience are internalized, the creator might experience the practice of selfie creation as liberating. In the next sections, we will disentangle this paradoxical character of the selfie in relation to the phenomenon of face filters.

2.2 Conventional selfies and stereotypical gender display

In line with Hampton's (2015) and Warfield's (2014) findings, the general practice of the selfie is still known to be very gender-specific and subject to conventional and heteronormative concepts of self-portrayal and beauty. The SelfieCity project (Manovich et al. 2014), a quantitative study on Instagram selfies from different cities around the world, provides statistics on the current practice of selfie creation. They report that around 60% of the selfies on Instagram is female and the estimated median age of selfie-takers is 24, although it largely varies from city to city (Manovich et al. 2014). Other studies similarly confirm that females are more likely to take selfies and their selfies are considered to be more personal (Qui et al. 2015). Women generally strike more extreme poses, as the head tilt is significantly higher among female selfies with an average of 12.3 degrees, compared to male selfies that show an average of 8.2 degrees (Manovich et al. 2014). Dhir et al. (2016, 551) additionally state that women are more active in editing and cropping selfies, and use photographic color-changing filters more often.

The presence of stereotypical gender display in selfies is explored by Döring, Reif and Poeschl (2015, 960). They compared selfies with mass media advertisements based on well-established studies by Goffman (1979) and Kang (1997). Goffman (1979) distinguishes five concepts of gender display in advertisements: 1) *relative size*, which means men are portrayed more dominant in relative size compared to women; 2) *the feminine touch,* referring to women that use their hands to trace their bodily outlines; 3) *function ranking*, i.e. the literal portrayal of a men in executive and powerful function; 4) *ritualization of subordination,* which refers to the upright position of body and head as stereotypical male, strong and superior, while the tilting the body and head is typical female, fragile and submissive; 5) *licensed withdrawal,* which means women are commonly depicted while gazing into the unknown or closing their eyes, being mentally absent. Kang (1997, 985) adds the concept of *body display,* which is the typical portrayal of naked or barely clothed women, sexualizing their bodies. Based on these concepts, Doring, Reif and Poeschl (2015, 960) had to conclude that selfies are even more gender-stereotypical than advertisements, regardless of their potential for liberation. Only the concept of body display and lack of clothing is less apparent in selfies compared to advertising. Social media specific concepts of gender portrayal, such as the typical female *kissing pout*, *faceless portrayal* and male *muscle presentation* are added to these codes of gender-stereotypical self-presentation (2015, 961).

Another gender-related concept is defined by Archer et al. (1983) as *face-ism*, which is related to Goffman's concept of relative size. Archer et al. (1983) found that in a large variety of media such as art, journals and advertisements, men are portrayed with their face as a more prominent part of the image, whereas women are depicted with more focus on their bodies. The original research examined photos that were taken by a photographer that was not the person portrayed. Again, scholars assumed that the enlarged control of self-presentation that came with mobile photography would diminish the concept of face-ism (Smith and Cooley 2012, 280). However, from examining profile pictures on Facebook, Smith and Cooley (2012, 291) concluded that despite the increased control and the ability of users to choose their own profile picture, face-ism continued to exist.

Both Doring, Reif and Poeschl (2015) and Smith and Cooley (2012) theorized the liberating effect of online self-presentation in comparison to mass media portrayal, but eventually concluded that the reality was different. People seem to have internalized the conventions of gender-display and reproduce them in their own selfies. Based on these studies, the question arises whether the current widespread use of face filters in selfies changes these long-standing gendered norms of self-portrayal. In this study, I will use the above mentioned concepts of gender display by Goffman (1997), Kang (1997), Doring, Reif and Poeschl (2015) and Archer et al. (1983) to explore their presence in filtered selfies versus normal selfies.

2.3 Hypothesizing the potential of face filters

Face filters are a recent addition to the interplay between affordances, audiences and aesthetics that define the practice of selfie creation, and again promise new ways to control our self-presentation. Selfie-editing, beautification and filtering apps come in great varieties. Instagram and Snapchat remain at the top of the photo-and-video category within the Dutch App store, and both platforms offer real-time face filters. These face filters are ranging from beautification (filters that usually soften the skin, enlarge eyes and make the face look thinner), to animal-like masks (filters that include for example animal ears and snouts), face swaps (a filter that swaps the faces of the people portrayed) and disfiguration of the face (similar to analogue distorting-mirrors). Other popular apps like Facetune, Filterra and SwapCam mainly focus on beautification and enable users to soften their skin, remove blemishes, apply make-up, enlarge the eyes and even apply tattoos and muscle mass. Meitu and B612, both very popular apps in Asian selfie culture, offer similar options and also include all kinds of figurative face filters such as animal features.

In order to make sense of the large variety of face filters and to specify the type of filters that are the research subject of this thesis, I propose the following typology of face filters based on their affordances and visual characteristics. First of all, I distinguish between *visible* and *invisible* filters. Visible filters are meant to be recognized as filters and can described as virtual masks. Invisible filters, on the other hand, are meant to blend in with and enhance the original image. Invisible filters include beautification and virtual make-up that is hard to distinguish from real make-up. Another distinction that can be made is *figurative* versus *non-figurative*. Figurative filters add visual, figurative elements to an image, while non-figurative filters are only changing the colors or general feel of the image. Non-figurative filters have been around since analogue photography and have been researched thoroughly (Rettberg 2014, 20-32), while figurative filters are a specific characteristic of contemporary digital and mediated photography. Finally, the distinction between *real-time* filters and *in-hindsight-applied* filters is important to make because they afford different types of usage. Real-time face filters use face detection technologies and are a type of augmented reality which affords interaction, while in-hindsight-applied filters are similar to decorative stickers and layers that change the final image but do not influence the original act of taking the selfie.

It should be noted that these categories of face filters do not have strict boundaries and show large areas of overlap, but do offer insight in how the different affordances and aesthetics of filters may influence the practice of selfie creation. Based on this typology, this study focuses on visible, figurative and real-time face filters.

More generally, the word *filter* is used to refer to the act of taking something away, to remove unwanted content from the original object (Rettberg 2014, 21). Face filters similarly remove original content from an image as they alter faces and place figurative masks on top. Accordingly, Rettberg (2014, 23) argues that "in this case, social media is not simply the kind of filter that removes impurities, but also shapes them and flavors people as the ground coffee beans flavor the water that passes through them." This metaphor of coffee beans effectively illustrates how face filters force users to fit into a normative mold. We might not even recognize these filters as limitations and simply act according to their logic. A lot of filters convey specific feminine norms of beauty; animal filters look rather fluffy and cute instead of hairy and strong, and a lot of filters add make-up, enlarge the eyes and make the chin smaller. These conventions of female beauty stem specifically from the Asian notion of cuteness or *kawaii*, which is based on the infantilization of facial characteristics and is increasingly influencing Western beauty ideals (Lichty 2017, 16). As such, I hypothesize that face filters are more popular among women as they are familiar with these aesthetics of femininity. This hypothesis is strengthened by the aforementioned study of Dhir et al. (2016, 551) which concludes that women are more active in editing and cropping selfies.

However, clearly visible and figurative filters may also have a different effect. Researching non-figurative photographic filters, Rettberg (2014, 26) states that "it gives the image that strangeness that defamiliarises our lives. The filter makes it clear that the image is not entirely ours." I speculate that when we use figurative face filters, the effect of defamiliarisation similarly liberates us from the pressure to create a conventional selfie. When the face filter depicts you with rainbows coming out of your mouth, it gives the image a strangeness which makes it seem pointless to subject yourself to other conventions of self-presentation. This creates room for self-expression and experimentation beyond the norms. I hypothesize that this will lead to a larger variety of facial expressions and play with gender-related aesthetics.

Thus, although some aspects of face filters seem liberating, they simultaneously subject our face to a new set of norms: the norms of machine vision (Rettberg 2017). The app scans the face in front of the mobile camera and places a biometric grid on top of it, which enables users to apply face filters and interact with them in real-time. Due to the affordances of the biometric grid, users are forced to point their face towards the camera when they apply a face filter. Additionally, the real-time interaction between the face of the user and the applied filter takes place on the screen, which draws the users attention towards it. Due to the focus that face filters put on the face, I hypothesize that selfies created with these filters will be taken more closely to the face and the face makes up a larger part of the image, compared to normal selfies. As a side-effect, the well-established code of femininity to display the body might be diminished by the use of face filters.

Based on this theorization of selfies and face filters, I hypothesize that face filters are more popular among women, they will lead to a larger variety of facial expressions and play with gender-related aesthetics, and filtered selfies will be taken more closely to the face. Aside from these hypothesis, there may be additional unforeseen ways in which face filters may transform the practice of selfie creation. These potential transformations of the practice of the selfie may be liberating people from longstanding standards of gender display and stereotypical self-portrayal. The next chapter will outline the methodological approach to examine this transforming practice.

3. Methodology

The potential of face filters will be examined through a large-scale comparative analysis of selfies *with* face filters and selfies *without* face filters. This chapter first contextualizes the methodology by discussing Cultural Analytics and the general use of computational methods within the humanities. Next, I carefully describe the processes of corpus selection, the computational measuring, the manual categorization, the tools for analysis and their limitations.

3.1 The promises and possibilities of large-scale image analysis

In order to get an overview of the phenomenon of filtered selfies, I will combine distant and close reading with use of both computational and manual methods. As the culture of selfies is far from unequivocal, any hypothesis can be confirmed or rejected by assessing individual selfies (Tifentale 2014, 7). Not a single selfie is representative for the culture of selfies altogether, and symbolic images do not necessarily represent larger trends. The use of computational methods to analyze selfies is inspired by Cultural Analytics, which is developed by Lev Manovich in 2005 and defined as "the analysis of massive cultural data sets and flows using computational and visualization techniques"

(2016, 1). Cultural Analytics fits within the realm of the digital humanities, in which computational tools are used to analyze both digitalized cultural phenomena and digital native artefacts. Cultural Analytics encourages the use of very large datasets, the use of the web as a primary source, the combination of data and metadata, the creation series of visualizations, graphs and maps, and the use of visual analytics, which aims to analyze data from data visualizations (Manovich 2007, 13). Manovich strongly believes that "the web and social networks content and user activities give us the unprecedented opportunity to describe, model, and simulate global cultural universe while questioning and rethinking basic concepts and tools of humanities that were developed to analyze 'small cultural data' (i.e., highly selective and non-representative cultural samples)" (2016, 7).

This statement by Manovich is grounded in the differentiation between *close reading* and *distant reading*. The terminology of close and distant reading stems from the field of literary criticism. Close reading refers to the traditional reading of a text, while distant reading is introduced by Moretti (2005) and designates the generation of an abstract view of a text by counting, scanning, graphing and visualizing it. This terminology is also applicable on the 'reading' of images when we explore their meaning. The shift from close reading to distant reading, that Manovich suggests, enables scholars in the digital humanities to examine large amounts of cultural data. This subsequently implies a shift from qualitative to quantitative research, but that does not necessarily have to be the case. Ideally, computational methods would enable scholars to explore the larger patterns of cultural phenomena and combine it with the analysis of individual artefacts. Manovich consequently questions how we can "combine computational analysis and visualization of large cultural data with qualitative methods, including 'close reading'" (Manovich 2016, 1). This question is also leading the methodological part of this thesis.

3.2 The implications and limitations of large-scale image analysis

Adopting the Cultural Analytics approach, and thus computationally analyzing a dataset of actual selfies created with filters, allows me to discover patterns that cannot be found through close-reading or small-scale textual analysis. However, the use of computational tools within the humanities unfortunately has implications for the type of research that can be done, as it frames the objects of research in specific ways. The use of computational methods to examine cultural phenomena essentially reduces culture to quantifiable phenomena and binary categories. Moreover, data is always taken outside of its context and should therefore be considered *capta,* because it is captured and constructed (Drucker 2011, 2). The SelfieCity project (Manovich et al. 2014) has often been criticized for lacking awareness of this constructed and reductive character of data. The project also defines gender as either male or female and lacks the possibility of non-binary identification (Losh 2015, 1653). Additionally, image-based research on selfies is often criticized, because focusing on the image suggests that the selfie is nothing more than *just* the image (Losh 2015, 1653; Cruz and

Thornham 2015, 2). Cruz and Thornham (2015, 2) argue that "it centers and elevates both the visual image ''itself'' and the methods for analyzing the image, which we argue undermines - if not negates - the wider practices, discourses, and ideologies that constitute the selfie phenomenon."

