Master Thesis Data Science & Marketing Analytics

"The Effectiveness of Influencer Marketing Campaigns on Instagram: A Visual Content Analysis"

Abstract

This research provides an in-depth analysis of the relationships between visual content features and influencer marketing campaign success on Instagram. Thereby, this research establishes visual content-wise engagement drivers of Instagram influencer photos through regression analysis. These content-wise engagement drivers are established as features through extensive text analysis. Furthermore, this research establishes thematic groups in the photo collection, as well as additional photo features: the extent of unexpectedness present in each photo and the sentiment expressed on each photo. These elements are also included in the regression model. The findings indicate positive significant relationships between human-including and low-performance activity features and engagement. Furthermore, a positive relationship is established between unexpectedness and photo engagement, when being combined with millennial-trendy topics. Moreover, the results indicate positive interaction effects for the interaction between portrait photography presentation and sentiments of high valence, of both directions. Also, positive interaction effects exist for the interaction between joy expressions or associations and semi-positive feature types, as well as the interaction between sadness expressions or associations and environment- and surroundings-oriented features. Surprise expressions or associations have a positive interaction with interior design or dynamic content features and trust expressions or associations have a positive interaction with authenticity reflecting features. Photos with higher negative valences lead to more engagement upon also including luxury features, whereas photos with higher positive valences lead to more engagement upon also including somewhat authentic features. Based on these findings, this paper presents a set of practical marketing recommendations and interesting directions for further research. The views stated in this thesis are those of the author and not necessarily those of the Erasmus School of Economics or Erasmus University Rotterdam.

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1. Introduction

Today's social media climate is characterized by the privileging of instantly sharing information and trends. This development has increased the commercial value of social media in the past decade. Specifically, influencers have made their mark on social media by generating attention and buzz, through constructing a personal brand in the online atmosphere (Khamis, Ang & Welling, 2017). Influencers are an effective means for companies to target and reach their audiences through large followings (Ranga & Sharma, 2014). To illustrate the size of the matter, approximately 75% of all marketers are employing influencer marketing on social media. Furthermore, marketing spending for 2020 amounts to around 10 billion dollars reserved for influencer marketing. These numbers hold for 65% of all multinational corporate organizations (Belton, 2019; Mediakix, 2018).

Especially on the social media channel Instagram (Casaló, Flavián & Ibáñez-Sánchez, 2018), candid and perfectly illuminated fashion, travelling, lifestyle, and beauty photos of social media influencers dominate people's timelines. Through these photos, influencers are selling products using personal brand and experience. Such personal brands are capitalized on by companies and advertisers who can enjoy the authenticity, credibility, and large following of influencers to generate consumer outreach (Khamis et al, 2017). Such photos demonstrate Instagram's main principle; it is a visual medium, that relies on the imaged representation of information. This is expressed through easy and accessible photo sharing and the optics thereof (Highfield & Leaver, 2016). The relation of social media influencers to commercial impact has increasingly been a topic of research in academics. However, the research on the role of visual content herein is less dominantly represented in the current literature.

Using influencers enables communication with consumers for businesses, in the form of engagement (Uzunoğlu & Kip, 2014). Previous research has proven significant positive relationships between the engagement of influencers on social media and company profitability (Hughes, Swaminathan & Brooks, 2013; Bakhshi, Shamma & Gilbert, 2014). Engagement (in the form of post comments and likes) thus comprises a logical measure of marketing impact or success, based on the idea that it indicates popularity (Schreiner, Fischer & Riedl, 2019). Furthermore, positive relationships between influencer marketing and product adoption (Glucksman, 2017; Van den Bulte & Joshi, 2007) as well as purchase intention (Lim, Radzol, Cheah & Wong, 2017) have been established. It follows naturally that different factors can play a role in this relationship, potentially driving the engagement and thereby the profitability of influencer marketing. One of the most relevant research constructs to examine as potential engagement drivers in this relationship entails the content itself that is used and distributed by influencers. This content is hereby used to generate engagement and therefore, profitability. Such as Ferguson (2008) states; a good content strategy is the most effective method to achieve sales provocation using social media. Several previous studies researched the role of general and textual content characteristics in this relationship. A relevant example is Hughes et al (2019), who examined the relationship between the general content characteristics of influencer marketing and engagement on Facebook.