As much as I understand and agree with these arguments, I am of the opinion that the image of the selfie still remains an element of selfie culture that deserves to be examined, and that visual data analysis can be an effective tool. As stated before, I approach the selfie as "an *image practice*—understood literally as image *and* practice at the same time" (Eckel, Ruchatz and Wirth 2018, 14-15). It is my aim to perform image-based research on filtered selfies that will provide us with new interpretative insights rather than clear statistical evidence. As a result of the chosen image-based methods, this study does focus more on the *visual expression* of conventions, liberation and suppression rather than the experiences of selfie creators. However, this does not undermine the importance of the wider practices, discourses and ideologies. Of course, the findings of this study should be grounded and combined with other methodologies in order to gain a full understanding of the phenomenon.

Manovich has also been criticized by Caplan for using "methods without methodology" (2016, 1). According to Caplan, Cultural Analytics' projects like SelfieCity (Manovich et al. 2014) do not acknowledge the interpretational nature of data analysis within the humanities. In order to maintain the standards of the humanities scholarship, Jessop (2008) emphasizes the importance of guiding principles such as provided by the London Charter, which is designed for the computer-based visualization of cultural heritage. The Charter is based upon the "absence of objectivity" within the humanities, and therefore focuses on "tracking the interpretative trail" (Denard 212, 67) of the research and visualization process. With its principles, it aims to structure the instinctive process of working with data and creating visualizations. Shortly summarized, the principles of the London Charter (Denard 2012, 63-70) are: 1) Implementation: a guideline on how to implement the other principles, 2) Aims and methods: computational and visualization methods should only be used when they are the most suitable means, 3) Research Sources: the used (data)sources should be carefully examined and evaluated before visualizing them, 4) Documentation: the research process and the choices of the researcher should be documented in order to enable evaluation of the final outcome, 5) Sustainability: documentation and visualizations should be preserved in a sustainable manner, and 6) Access: the preservation of the project should allow access and use in new contexts. In this thesis, I test these principles by keeping track of my process carefully and reflecting critically on the implications of the choices that I make. These reflections will be discussed in chapter 5, in which we discuss the use of computational tools for large-scale image analysis within the humanities. In the next sections, I will explain the specific corpus, methods and their limitations.

3.3 Methods and tools

The combination of methods that I chose to use in this thesis is experimental and explorative. In the next paragraphs, I will carefully report on the choices that I made, and the issues and limitations that I encountered.

3.3.1 Data collection

In order to analyze how the practice of selfie creation has changed due to face filters, I have collected two datasets from Instagram based on the hashtags #selfie and #filterselfie. These tags are chosen because they represent the phenomena most clearly, and enable me to compare the new phenomenon of filtered selfies with established selfie culture. The #selfie tag is one of the most popular tags on Instagram and generally used for a large variety of self-portraits. The tag #filterselfie includes selfies created with all kinds of different filters and apps, which provides us with data on the general phenomenon of face filters. The size of the unprocessed datasets is deliberately set at 3000 images per hashtag. This is large enough to observe quantitative patterns and small enough to categorize the images manually.

The collection of images has been done with help of the Instagram-Scraper which is an open-source Python script created by Richard Arcega. The images that are collected are the latest additions to the used tags, which is the default setting of the scraper. This setting is a limitation of this research as the datasets I collected are limited to a images posted between 30th of April and 15th of May 2018. As face filters on for example Snapchat and Instagram regularly change, this results in a dataset which contains a lot of the same face filters that were popular during that time. The datasets can therefore not be considered representative for all content that is tagged with #filterselfie or #selfie over the years, but does provide us insight in the current use of filters.

Furthermore, it should be noted that Arcega's Instagram-Scraper works around Instagram's API to collect images from the platform. In June 2016 Instagram changed its API, and does not allow the large-scale collection of images ever since. The new API makes researching the content of Instagram almost impossible. However, as Bernhard Rieder (2016) states in his blogpost, it is a researchers' duty to understand the platforms' effects on society and to examine "the concrete results of large masses of users actually integrating these technical elements (i.e. the platforms' affordances) into their practices." I especially agree with his final statement that "privacy is important, but public understanding of outcomes is as well" (Rieder, 2016). Therefore, I decided to continue my study and use Arcega's Instagram-Scraper in order to pursue my research interests. I am however aware of the ethical implications. In order to minimize the violation of privacy, metadata such as usernames or location will not be collected or included in this study.

After the collection process, I have manually removed all images from both datasets that did not contain a face (see Table 1). Images have been deleted when they did not contain a face at all or

less than half of a face, or when they were clearly advertisements or memes. Due to the fact that the hashtag #selfie is popular among advertisers and used to promote posts, the #selfie dataset consisted for almost half the amount out of non-selfies, which limited the dataset to 1635 images.
I am aware that I have hereby reduced the term 'selfie' to an image that contains at least one face, even though in a broader understanding of the term, not all selfies have to contain a face (for example body selfies, artistic selfies, objects that represent a person). This was a necessary choice that I had to make to perform computational analysis, which can be considered a limitation of the method.

3.3.2 Computational measurements

The way in which stereotypical self-portrayal is changing due to face filters, the datasets of selfies will be analyzed alongside the concepts of gender display by Goffman (1997), Kang (1997), Doring, Reif and Poeschl (2015) and Archer et al. (1983). In order to examine *face-ism* and *relative size* in selfies, I had to measure the ratio of the face in relation to the size of the image. The concept of *ritualization of subordination* (in other words, feminine fragility and imbalance) becomes apparent in the degree of head tilt. These elements have been measured in MATLAB (The MathWorks, Inc. 2017) with the Image Processing and Computer Vision System toolboxes. More specifically I used the vision.CascadeObjectDetector System function and the enhanced version that detects rotated faces by Masayuki Tanaka (2012). This function is based on the Viola-Jones face detection algorithm (Viola and Jones 2004) and produces bounding boxes around the face and facial features such as the eyes, nose and mouth. I have used the default settings of Tanaka's version (2012), after I tested them on a sample of 100 images as most accurate. However, MATLAB still caused an amount of errors which are images that do not contain a face according to MATLAB (see Table 1). These errored images have been removed from the usable datasets.

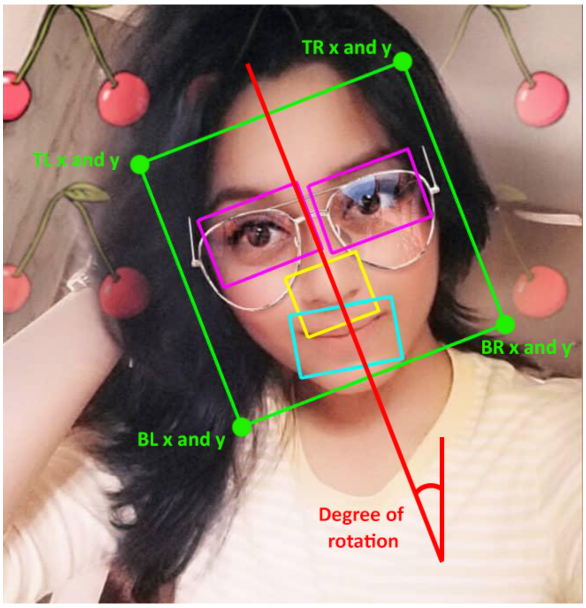


Image 1. MATLAB measurements

After importing the data to Excel, the data was split up per face (F1 = Face 1, F2 = Face 2, etc.), per point (BL = Bottom Left, BR = Bottom Right, TL = Top Left and TR = Top Right) and per axis (x and y) and finally the degrees of each face detected. Due to trouble with importing the measurements from MATLAB to Excel, the data of a maximum of 5 detected faces per image is included in the spreadsheet (see 'Excel errors' in Table 1). As a result, this excludes large group selfies with more than 5 faces from the analysis.

Next, both datasets were measured with ImagePlot. ImagePlot (Software Studies Initiative, n.d.) is a plugin of ImageJ (National Institutes of Health, n.d.), which is a software program for measuring and analyzing images. ImagePlot affords the measurements of image size, brightness, hue and saturation (either median or standard deviation). Although I measured all images on these values, I have only used the data on image size in the final analysis as the other values proved not useful to answer the research questions. Again, the ImagePlot measurements contained some errors which were removed from the usable datasets. After the computational measurements, the dataset of #selfie contained 1228 images and the #filterselfie dataset contained 2183 images.

	#Selfie		**#Filterselfie**	
Unprocessed dataset	3000		3000	
Manual selection of selfies		-1365		-223
	1635		2777	
MATLAB errors		-304		-436
	1331		2341	
Excel errors		-64		-81
	1267		2260	
ImagePlot errors		-39		-77
	1228		2183	

Table 1. Amount of images in each dataset after the computational measurements.

After these initial measurements, the size of the total image had to be combined with the four points of the bounding boxes to calculate the ratio of the face in relation to the size of the image. Because the faces are rotated in varying degrees, I used the formula below to calculate the size correctly for both straight and turned square and rectangle bounding boxes. MAX uses the largest number of the selection, and MIN the smallest. That way the calculation is correct for both left and right rotated bounding boxes.

Ratio face to image = surface of the bounding box / image size
Surface of the bounding box = Length of x * Length of y
Length of x = √((MAX(BRx;BLx)-MIN(BRx;BLx))^2+(MAX(BLy;BRy)-MIN(BLy;BRy))^2)
Length of y = √((MAX(TLx;BLx)-MIN(TLx;BLx))^2+(MAX(BLy;TLy)-MIN(BLy;TLy))^2)

A complication of this method is that MATLAB regularly detected more faces than actually present in the image. It sometimes also detected the correct face, but drew a non-square bounding box which makes the ratio formula error. Additionally, comparing the degree and ratio of a face in selfies cannot be done based on multiple faces. Therefore, it is important to distinguish between correctly and incorrectly detected faces, and to make sure the measurements of the most prominent face of the image are used in the comparative analysis. This second issue of distinguishing the most prominent face has been solved by calculating the size of the first 5 faces detected with the formula above, and using the face that is the largest for comparison with other selfies. Most of the wrongly detected faces are relatively small, because they are detected in for example prints on clothing and patterns of wallpaper. In group selfies, the taker of the selfie is usually up front and therefore the largest face present. However, the solution to use the largest face does not delete all incorrect measures from the dataset, so it still remains a slight limitation of using MATLAB to measure faces. In the manual categorization, I have filtered these incorrect measured images out of the dataset.

3.3.3 Manual categorization

Before the manual categorization started, the dataset of #selfie contained 1228 images, and the #filterselfie dataset contained 2183 images. The final datasets need to be the same size in order to be able to compare them in a plot. I aimed to end up with 1000 correctly detected and categorized images per dataset. Therefore, I manually analyzed around 1200 images of each tag. During the manual categorization, the images have been assessed on the following elements: correct/incorrect detection, actual amount of faces in the image, gender of the most prominent face, yes/no face filter applied, and facial expression of the most prominent face. The elements of detection and the actual amount of faces were chosen to make up for the limitations and errors of MATLAB. The yes/no face filter category has been added to verify the purity of the hashtags #selfie and #filterselfie. In line with the proposed typology of face filters, the face filters that this category refers to are specifically defined as *visible* and *figurative*. The categories of gender and facial expressions are additional data points that enable us to examine the concepts of gender display. During the manual categorization, I made notes about specific images referring to the other concepts of gender display.

In order to make the categorization less time-consuming, I asked people with no prior knowledge about my research and hypothesis to help me with the categorizations. Around half of the images is categorized by me, and half by the assistants. The images of both datasets were uploaded to a Google Drive folder, that has been shared only with them. The datasets were accompanied by instructions that outlined the categories as precisely as possible (see Appendix 1). Using Google Drive allowed me to keep track of the progress in the spreadsheet, and I regularly sampled the categorization to verify the findings. However, it is impossible to avoid individual differences in assessment and especially facial expressions are hard to divide into clear categories, which will be accounted for during the analysis.

Finally, the computational measurements and manual categorization of images have been combined and wrongly detected images have been deleted. Both datasets have been cropped randomly to 1000 images per hashtag, and these datasets will be used for the analysis.

	#Selfie		#Filterselfie	
Total amount of manually assessed images	1228		1217	
Incorrect detected faces		- 227		-192
	1001		1025	
Cropped to 1000 images		-1		-25
	1000		1000	

Table 2. Amount of images in each dataset after the manual categorization.