This research, however, aims to specifically focus on visual content as a potential driver of engagement. The inclusion of visual content in other social media channels than Instagram has already been proven to significantly increase engagement (Schreiner et al, 2019). Furthermore, Lee, Hoang & Lim (2017), Jaakonmäki, Müller & vom Brocke (2017) and Bakhshi et al (2014) researched the characteristics present in visual content, and the impact of several visual content features on engagement, respectively. Both entailed a context of user-generated Instagram content.

The actual substance of this visual content (the features or elements thereof) has not previously been linked to engagement in an influencer marketing context on Instagram. This denotes how this paper enriches the current academic literature and attains its scientific relevance. Such relationships could provide a fundament for how the inclusion of visual content causes engagement. Thereby, they could provide information as to which visual content features should be depicted on Instagram photos to inspire engagement and profitability. This could aid both companies and influencers to improve marketing decision making. Given the abovementioned size and relevance of the issue, the recommendations derived from this research therefore also provide sufficient managerial relevance. Instagram is, because of its visual essence, the most relevant medium of research for this paper. For these reasons, this research aims to answer the following main research question:

“Which in image depicted content makes influencer marketing campaigns on Instagram successful?”

To answer this question, this paper presents scientific manners to detect and represent the visual content features and elements that are present in influencer photos on Instagram. Also, this paper presents scientific methods to research the relationship of these features and elements to engagement. These features and elements entail both visual content substance itself, as aspects of visual content substance. An interesting insight from other content types is that often, the unexpected causes more engagement than the expected (Tellis, MacInnis, Tirunillai & Zhang 2019). This is considered a crucial component in the relationship of interest, being an element of visual substance as well as a useful contribution to the academic knowledge on this topic. This paper therefore aims to research the role of this element in influencer photo engagement as well. Furthermore, this paper takes into account the presence of different underlying themes in the relationship between established visual content elements and engagement, based on Lin & He (2009) and Lee et al (2017). Therefore, the following sequence of sub research questions is in this paper consecutively answered:

RQ1: "Which visual content features can be detected in the photo content of influencer marketing campaigns on Instagram?"
RQ2: "Which groups or themes can be found in the photo content, and how can these groups be characterized?"
RQ3: "What is the extent of unexpectedness present in the photos?"
RQ4: "Which content elements lead to the most campaign success, measured by post engagement within each group?"

This paper proposes a set of scientific methods, entailing topic modelling, word embeddings, cluster analysis and regression, to provide accurate and useful answers to these research questions. Hereby, this research also provides a methodological contribution to current literature on visual content analysis. Currently, this literature is relatively scarce as a result of the complexity of visual content. Previous relevant research, such as Bakhshi et al (2014) and Ging and Garvey (2018), provide solely an unsupervised approach to (visual) Instagram content analysis, respectively through cluster analysis and qualitative text analysis. Jaakonmäki et al (2017) do present a supervised research approach utilizing both topic modelling and regression to determine the relationship between content and engagement, however without the establishment of significance. Hughes et al (2019) in turn operated with the establishment of significance, but without the employment of a predictive model.

This paper methodologically advances previous research by integrating both unsupervised and supervised research and establishing significance for the latter. Furthermore, this paper introduces both non-negative matrix factorization and global vectors for word representation as methods for visual content analysis, which has not been done in previous research. Lastly, this paper introduces unexpectedness as an element to model engagement as a result of visual content by empirically quantifying unexpectedness.

2. Theoretical Framework

2.1 Literature Review

2.1.1 Characterizing Visual Content on Instagram: Visual Content Entities

Highfield & Leaver (2016) provide a global profiling of the characterization of visual content on social media. They describe it as the crucial operator behind story-telling and meaning-making, thereby integrating authentic images with refinements, photomontage and retained messages. They furthermore state that visual content on Instagram, which takes the form of photos, can be characterized globally with three main drivers. In the first place, the aesthetic characteristic, which is expressed in the availability of numerous filters. In the second place, the enablement of immediately sharing material. This is voiced through the ease and accessibility of photo sharing and the domination of instantaneous life-sharing photographs and spontaneous snapshots. Lastly, the presence of hashtags dominates visual Instagram content. Hashtags are often displayed on top of photo content as an overlay to involve another user or to draw more user attention to the subject placed behind the trope. More specifically, unsupervised content analysis by Lee et al (2017) points out that regarding the substance of the depicted content, the most popular general Instagram photos respectively show Gatherings and Outings (22.5%), Fashion (20.9%), Food, Drinks (10.0%) and Landscape and Travel (7.7%).