3.3.4 Analytical methods

In line with Cultural Analytics' encouragement of data visualization, I planned to use ImagePlot to plot the images. One of the main characteristics of ImagePlot is that it displays the actual images instead of dots or lines. Two measurements must be chosen and will be placed along the Y-axe and X-axe. Images will then be plot alongside those axes, in either a square or polar layout. This enables visual analysis, which is the exploration of patterns by looking at data visualizations. However, one limitation of ImagePlot, and plotting images in general, is that images with the same values will overlap. Because I use mostly integers as values, the images are plot in straight rows rather than loose groups (see Appendix 8.3). Due to overlap, the size of a row or group is not representative for the amount of images with these values. As such, the plotting of images in ImagePlot has turned out less useful than I expected up front and I did not use these plots as means for analysis.

Instead of visualizing the data, I eventually based the analysis on the statistical comparison of both datasets in Excel. Additionally, I compared the datasets by gender separately and created simple graphs to gather insights. However, to avoid the pitfall of considering the statistical data as objective truth, I decided not to include the graphs in the analytical chapter. For every pattern or phenomenon that I discovered, I looked back at the actual data to ground the finding and select fitting examples. These examples do not necessarily represent the whole datasets, but do provide insight in the presence of stereotypical practices.

4. #Selfie versus #Filterselfie

In this analytical chapter, I will first examine how face filters confirm or enlarge gender stereotypes and conventions of selfie creation. Next, I explore how face filters disrupt or subvert gender stereotypes and conventions of selfie creation. The chapter ends with discussing how face filters offer possibilities for liberated or suppressed practices of selfie creation.

4.1 The confirmation of stereotypical selfie creation

In chapter 2, it has become clear that the general selfie is still largely subject to the same conventions and norms of gender display as mass media advertisements (Doring, Reif and Poeschl 2015). How does the relatively new phenomenon of face filters confirm or enlarge these gender stereotypes and conventions of selfie creation?

When we first compare the datasets based on gender, it becomes apparent that face filters are definitely more popular among women. Of the #selfie dataset 72,9 % is female, compared to 86,9% of the #filterselfie dataset. Only 12,3% of the #filterselfie images portrays men, and 43,1% of these male selfies do not actually contain a figurative face filter. These results reinforce the statement of Dhir et al. (2016, 551) that women are more active in editing and cropping selfies.

The conventions of self-portrayal and gender display are apparent in both the #selfie and #filterselfie dataset, and most clearly recognizable among normal female selfies. This is exemplified by the degree of head tilt. The degree of head tilt is quite similar in both datasets as the average angle is 16 degrees in the #filterselfie set, and 19 degrees for the #selfie dataset. The #selfie dataset shows a slightly larger variation of angles, and the #filterselfie dataset shows less straight faces. When we compare the angles based on gender, the #selfie dataset shows a quite stereotypical diversion with an average of 16 degrees among men, and 20 among women. The average degree is slightly higher than findings from SelfieCity, as Manovich et al. (2014) report a degree of rotation of 8 among men, and 12 among women[1]. Nonetheless, both the SelfieCity project and this study confirm that women tend to tilt their head more. In terms of Manovich et al. (2014), this suggests that women have a tendency to strike extremer poses.

However, in light of Goffman's (1979) concepts of gender display, the head tilt in female selfies might also exemplify the *ritualization of subordination* of women. The examples of both the #selfie and #filterselfie datasets shown in Image 3 and 4 resemble the stereotypical feminine imbalanced posing that commonly appears in mass media advertisements (Doring, Reif and Poeschl 2015, 960) and portrays women as fragile, helpless and submissive. The female examples of

[1] It is likely that the general dissimilarities between SelfieCity and this study on #selfie are caused by the implementation of different methods to measure the degree of head tilt.

conventional selfies also show other concepts of gender display, such as the feminine touch, body display and the kissing pout. The male examples in Image 2 exemplify the concepts of muscle representation and face-ism, as their faces take up more space of the image and are pictured from beneath which makes them look more dominant.

The most remarkable and significant difference regarding facial expressions is that the #filterselfie dataset shows almost twice the amount of pouted lips compared to the #selfie dataset. Pouted lips are specifically related to female selfie culture and commonly used as a seductive pose, although it is often made fun of and ironically referred to as ‘duck face’ (Doring, Reif and Poeschl 2015, 961). In this case, it seems like the gendered aesthetics of the filters themselves might encourage other stereotypical feminine conventions such as posing and facial expressions (see Image 4).

We may conclude that the concepts of gender display and the stereotypical conventions of self-portrayal are apparent in both the #selfie and #filterselfie datasets. In the most stereotypical female filtered selfies, the used face filter seems to enlarge the effect of gender display. But are these conventions present in both datasets to the same degree, or does the use of face filters also lead to less conventional practices of selfie creation?

Image 2. Conventional male selfies, showing muscle representation and relative size

Image 3. Conventional female selfies showing body display, feminine touch and ritualization of subordination

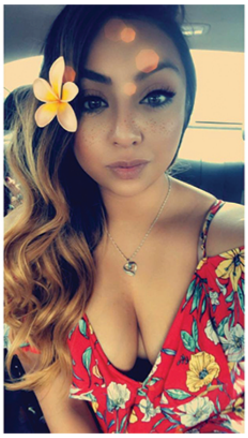
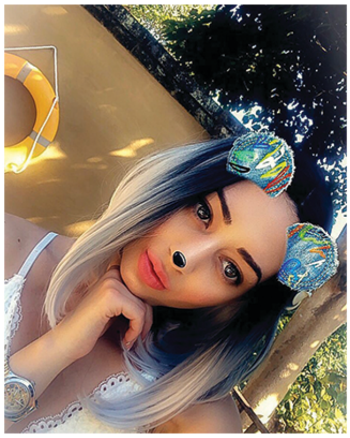
  

Image 4. Stereotypical female filtered selfies showing body display, feminine touch and ritualization of subordination

4.2 The disruption of stereotypical selfie creation

In the previous section we concluded that the concepts of gender display are present in both datasets. It is however questionable whether both datasets represent those concepts to the same degree. What is the specific effect of face filters on the concepts of gender display, and do face filters have a subversive influence on the stereotypical self-portrayal?

The degree of head tilt proves again useful to examine these questions. It is remarkable that the #filterselfie dataset not only shows a lower average degree of head tilt, but also diminishes the difference between genders with an average of 15 degrees among men and 16 degrees among women. This implies that head tilt in filtered selfies is *not* related to gendered norms of self-presentation and the concepts of gender display. Instead, the findings suggest a causal relation between head tilt and the relative size of the face compared to the size of the image. Aside from showing a lower average degree of head tilt, filtered selfies are also commonly taken closer to the face. The average #filterselfie contains a face that covers 26% of the total surface of the image, while the average face in the #selfie dataset only covers 13% of the surface. And when a portrait is taken from a distance there is more space to move around and tilt the head, while a close-up limits the freedom of movement and consequently leads to a lower degree of head tilt. But what causes this difference in face-image ratio between the two datasets?

First of all, face filters are more commonly used alone, rather than in groups. The #selfie dataset contains a smaller percentage of 1-person selfies (77,7%) compared to the #filterselfie dataset (84,6%). The percentages of images with 2 or more persons depicted are slightly larger in the #selfie dataset. My speculation is that normal selfies are more regularly taken to create memories of social events and as proof of presence, while filtered selfies are more commonly created during individual sessions of self-portrayal at home. The higher average of people portrayed in each selfie in the #selfie dataset, logically forces people to take a photo from a distance in order to fit more people into the frame. This leads to relatively smaller faces compared to the size of the image.

Secondly, most face filters naturally emphasize the facial features. As stated by Rettberg (2017), face filters subject our face to the systematic norms of machine vision which forces users to point their face directly to the camera. The real-time interaction between the screen and the user invites users to look closely at their phone while playing with the filters, which eventually causes pictures to be taken more closely to the face. Additionally, I noticed during the manual assessment of the #filterselfie dataset that most filters do not add any figurative elements outside of the facial area. Each filter has its own ideal composition in which the whole figurative filter is included in the image. As such, the photographic composition of the selfie, and thus the ratio of the face to the image size, is partly enforced by the filter itself.

These findings indicate that the larger relative size of the face and the lower head tilt in filtered selfies is instigated by the filters' affordances. The affordances unintentionally suppress the concepts of gender display such as body display, ritualization of subordination and especially face-ism. The filters' focus on the face is very atypical and historically connected to masculinity, even though most filters conform to typical feminine aesthetics. This contradiction demonstrates the inherently paradoxical nature of face filters.

Image 5. Non-conventional male filtered selfies that conform to feminine aesthetics

Aside from this paradox caused by the filters' affordances, users themselves also utilize face filters to subvert conventions of self-presentation. I already mentioned in section 4.1 that the presence of the typically female pouted lips is increased in amount in the #filterselfie dataset. However, it is remarkable that the use of face filters equally enlarges the recurrence of pouted lips among both men and women. I encountered some filtered selfies of men that seemed to be subject to specific feminine aesthetics and female gender display, such as imbalanced posing, touching the face and pouting the lips (see Image 5). The virtual make-up and female face features that are inherent to a lot of face filters made it sometimes even impossible to fit someone's gender into binary categories. Although the filters itself convey stereotypical norms of gender, it is interesting to note that they are not necessarily used in stereotypical ways and users do not always conform to conventions of gendered self-presentation. Even the face filters that convey stereotypical aesthetics of gender and beauty may facilitate experimentation with gendered self-portrayal.

In contrast to conventional selfies, filtered selfies also show a slightly smaller percentage of neutral expressions and a slightly larger percentage of people sticking out their tongue. These numbers alone are not enough to confirm my hypothesis that face filters encourage more facial expressions. However, some images that I encountered during the manual assessment did indeed suggest that face filters stimulate playful expressions. The visual characteristics of the filter itself may encourage specific expressions, as can be seen in Image 6. The collages in Image 7 also show experimental facial expressions. Instead of a single filtered selfie, those users posted a collage of filtered selfies. The choice to share those images in the form of collages suggests that the single selfies do not deserve all the attention, or might not fit with the audience and conventions of selfies on Instagram. They are the report of an experimental selfie session, and the form communicates that they are not to be taken seriously.

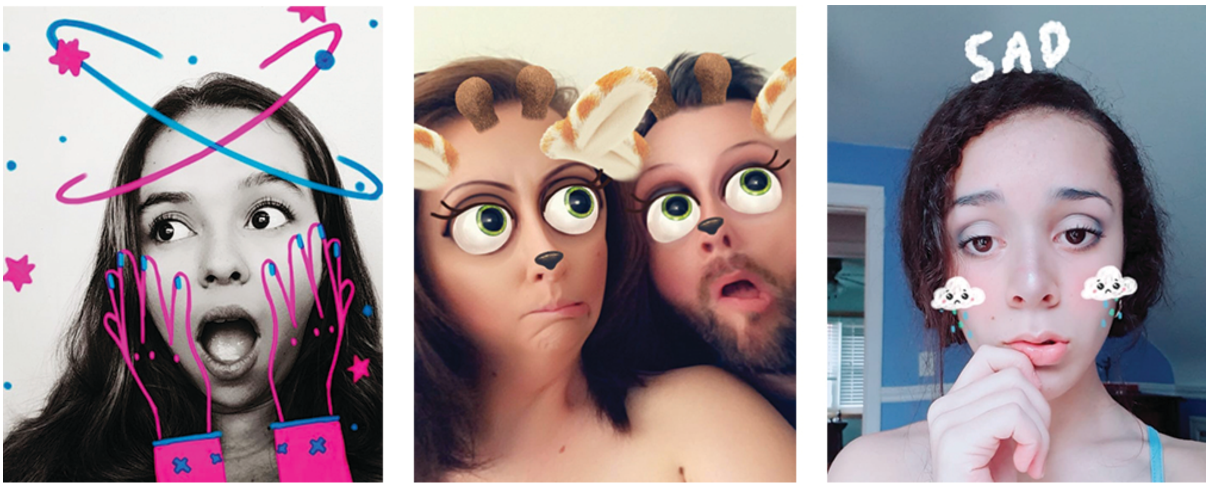


Image 6. Face filters that specifically encourage facial expressions

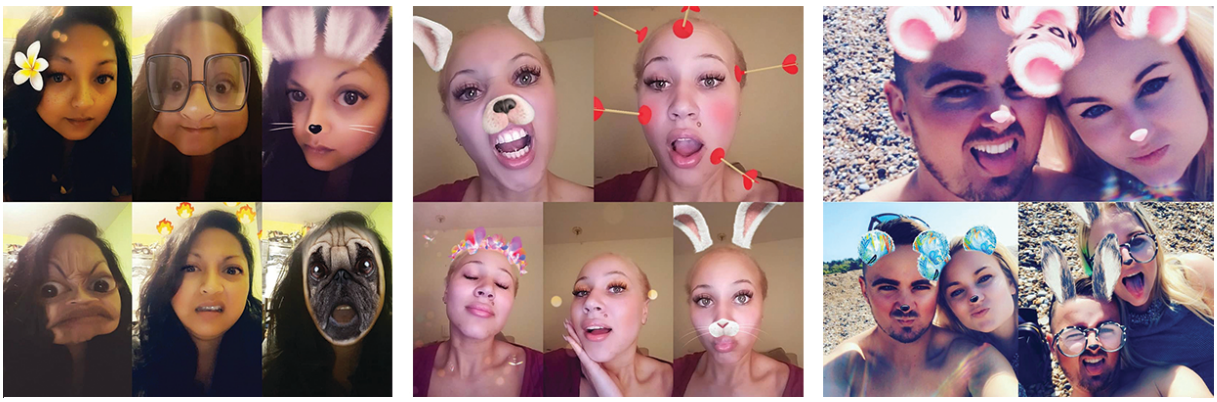


Image 7. Filtered selfies that show experimentation with facial expressions in the form of collages

4.3 Discussing liberation and suppression

The previous two sections sketched an overview of different practices of selfie creation and how face filters offer options for the confirmation and subversion of stereotypes. We will now discuss how this might lead to liberated or suppressed practice of selfie creation.

It is interesting to notice that a large part of the so-called subversive practices seem to be caused by the filters' affordances. Face filters emphasize the face as part of an image, and the real-time interaction naturally draws us closer to the camera. Without knowing, women who use face filters automatically discard the long-standing norm of face-ism. An exception to this pattern are the male filtered selfies, where men seemingly willingly experiment with feminine aesthetics and gender display. Unfortunately, image-based research gives limited insights in their motivations and experiences, but the typically feminine aesthetics of filters at least enable this experimental practice and I can imagine that transgender people find this empowering. The lack of typically male face filters, on the other hand, obstructs women to experiment with male gender display and excludes men to use face filters to emit conventional masculinity. We may thus conclude that the liberating effect of face filters on gender display is one-sided.

One of the factors that causes this is the fact that the outlook of the filter itself cannot be controlled by the user. Users can decide which filter to apply, but not design their own filter.[2] The use of pre-made face filters on for example Snapchat and Instagram, is more restrictive but also more accessible than using general photo-editing software. It is thus debatable whether face filters actually add or take away control over one's selfie. I suggest that the restrictive characteristic of most filters is exactly that which liberates users from the pressure to live up to conventions and norms. The fact that users cannot design their own filters, relieves them from the responsibility to do so. In the case of face filters, it might actually be the *lack* of control that has a liberating effect. It causes the feeling of defamiliarisation that Rettberg (2014, 26) discussed, which enables them to use the pre-made filters freely. Similar to the form of collage in Image 7, the use of face filters itself tells the audience that 'this selfie is not to be taken seriously'.

However, this restrictive and non-editable quality of face filters also means that most filters still convey stereotypical aesthetics of femininity, even if they are used by men in a subversive matter. Barnard's (2016) term (dis)empowerment paradox describes the tension between these overviews of liberated and suppressed practices of face filter usage. This theory is exemplified by the aforementioned experience of columnist Katherine Timpf (2017), who reports that she experiences face filters as liberating because she does not have to wear real-life make up before she posts a selfie. The face filter may be liberating for her individually, while it simultaneously reinforces the cultural

[2] At the end of 2017, Snapchat did launch a feature called Lens Studio. This enables 3D artists and programmers to create and upload their own filters. However, this requires skills that most users do not possess. Therefore, this functionality is not included in this study.

ideal of feminine beauty. Subsequently, we have to conclude that face filters can be experienced as liberating and maybe even empowering in some cases, but generally still reinforce the stereotypical practice of the selfie.

5. Discussing the computer-based analysis of (online) visual culture

The mixed methods approach of this study has enabled me to do a large scale analysis of an otherwise diffused and elusive phenomenon. However, the computational methods that I used have their implications on the type of research that can and has been done. Thus, their effectivity within the field of the digital humanities should be discussed.

There are a lot of ways in which the use of computational methods may influence research findings. This effect is not uniquely part of computational methods; generally, every research method has its own possibilities and limitations. However, most computational tools lack transparency and require more practical skills, which makes it harder – and also more important - to reflect on their consequences. For example, this study has restricted intrinsically fluent cultural phenomena such as 'selfies' and 'gender' to clear binary categories in order to process them computationally. Up until now, datafication and quantification always takes place when using computational tools. Consequently, the concept of the selfie is operationalized in this thesis as the restrictive 'image of a face, that is published on Instagram and tagged with #selfie or #filterselfie', and gender has been narrowed down to either male, female or other. Although I have tried to look beyond these strict categories in the manual and explorative part of this research, it still remains a severe issue of using computational methods that deserves further investigation.

Another example of the impact of computational methods and its limitations on research findings are the misdetection of the collages of facial expressions of Image 5. Initially, they were wrongly detected because they contained more than 5 faces. I encountered them during the manual categorization and included them in the analysis anyway. This shows that the manual categorization was necessary to make up for the errors of the software, and the analysis would have been different if I blindly trusted the computational measurements. Of course it is not always possible to manually check all measurements and processes due to the large scale of computational research projects, and a highly skilled researcher might be able to program the measurements differently in order to solve the issue. However, reflecting critically on the used methods and tools offers researchers insights in the limitations and their possible influence on the findings, and thus deserves more attention in the digital humanities field.

Ideally, we would be able to use computational tools without their reductive characteristics and connotation of truthfulness. This concept may sound utopian, because those elements are deeply intertwined with contemporary computer science. It is hard to even imagine computation in any other way. However, digital humanities scholars have the task to take computational tools outside of their scientific paradigm. Would it be able to use computation without quantification and datafication of culture? This is one of the questions that, from my perspective, is radically difficult to answer and simultaneously very important to explore.

Manovich (2007, 13) has done an attempt to answer this question, and encourages the use of visual analytics which combines distant and close reading of images. Close reading is not only a way to get insight in the details and individual differences of the data, it is also a means to verify the computational processes of distant reading and to create room for personal interpretations next to computational measurements. This is in line with the Visual Information-Seeking Mantra "Overview first, zoom and filter, then details-on-demand" (Shneiderman 1996, 2). Shneiderman (1996, 4-5) emphasizes that information visualizations offer opportunities for analysis that other methods do not: to gain an overview, to zoom in on specific items, to filter out irrelevant items, to get details when needed, to analyze relations among items, to keep a history of actions, and finally to extract collections of items. Manovich often promotes Imageplot, which is developed by Software Studies Initiative, as a tool that translates visual data analysis into the humanities paradigm.

However, I experienced during the analysis that ImagePlot is not up to the complexity of this task. It is effective when working with visual data and the analysis of color, hue and saturation, but is not effective when the data is based on the actual content of images, such as gender or facial expression. Additionally, Imageplot does not allow you to filter out irrelevant items, to analyze relations, to keep a history of actions or to extract collections of images. The field of visual analytics needs software that enables researchers to overview, filter, zoom and dissect visual data. The existence of this software would have, for example, enabled me to look for *relations* between data, such as the relation between the head tilt and image-face ratio. It would also enable researchers to create less binary categories (for example related to gender or facial expressions) because they can be visually organized on a scale. I thus completely agree with Burdick et al. (2012, 104), who state that "building tools around core humanities concepts—subjectivity, ambiguity, contingency, observer-dependent variables in the production of knowledge—holds the promise of expanding current models of knowledge. As such, the next generation of digital experimenters could contribute to humanities theory by forging tools that quite literally embody humanities-centered views regarding the world."

Another issue that I have encountered during this study, is that each individual methodological choice that I made has largely influenced the outcome of the analysis. This emphasizes the importance of "tracking the interpretative trail" (Denard 2012, 67) like the London

Charter encourages. Essentially all pointers of the London Charter (aims and methods, research sources, documentation, sustainability and access) have proved to be essential when working in the field of the digital humanities. As they are originally written for the computer-based visualization of cultural heritage, I attempted to rewrite them specifically for the computer-based analysis of (online) visual culture, with more emphasis on the documentation of tools.

1) Aims and methods:	Computational and visualization methods should only be used when they are the most suitable means and if possible, be part of a mixed-method approach that includes both distant and close reading.
2) Research Sources:	The used (data)sources should be carefully examined and evaluated before visualizing them. Limitations of the data should be defined.
3) Tools:	The computational tools should be critically examined and evaluated before using them. Limitations of the tools should be defined and described in the research report.
4) Documentation:	The research process and the choices of the researcher should be documented in order to enable evaluation of the final outcome. Transparency regarding software and code is necessary to enable researchers to build upon each other's knowledge and experience.
5) Sustainability:	Documentation and visualizations should be preserved in a sustainable manner that includes the original context in which they are created.
6) Access:	The preservation of the project, including the methodology and its tools, should allow access and use in new contexts.

These pointers could be a starting point towards a coherent and academic execution of the ideals and dreams that belong to the digital humanities and cultural analytics. Of course, each of the pointers is debatable as the current immature state of the field requires experimentation and out-of-the-box research projects. In the exploratory phase, the chosen method might not always be the best suitable because this can only be learned through experience and experimentation. This list is not perfect, but it can be considered as an invitation to scholars in the field to discuss the guiding principles. Let's strengthen the academic practice of the digital humanities and prevent that each researcher has to reinvent the wheel once again.

6. Conclusion

In the introductory part of this thesis, I phrased the following research question: How do face filters transform the stereotypical practice of selfie creation? In the analytical chapter, I subsequently examined how face filters confirm or enhance gender stereotypes and conventions of selfie creation, how they disrupt or subvert gender stereotypes and conventions of selfie creation, and how they lead towards liberated or suppressed practices of selfie creation. From the analysis, I found that the concepts of gender display are present in both the #selfie and #filterselfie dataset. In the most stereotypical female filtered selfies, the filters seem to make the image even more stereotypically feminine. However, the filters that convey stereotypical norms of gender are not necessarily used in conventional ways. Some men subvert their meaning by using them as a way of identity experimentation. The feminine aesthetics that are inherent in most face filters are actually useful for them to play with. However, even then the existence of these filters still reinforces the norms of femininity. Generally, we can conclude that face filters may be liberating on an individual level, while they simultaneously reinforce the cultural conventions of gender display and self-portrayal. This is in line with Barnard's (2016) concept of the (dis)empowerment paradox.

What instead really seems to transform the stereotypical practice of selfie creation are the affordances of face filters. The biometric grid and the focus on the face unintentionally reduce the presence of female gender display and face-ism. In this case, the users have no awareness of this and are thus not pressured to keep up with conventional self-presentation. In the case of face filters, it may thus actually be the *lack* of control that has a liberating effect because it relieves people from the responsibility of how they look.

The general setup of this thesis actually included two main aims: researching the practice of selfie creation with the use of face filters, and exploring *how* to research this practice with the use of computational tools. The presence of this second aim and the resulting experimental methodology, might have been a distraction from answering the actual research question. The resulting methodology might not have been the most effective strategy for answering the research question, although I still value the setup of this thesis because it has provided insight into the functioning of computational image analysis and it has been a truly educational project for me as a researcher. Taking this into account, this study has its limitations and requires the findings to be grounded with more research.

First of all, the use of publicly available selfies on Instagram has narrowed the research down to filtered selfies that have been published. Instagram has its own affordances and specific audience, and users consciously curate their images to fit expectations of the audience and the platform. As such, I speculate that the most experimental filtered selfies will probably not be shared on Instagram and the differences between normal selfies and filtered selfies are presumably even more apparent in non-published selfies. The private practice of selfie creation and the use of filters should therefore be researched with an ethnographic approach, to further ground and deepen the initial findings of this analysis of published selfies.

Secondly, this study has examined isolated selfies that are posted along with the hashtags #selfie and #filterselfie. In reality, not all published selfies are tagged correctly or even tagged at all. Moreover, by only examining tagged selfies, we have lost the relation between selfies taken by the same person. In order to explore the depth of the practice of selfie creation, more research could be done into series of selfies by individual accounts, and for example how their practice of selfie creation changes over time.

Finally, within this thesis I have examined the aesthetics of selfies to make interpretations about the affordances and audiences by which they were created. Although this image-based angle has provided some interesting insights, using the affordances or audiences as point of departure could also lead to additional and equally valuable findings. Additionally, the concepts of liberation, empowerment and suppression are also grounded in the individual experience of selfie creators, which this thesis does not cover. As such, empirical research should be done on the phenomenon of face filters and how people experience the use of these filters individually.

7. References

Archer, Dane, Bonita Iritani, Debra D. Kimes and Michael Barrios. 1983. “Face-ism: Five studies of sex differences in facial prominence.” *Journal of Personality and Social Psychology 45, no. 4*: 725-735. doi: 10.1037/0022-3514.45.4.725

Barnard, Stephen R. 2016. "Spectacles of Self(ie) Empowerment? Networked Individualism and the Logic of the (Post)Feminist Selfie." *Communication and Information Technologies Annual* 11: 63-88.

Burdick, Anne, Johanna Drucker, Peter Lunenfeld, Todd Pressner and Jeffrey Schnapp. 2012. *Digital_Humanities*. Cambridge and London: The MIT Press.

Caplan, Lindsay. 2016. “Method Without Methodology: Data and the Digital Humanities.” *E-flux journal*, no. 72.

Chae, Jiyoung. 2017. “Virtual makeover: Selfie-taking and social media use increase selfie-editing frequency through social comparison.” *Computers in Human Behavior* 66: 370-376.

Cruz, Edgar Gomez and Helen Thornham. 2015. “Selfies beyond self-representation: the (theoretical) f(r)ictions of a practice.” *Journal of Aesthetics & Culture* 7, no. 1. doi: 10.3402/jac.v7.28073

Denard, Hugh. 2012. “A New Introduction to the London Charter.” In *Paradata and Transparency in Virtual Heritage Digital Research in the Arts and Humanities Serie*s, edited by A. Bentkowska-Kafel, D. Baker & H. Denard. Ashgate: 57-71.

Dhir, Amandeep, Ståle Pallesen, Torbjørn Torsheim and Cecilie Schou Andreassen. 2016. “Do age and gender differences exist in selfie-related behaviors?” *Computers in Human Behavior* 63: 549-555. doi: 10.1016/j.chb.2016.05.053

Döring, Nicola, Anne Reif and Sandra Poeschl. 2015. “How gender-stereotypical are selfies? A content analysis and comparison with magazine adverts.” *Computers in Human Behavior* 55: 955-962.

Drucker, Johanna. 2011. “Humanities Approaches to Graphical Display.” *Digital Humanities Quarterly* 5, no. 1.

Eckel, Julia, Jens Ruchatz and Sabine Wirth (ed.). 2018. *Exploring the Selfie*. Marburg, Germany: Palgrave MacMillan.

Elias, Ana Sofia and Rosalind Gill. 2018. “Beauty surveillance: The digital self-monitoring cultures of neoliberalism.” *European Journal of Cultural Studies* 21, no. 1: 59-77.

Goffman, Erving. 1979. *Gender Advertisements.* Cambridge MA: Harvard University Press.

Hampton, Claire. 2015. “#nomakeupselfie: the Face of Hashtag Slacktivism.” *Networking Knowledge* 8, no. 6.

Jessop, Martyn. 2008. “Digital Visualization as a Scholarly Activity.*” Literary and Linguistic Computing* 23, no. 3. doi: 10.1093/llc/fqn016

Kang, Mee-Eun. 1997. “The Portrayal of Women’s Images in Magazine Advertisements: Goffman’s Gender Analysis Revisited.” *Sex Roles* 37, no. 11/12: 979-996.

Kedzior, Richard and Douglas E. Allen. 2016. “From liberation to control: Understanding the selfie experience.” *European Journal of Marketing* 50, no. 9: 1893-1902.

Kuntsman, Adi. 2017. *Selfie Citizenship*. United Kingdom: Palgrave MacMillan.

Leary, Mark R. 2013. “Scholarly reflections on the selfie”. *Oxford University Press blog*. URL: https://blog.oup.com/2013/11/scholarly-reflections-on-the-selfie-woty-2013/

Leclercq, Charlotte. 2016. “Do you ‘Lensit’? A Call for Research on Modified Selfies.” On *Masters of Media* blog. URL: https://mastersofmedia.hum.uva.nl/blog/2016/10/20/do-you-lensit-a-call-for-research-on-modified-selfies/

Lichty, Patrick. 2017. “The Mutant Cute: Meitu, The Selfie and the Rewriting of Global Identities.” *DIGIMAG: Digital Identities, Self Narratives,* 75 (Spring): 16-21.

Losh, Elizabeth, 2015. “Feminism Reads Big Data: ‘Social Physicaics,’ Atomism and Selfiecity.” *International Journal of Communication* 9: 1647-1659.

Manovich, Lev. 2007. “Cultural Analytics: Analysis and Visualization of Large Cultural Datasets.” Unpublished, available at Lab.Culturalanalytics.info. URL: http://lab.culturalanalytics.info /p/publications.html.

———. 2016. “The Science of Culture? Social Computing, Digital Humanities and Cultural Analytics.” *CA: Journal of Cultural Analytics* 1, no. 1. doi: 10.22148/16.004

Manovich, Lev, Moritz Stefaner, Mehrdad Yazdani, Dominikus Baur, Daniel Goddemeyer, Alise Tifentale, Nadav Hochman and Jay Chow. 2014. *SelfieCity*. URL: http://selfiecity.net/

Moretti, Franco. 2005. “Graphs, Maps, Trees: Abstract Models for a Literary History.” New Left Review 24: 67-93.

Peraica, Ana. 2017. *Culture of the Selfie.* Amsterdam: Institute of Network Cultures.

Qiu, Lin , Jiahui Lu, Shanshan Yang, Weina Qu and Tingshao Zhu. 2015. “What does your selfie say about you?” *Computers in Human Behavior* 52: 443-449.

Rettberg, Jill Walker. 2014. *Seeing Ourselves through Technology: How We Use Selfies, Blogs and Wearable Devices to See and Shape Ourselves.* United Kingdom: Palgrave MacMillan.

———. 2017. “Biometric Citizens: Adapting Our Selfies to Machine Vision.” *In Selfie Citizenship,* edited by Adi Kuntsman. United Kingdom: Palgrave Macmillan*: 89-96.*

Schreiber, Maria. 2017. “Audiences, Aesthetics and Affordances: Analysing Practices of Visual Communication on Social Media.” *Digital Culture and Society* 3, no. 2: 143-163.

Schwarz, Ori. 2010. “On friendship, boobs and the logic of the catalogue: Online self-portraits as a means for the exchange of capital.” *Convergence: The International Journal of Research into New Media Technologies* 16, no. 2: 163-183.

Shneiderman, Ben. 1996. “The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations.” In *Proceedings of the IEEE Symposium on Visual Languages*: 336-343.

Smith, Lauren Reichart and Skye C. Cooley. 2012. “International Faces: An Analysis of Self-Inflicted Face-ism in Online Profile Pictures.” *Journal of Intercultural Communication Research* 41, no. 3: 279-296.

Tifendale, Alise. 2014. “The Selfie: Making sense of the ‘Masturbation of Self-Image’ and the ‘Virtual Mini-me.’” Unpublished, available on *SelfieCity.net*. URL: http://www.selfiecity.net/#theory

Tiidenberg, Katrin and Edgar Gomez Cruz. 2015. “Selfies, Image and the Re-making of the Body.” *Body & Society* 21, no. 4: 77-102.

Viola, Paul and Michael Jones. 2004. “Rapid Object Detection using a Boosted Cascade of Simple Features.” *TR2004-043.*

Vivienne, Son. 2017. “I will not hate myself because you cannot accept me”: Problematizing empowerment and gender-diverse selfies.” *Popular Communication* 15, no. 2: 126-140.

Warfield, Kate. 2014. “Making Selfies/Making Self: Digital Subjectivities in the Selfie.” *Proceedings of the Image Conference Berlin, October 30th*.

Non-academic references

Instagram. 2017. “Face Filters”. Blog entry on *Instagram.tumblr.com*, 16 May 2017. URL: http://instagram.tumblr.com/post/160730363267/170516-facefilters

Oxford Living Dictionaries. N.d. *Selfie*. Accessed at 11 May 2018. URL: https://en.oxforddictionaries.com/definition/selfie

Rieder, Bernhard. 2016. “Closing APIs and the Public Scrutiny of Very Large Online Platforms.” Blog entry on *The Politics of Systems*, 27 May 2016. URL: http://thepoliticsofsystems.net/2016/05/closing-apis-and-the-public-scrutiny-of-very-large-online-platforms/

Snap Inc. 2015. “A Whole New Way to See Yourself(ie).” Blog entry on *Snap.com*, 15 September 2015. URL: https://www.snap.com/en-GB/news/page/3/

Snap Inc. 2017. “Snap Inc. Reports Third Quarter 2017 Results.” *Investor.Snap.com*, 2017. URL: https://investor.snap.com/news-releases/2017/11-07-2017-211621749

Simeon, Aimee. 2017. “Why Snapchat Filters are More Problematic than Pretty.” *Popsugar.* URL: https://www.popsugar.co.uk/beauty/Problem-Snapchat-Filters-44439340

Timpf, Katherine. 2017. “Apparently, Snapchat filters are ‘problematic’.” *National Review Online*. URL: https://www.nationalreview.com/2017/12/snapchat-filters-problematic-popsugar-column/

Software

Arcega, Richard. n.d. *Instagram-scraper.* Command-line application. URL: https://github.com/rarcega/instagram-scraper

National Institutes of Health. n.d. *ImageJ.* Image Processing and Analysis in Java. URL: https://imagej.nih.gov/ij/

Software Studies Initiative. n.d. *ImagePlot.* ImageJ macro. URL: http://lab.softwarestudies.com/p/imageplot.html

Tanaka, Masayuki. 2012. *Face Parts Detection*. URL: https://nl.mathworks.com/matlabcentral/fileexchange/36855-face-parts-detection

The MathWorks, Inc. 2017. *MatLab*.

8. Appendix

8.1 Data processing logbook

1. **Collect two datasets of 3000 images with the Instagram-scraper, using the tags #selfie and #filterselfie.**

2. **Test the most effective threshold on a sample of 25 images of both datasets. Report findings.**

	Correct amount		More faces detected		Less faces detected		Correct faces detected		Non-existent faces detected	
Whole sample (50)	24	48%	24	48%	2	4%	27	54%	27	54%
No face (14)	8	57%	6	43%						
One face (25)	12	48%	13	52%			19	76%	15	60%
Two faces (5)	2	40%	2	40%	1	20%	5	100%	3	60%
Multiple faces (3)	2	66%			1	33%	2	66%		
Part face (2)			2	100%					2	100%

From this test, we may conclude (carefully, because the samples are really small):
- The algorithm is way more likely to detect too much faces then not enough faces
- The percentage of correct faces when no faces are present 57%, which is not enough to use the algorithm to clean up the dataset
- The algorithm performs better at detecting multiple faces

3. **Manually remove all images that do not contain a face. Leave group selfies in. Report the amount and percentage of non-selfies for each tag.**

Images will be deleted when:
- they do not contain a face at all or less than half of a face.
- they are clearly advertisements or memes.

Limitation: for the operationalization of this research, the term 'selfie' is reduced to an image that contains at least one face, even though in a broader understanding of the term, not all selfies contain a face.

Filterselfie: amount of non-selfie images: 223 of 3000
Non-selfie images mainly consist of: body selfies, quotes, animals, food, partial selfies.

Selfie: amount of non-selfie images: 1365 of 3000
Non-selfie images mainly consist of: selfies with person looking away/taken from the back by someone else, body selfies, food, travel photos, clothing/jewellery advertisements, quotes.

The different amounts can be caused by different things. The selfie tag contains way more mirror selfies, in which people are holding their phone in front of their face. These are selfies, but due to the absence of a face, they are deleted from the dataset. I speculate that the filter narrows the definition of the selfie to 'an image with a face' rather than 'an image that portrays the taker in one way or another'.

4. **Measure the images.**

   Matlab: The four points of each face detection rectangle and the degree of rotation, and save each image with visual bounding box for reference.
   ImagePlot: image size, saturation, brightness and hue.

5. **Gather the measurements in an Excel sheet for each dataset. Report the amount and percentage of correct measurements regarding the face detection.**

Cleaning up and organizing the Matlab data existed out of:
- Round off all numbers to an integer for easy handling.
- Splitting the data per face (F1 = Face 1, F2 = Face 2, etc) and the point (BL = Bottom Left, BR = Bottom Right, TL = Top Left and TR = Top Right) and x- and y-axis.
- A maximum of 5 faces per image are included in the sheet. I will not use all the measurements and aim to keep the spreadsheet manageable, and I have trouble importing more than 5 measurements from MatLab to excel. Therefore I set the maximum of measurements in the sheet to 5.

6. **Calculate the position of the face in connection to the size of the image.**

Issue: A lot of images have multiple faces (actually) or multiple faces recognized by Matlab while there is only one face present.
Solution: Most of these wrongly detected faces are quite small, because they are detected in for example prints on clothing, patterns of wallpaper, etc. Also in group selfies, the taker of the selfie is usually up front and therefore the largest face present. Therefore I decided to calculate the size of the first 5 faces detected, and use the face that is the largest to compare in my analysis.
Limitation: However, this does not delete all incorrect measures from the dataset so it still remains a slight limitation of using MatLab to measure faces. Furthermore, the degree I will use is still based on the F1 column, and might therefore not correspond with the largest face.

Issue: How do I calculate the size of each bounding box precisely based on a single formula, because a lot of them are rotated, and not all of them are exactly square or rectangle shaped.
Solution: I have done it in a way that comes closest, and the formula below calculates the size correctly for both straight and turned square and rectangle bounding boxes. MAX uses the largest number out of the selection, and MIN the smallest. That way the calculation is correct for both left and right rotated bounding boxes.
Surface of the bounding box = Length of x * Length of y
Length of x = √((MAX(BRx;BLx)-MIN(BRx;BLx))^2+(MAX(BLy;BRy)-MIN(BLy;BRy))^2)
Length of y = √((MAX(TLx;BLx)-MIN(TLx;BLx))^2+(MAX(BLy;TLy)-MIN(BLy;TLy))^2)
Limitation: Unfortunately, the bounding boxes that aren't square or rectangle, will still be calculated based on the above formula, which comes closest to their actual surface but doesn't provide the exact number. It is (from my knowledge) impossible to come up with a single formula to calculate all different surfaces that would solve this problem, so it remains a limitation of this method.

Issue: Degree's are provided by MatLab from 0 to 360. However, a degree of 20 is actually the same amount of angle as 340, but angled to the other side. To plot this logically, I have to change all degrees above 180.
Solution: The 'Degree to Plot' colon is created by using the F1 degree and applying the formula:
=IF(F1 Degree>180 ; F1 Degree-360 ; F1 Degree)
This means that if the degree is above 180, 360 is subtracted from it. Instead of for example 340, it will be -20. When plotting the degrees, this makes more sense.

Limitation: None.

	Selfie		Filterselfie	
Raw dataset	3000		3000	
Manual selection of selfies		-1365		-223
	1635		2777	
MatLab errors		-304		-436
	1331		2341	
Excel errors (f.e. one missing measurement or more than 5 faces)		-64		-81
	1267		2260	
ImagePlot measuring errors		-39		-77
	1228		2183	

7. **Manually assess if the Matlab measurements are correct (delete all images with wrongly detected faces from the dataset) and asses photos based on gender (male/female/other), facial expression.**

Initial findings during the data entry process:
Lot more females in the filterselfie dataset
More expressive faces in the filterselfie dataset
Less group photos in the filterselfie dataset
Faces are portrayed more closely in the filterselfie dataset
Some photos in the filterselfie dataset do not contain figurative facial filters, but beautifying make-up (like Meitu). These are not categorized as a 'face filter' although they are some kind of filter and different from a photographic color filter.
Man that use face filters seem to object themselves to female selfie taking standards, i.e. pouting lips etc.
Face expressions are a really subjective element to analyze this way. Especially sad/angry are values applied to expressions rather than explicit expressions.
Extreme close ups are errored in Matlab because one of the four points is outside of the images' boundary.

8. **Randomly crop both datasets to the same amount of images (probably 1000 per dataset) in order to facilitate visual comparison.**

9. **Import images and measurements into ImagePlot to perform analysis.**

8.2 Instructions for manual categorization

Thank you for helping me!

For my thesis, I am analyzing two datasets of images. The datasets are called “SELFIE” and “FILTERSELFIE”.

- Pick one and open one of the folders that still needs to be done.
- Rename the folder to include your name, so other people will know that you’re working on this.
- Open the accompanying spreadsheet in another screen or tab. It is most convenient if you can see both the images and the spreadsheet at the same time.
- Before you start, pay attention to the filename of the image and the filenames listed in this spreadsheet. Not all images that are in the folder, are included in the sheet. You only need to look at the images that are included in this sheet. Be very careful to align your answers with the correct filename in the sheet.
- For every picture that you look at, you need to answer the following questions.

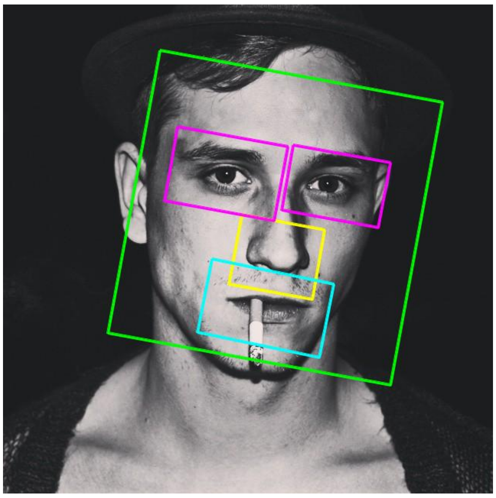
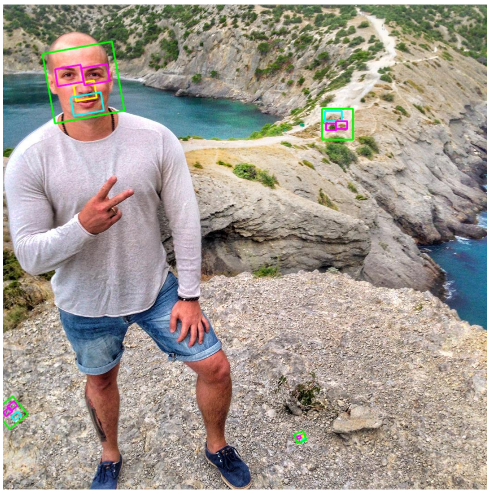
1. IS THE FACE DETECTED CORRECTLY?
Each image shows (multiple) colored rectangle(s). You only need to focus on the green rectangle(s) and ignore the rest. Now asses if it has detected the most prominent face (or multiple faces) correctly.

c = CORRECT = the green square is (almost) **square-shaped** around the face AND at least the most prominent face of the image is framed with a green square.
i = INCORRECT = the green square is **not square** OR the (largest) green square does **not cover an actual face**, but something else.

If the detection is incorrect, you do not have to proceed with this image. Simply put an 'i' and go to the next image.

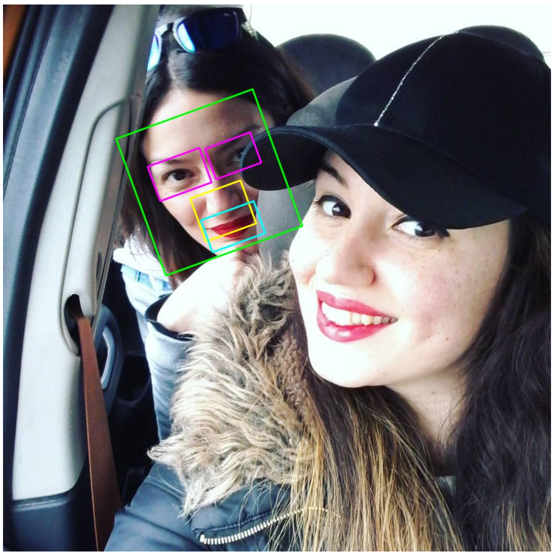
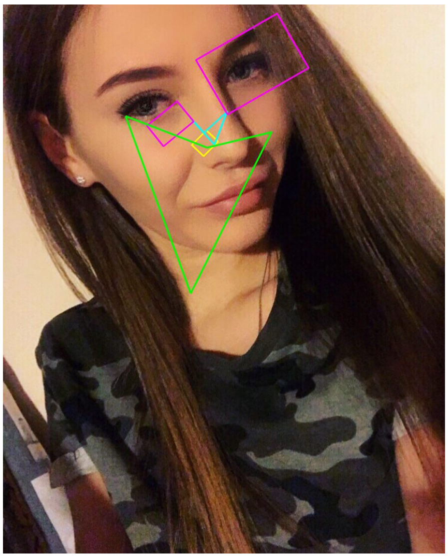
Examples:

CORRECT

The green square frames the face; In the second picture, at least the most prominent face is detected even though it detected some others things as well. This is still correct.

INCORRECT

Most prominent face is not detected; the green square is not square-shaped.

2. AMOUNT OF PEOPLE
Write down the number for the amount of people that are CONSCIOUSLY portrayed in the image. Include everyone that is for example posing and taking part in the image taking process, and exclude by passers. If an image includes multiple selfies of the same person as a collage, count it as 1 person.

3. GENDER
Write down the gender of the person depicted most prominently in the image (the largest face depicted).

m = MALE
f = FEMALE
o = OTHER/NON-BINARY GENDER/UNCLEAR ETC.

4. FACE FILTER
Is a face filter applied to this image? Note: simple color filters do NOT count as face filters. Face filters are virtual layers with figurative elements such as animal ears, sunglasses, crowns, flowers, hearts etc.

y = YES
n = NO

5. FACIAL EXPRESSION
What is the facial expression of the person depicted most prominently (the largest face in the image)? Pick only ONE of the following options:

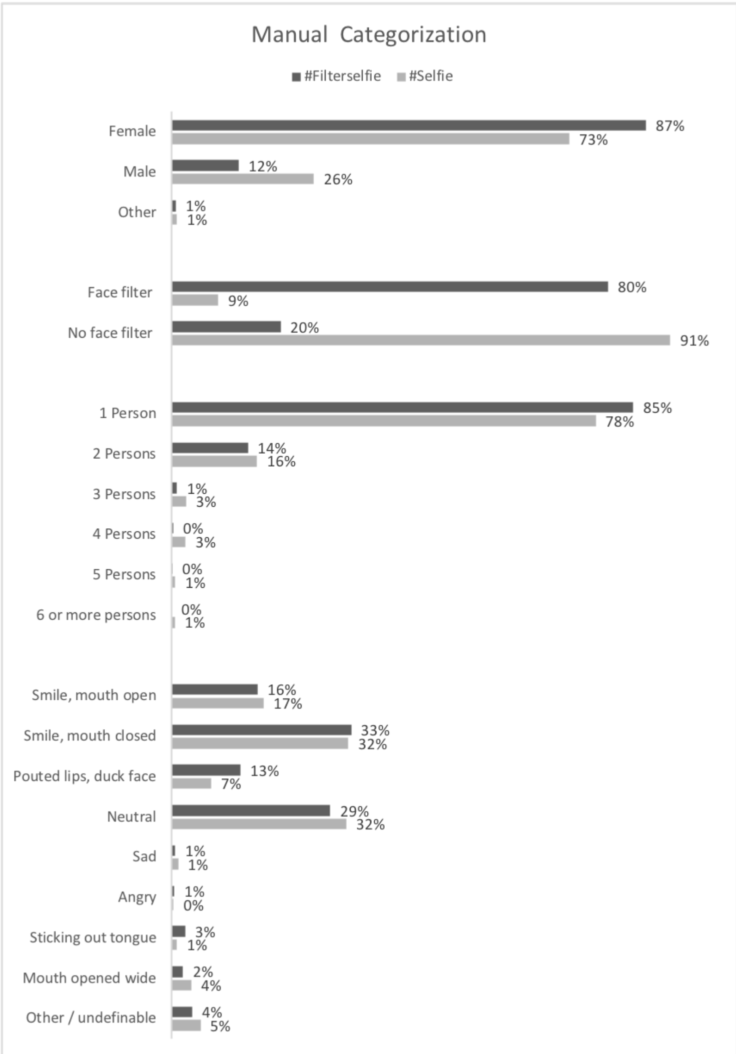
1 = Smile with mouth open, showing teeth
2 = Smile with mouth closed
3 = Duck face / lips pouted
4 = Neutral
5 = Sad
6 = Angry
7 = Sticking tongue out
8 = Mouth open
9 = Other / hard to define expression

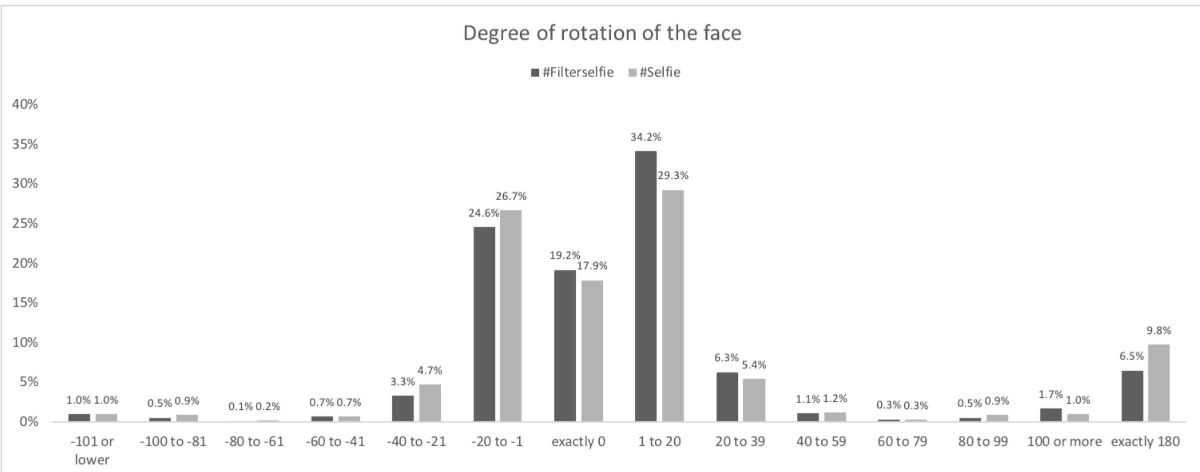
6. NOTE
If you have a note or doubt about a specific image, leave it here.

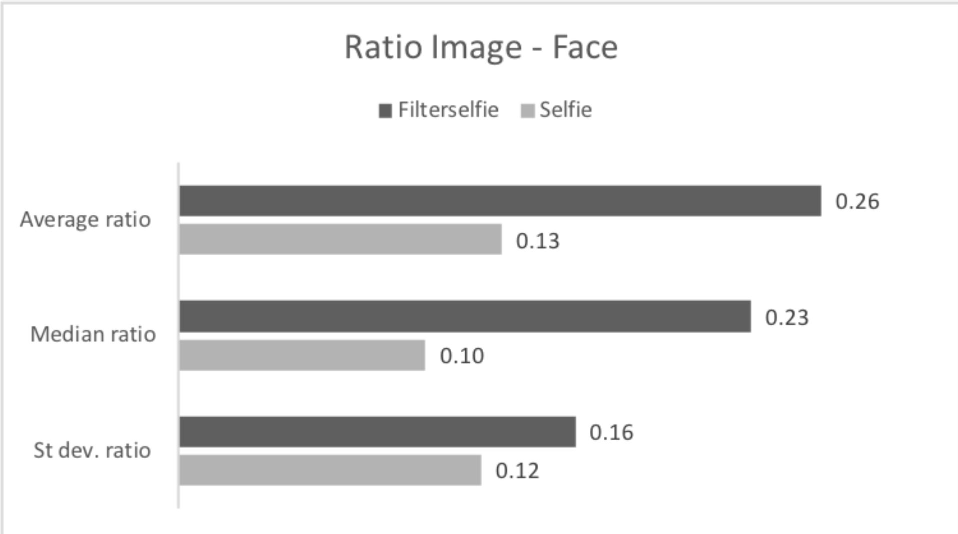
Thanks again for helping me out and if you have any questions, just ask!

8.3 Excel graphics

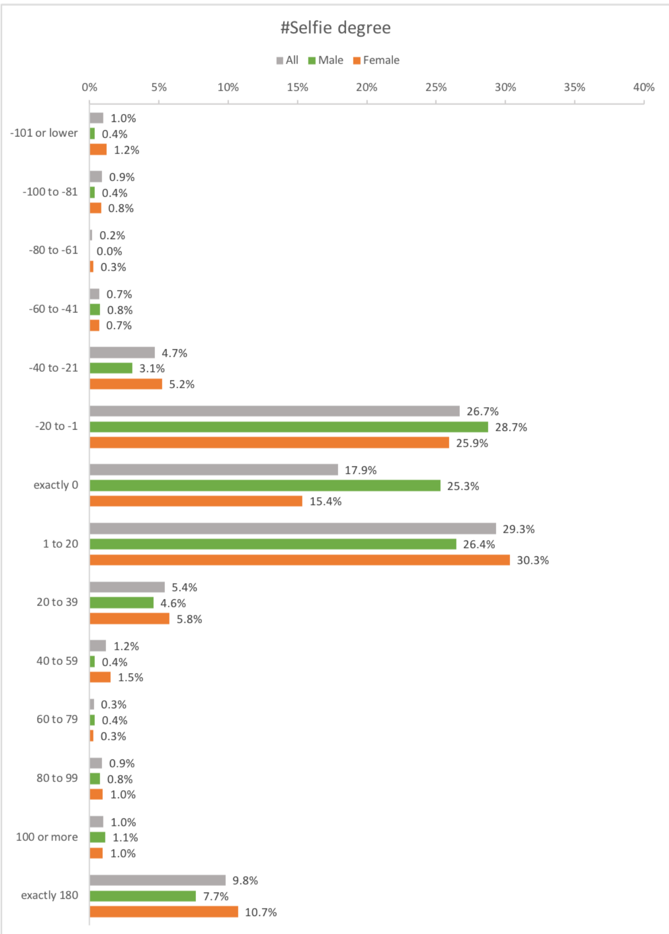
8.3.1 General comparison of the #selfie and #filterselfie datasets

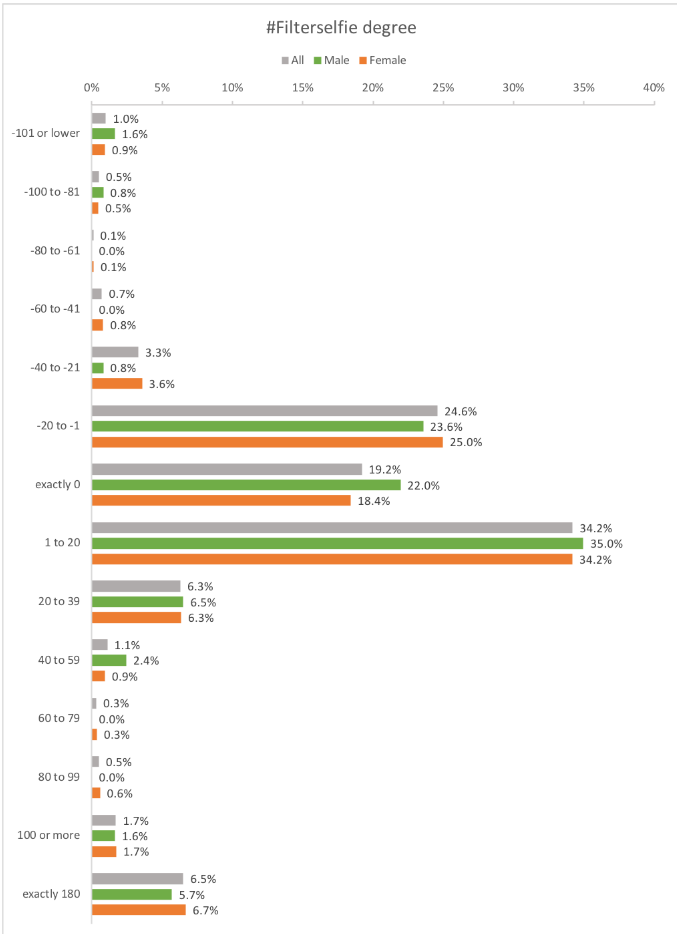


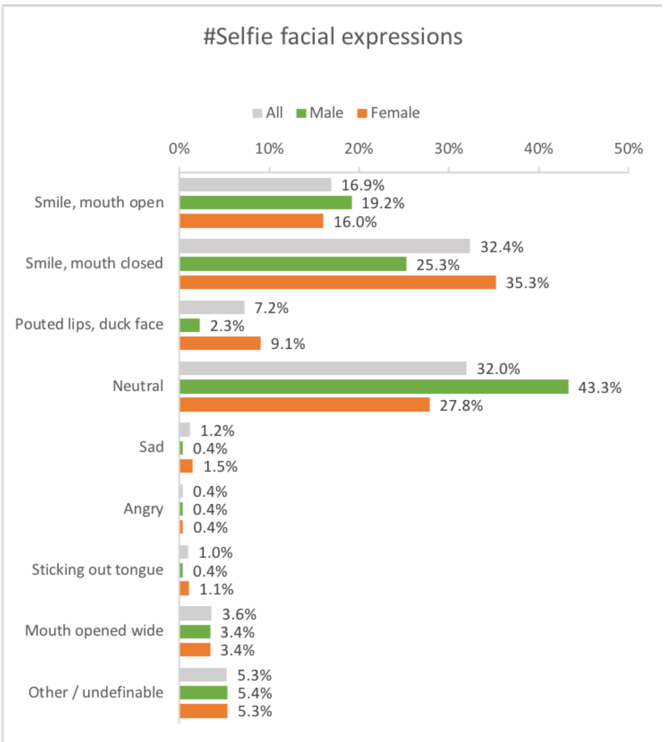


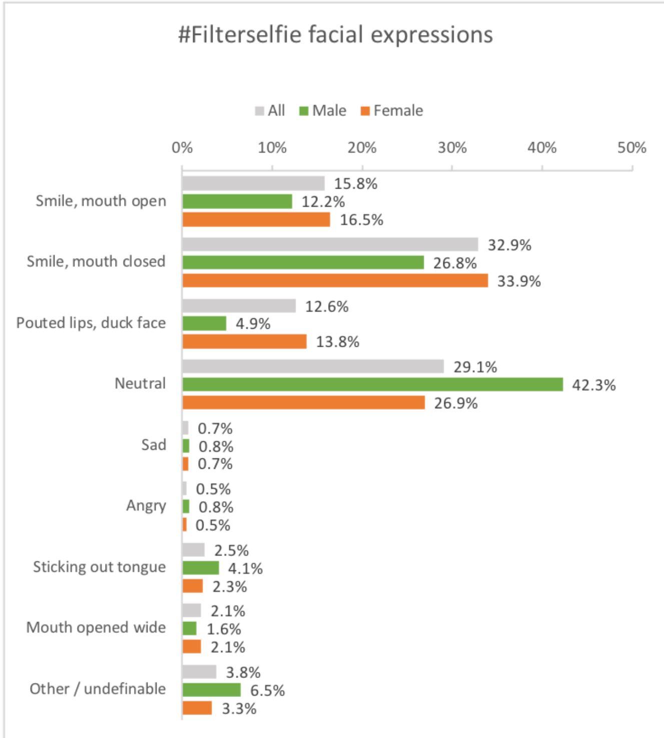


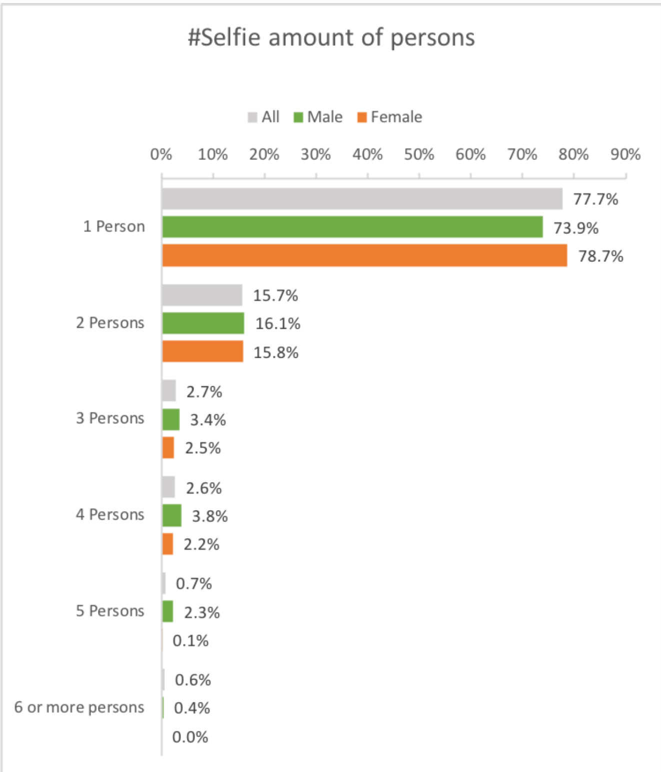
8.3.2 Comparison of #selfie and #filterselfie based on gender

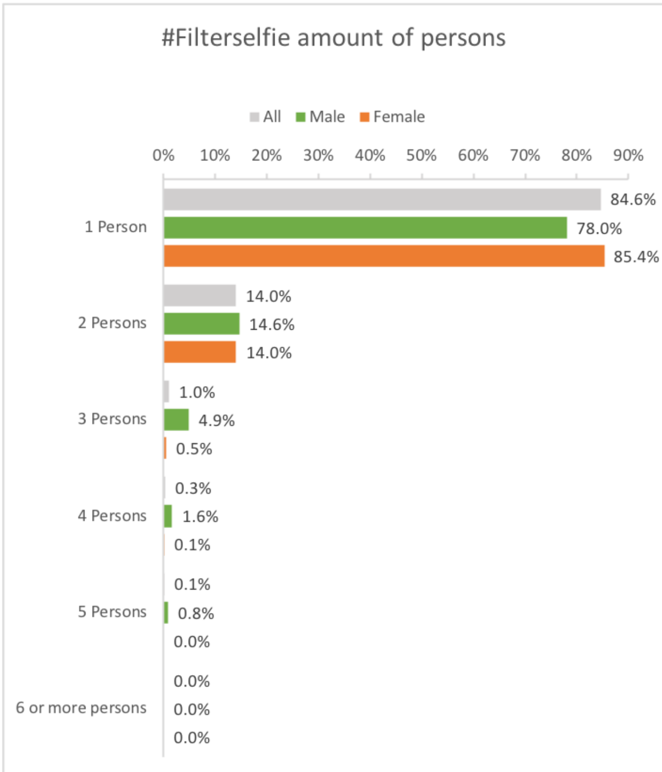





#Selfie facial expressions
All Male Female
0% 10% 20% 30% 40% 50%
Smile, mouth open
16.9%
19.2%
16.0%
Smile, mouth closed
32.4%
25.3%
35.3%
Pouted lips, duck face
7.2%
2.3%
9.1%
Neutral
32.0%
43.3%
27.8%
Sad
1.2%
0.4%
1.5%
Angry
0.4%
0.4%
0.4%
Sticking out tongue
1.0%
0.4%
1.1%
Mouth opened wide
3.6%
3.4%
3.4%
Other / undefinable
5.3%
5.4%
5.3%

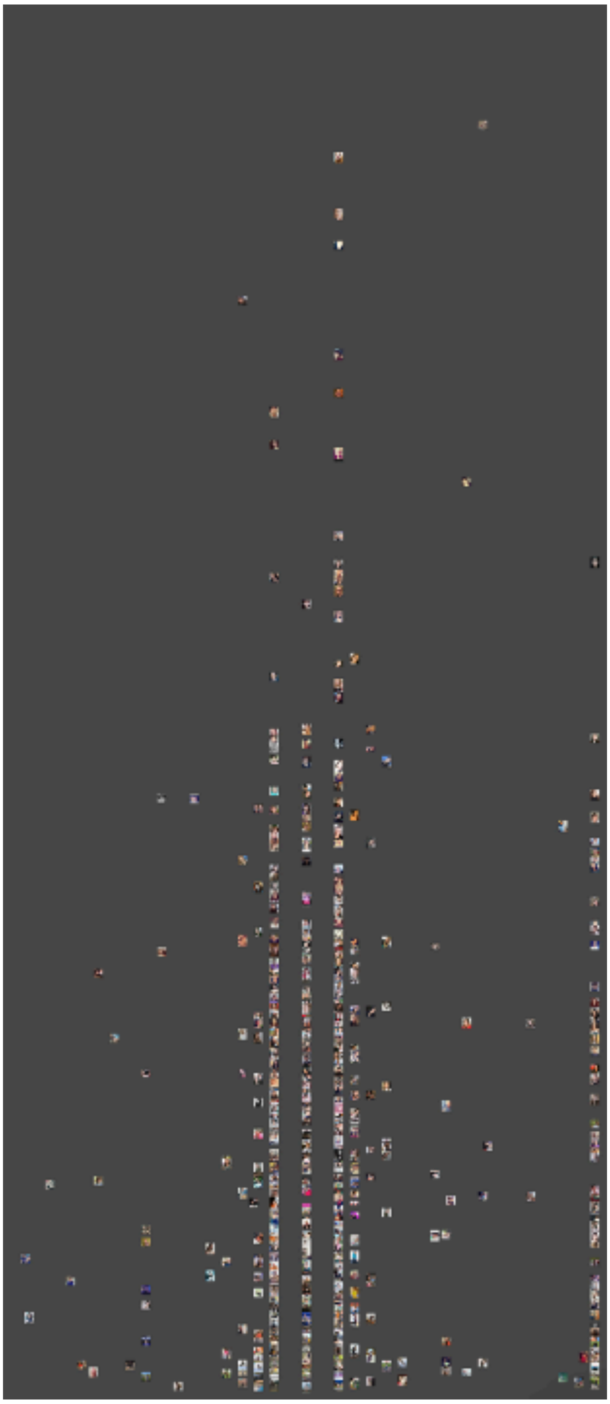

#Filterselfie facial expressions
All Male Female
0% 10% 20% 30% 40% 50%
Smile, mouth open
15.8%
12.2%
16.5%
Smile, mouth closed
32.9%
26.8%
33.9%
Pouted lips, duck face
12.6%
4.9%
13.8%
Neutral
29.1%
42.3%
26.9%
Sad
0.7%
0.8%
0.7%
Angry
0.5%
0.8%
0.5%
Sticking out tongue
2.5%
4.1%
2.3%
Mouth opened wide
2.1%
1.6%
2.1%
Other / undefinable
3.8%
6.5%
3.3%


#Selfie amount of persons
All Male Female
0% 10% 20% 30% 40% 50% 60% 70% 80% 90%
1 Person
77.7%
73.9%
78.7%
2 Persons
15.7%
16.1%
15.8%
3 Persons
2.7%
3.4%
2.5%
4 Persons
2.6%
3.8%
2.2%
5 Persons
0.7%
2.3%
0.1%
6 or more persons
0.6%
0.4%
0.0%

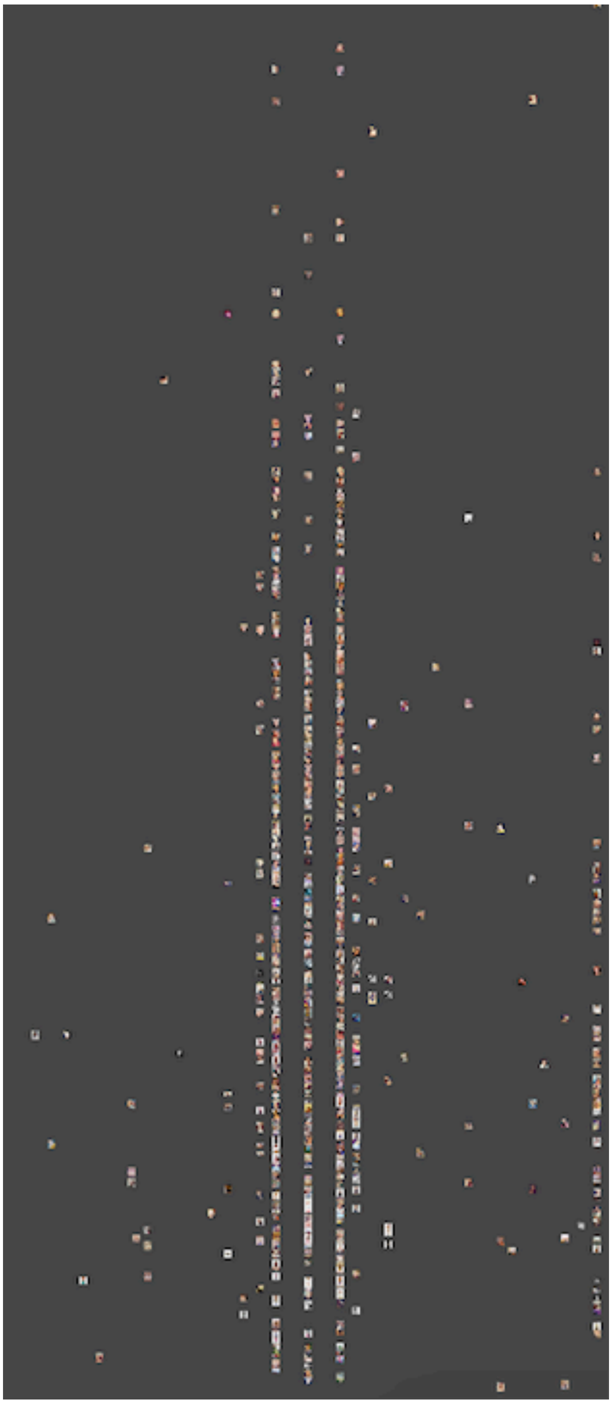

#Filterselfie amount of persons
All Male Female
0% 10% 20% 30% 40% 50% 60% 70% 80% 90%
1 Person
84.6%
78.0%
85.4%
2 Persons
14.0%
14.6%
14.0%
3 Persons
1.0%
4.9%
0.5%
4 Persons
0.3%
1.6%
0.1%
5 Persons
0.1%
0.8%
0.0%
6 or more persons
0.0%
0.0%
0.0%

8.4 ImagePlot plots

#Selfie: degree (x) versus ratio (y)



#Filterselfie: degree (x) versus ratio (y)



What we can see from these plots is that the degree is measured in integers in steps of 5, which results in lines of images that overlap, which makes them not trustworthy as a means for visual analysis. The ratio is not measured in integers, which results in a more useful expansion of images along the y-axis. From this, we can see that the #filterselfie dataset shows a generally larger number as ratio compared to the #selfie dataset.

8.5 Plagiarism Rules Awareness Statement

Universiteit Utrecht

Faculty of Humanities
Version September 2014

PLAGIARISM RULES AWARENESS STATEMENT

Fraud and Plagiarism
Scientific integrity is the foundation of academic life. Utrecht University considers any form of scientific deception to be an extremely serious infraction. Utrecht University therefore expects every student to be aware of, and to abide by, the norms and values regarding scientific integrity.

The most important forms of deception that affect this integrity are fraud and plagiarism. Plagiarism is the copying of another person's work without proper acknowledgement, and it is a form of fraud. The following is a detailed explanation of what is considered to be fraud and plagiarism, with a few concrete examples. Please note that this is not a comprehensive list!

If fraud or plagiarism is detected, the study programme's Examination Committee may decide to impose sanctions. The most serious sanction that the committee can impose is to submit a request to the Executive Board of the University to expel the student from the study programme.

Plagiarism
Plagiarism is the copying of another person's documents, ideas or lines of thought and presenting it as one's own work. You must always accurately indicate from whom you obtained ideas and insights, and you must constantly be aware of the difference between citing, paraphrasing and plagiarising. Students and staff must be very careful in citing sources; this concerns not only printed sources, but also information obtained from the Internet.

The following issues will always be considered to be plagiarism:

- cutting and pasting text from digital sources, such as an encyclopaedia or digital periodicals, without quotation marks and footnotes;
- cutting and pasting text from the Internet without quotation marks and footnotes;
- copying printed materials, such as books, magazines or encyclopaedias, without quotation marks or footnotes;
- including a translation of one of the sources named above without quotation marks or footnotes;
- paraphrasing (parts of) the texts listed above without proper references: paraphrasing must be marked as such, by expressly mentioning the original author in the text or in a footnote, so that you do not give the impression that it is your own idea;
- copying sound, video or test materials from others without references, and presenting it as one's own work;
- submitting work done previously by the student without reference to the original paper, and presenting it as original work done in the context of the course, without the express permission of the course lecturer;
- copying the work of another student and presenting it as one's own work. If this is done with the consent of the other student, then he or she is also complicit in the plagiarism;
- when one of the authors of a group paper commits plagiarism, then the other co-authors are also complicit in plagiarism if they could or should have known that the person was committing plagiarism;
- submitting papers acquired from a commercial institution, such as an Internet site with summaries or papers, that were written by another person, whether or not that other person received payment for the work.

The rules for plagiarism also apply to rough drafts of papers or (parts of) theses sent to a lecturer for feedback, to the extent that submitting rough drafts for feedback is mentioned in the course handbook or the thesis regulations.
The Education and Examination Regulations (Article 5.15) describe the formal procedure in case of suspicion of fraud and/or plagiarism, and the sanctions that can be imposed.

Ignorance of these rules is not an excuse. Each individual is responsible for their own behaviour. Utrecht University assumes that each student or staff member knows what fraud and plagiarism

Universiteit Utrecht

entail. For its part, Utrecht University works to ensure that students are informed of the principles of scientific practice, which are taught as early as possible in the curriculum, and that students are informed of the institution's criteria for fraud and plagiarism, so that every student knows which norms they must abide by.

I hereby declare that I have read and understood the above.
Name: Meike Schipper Student number: 5944635
Date and signature: 24/9/2018 M Schipper

Submit this form to your supervisor when you begin writing your Bachelor's final paper or your Master's thesis.

Failure to submit or sign this form does not mean that no sanctions can be imposed if it appears that plagiarism has been committed in the paper.