2.1.2 Quantifying Visual Content on Instagram: Visual Content Features

A general positive relationship between the inclusion of visual content entities (such as photos) and post success, measured by engagement, was already established in multiple previous studies (Schreiner et al, 2019). However, the current literature on how visual content itself, or the actual substance of image content, can be tied to success in a social media marketing setting is still relatively scarce. This is an inherent result of the complexity of quantifying and measuring the substance in visual content. However, previous literature offers relevant insights and precedents on how to characterize visual content entities, such as photos, using visual content features.

Instagram photos, which represent visual content entities, can be summarized as the sum of visual content features. Visual content features are characteristics or parts of visual content entities, such as depicted objects or actors, lighting characteristics, colour use or background features. This quantification is based on

Bulmer & Buchanan-Oliver (2006), who present visual rhetoric as a concept to describe visual content. Visual rhetoric entails that the communication manner in which images are employed to capture an essence, generate an understanding and convey reasoning. Looking at the visual rhetoric of content means considering the optical whole of the content, through analyzing all the visual content features of the visual content itself as well as their interactions. Examples of visual content features are objects, actors, colour use, placement and presentation.

This paper therefore hypothesizes such visual content features as potential success-drivers for engagement, rather than the visual content entities (the photos) themselves. This means that all the visual elements of that visual content entity, such as objects, actors, colour, placement and presentation should be identified and considered. Hereby, it is identified how a visual content entity as an optical whole causes engagement, through the sum of its elements. The visual rhetoric theory thus reflects that visual content should be considered as different visual content parts, instead of one visual content entity.

Visual content features entail a better operationalization of visual content compared to content entities because it is a better approximation of how people psychologically process visual content. The structure of image content is distinctly different from conventional content, such as text. Textual content entails arbitrary relations between its different elements. The sound of a word is generally perceived to be in accordance with the appearance as well as the meaning of that word. For imagery, however, this is not the case. The relations between different elements that make up the whole are too complex to arbitrarily consider and understand (Phillips & McQuarrie, 2004; Hjelmslev, 1961; Bulmer & Buchanan-Oliver, 2006). Therefore, it is more logical to consider all these separate elements (the features) of the visual content, to simulate the manner of consumer processing of the content. Furthermore, Unnava & Burnkrant (1991) state that human memory codes visual and textual content in different ways, whereby visual leads to more spontaneous psychological labelling and entails more imaginary power. This suggests that elements of a visual content entity have a rather strong identity in the interpretation of visual content, making it also more likely to consider all these elements (features), rather than just a whole image, in order to simulate the manner of consumer processing of the content. These theories show that consumers psychologically process (understand as well as remember) visual content through the visual content features of that content, as opposed to considering the visual content as one entity.

The applicability of the theory of visual rhetoric in marketing was already established in renowned marketing theory by Scott (1994); in advertising, consumers' processing of imagery is dependent on the visual rhetoric of the respective image. Campelo, Aitken and Gnoth (2011) elaborate hereupon by stating that the use of visual rhetoric, comprising image content as a primary element, should in advertising be used as an instrument to deliver and shape the marketing message in the mind of the consumer. Furthermore, Highfield & Leaver (2016) provide precedent on how the theory of visual rhetoric can be linked to marketing impact. They show that considering elements of a picture as the crucial operative of that picture maximizes the consideration of the role of the sentimental value of the visual in causing marketing impact.

This theory is likely to also apply in a social media influencer context. This paper anticipates hereupon by viewing the Instagram photos as visual content entities and establishing visual content features to reflect the visual elements that make up this entity ("*Which visual content features can be detected in the photo content of influencer marketing campaigns on Instagram?").*

A typical manner, as presented in the current literature, to quantify and establish visual content features present in visual entities, is the usage of word tags. These are textual descriptions of the subject matter that is present in a photo. The *Clarifai* algorithm produces a common format for such word tags. *Clarifai* is a third-party tool that relies on image recognition through complex neural networks, to extract textual descriptions in the form of tags of the content present in a picture (Wang, Mao, Wang, Rae & Shaw; 2018). The algorithm produces objects and presentational themes in noun form (e.g. woman, fall), actions in verb or noun form (e.g. swimming, relaxation) and expressions or feelings in adjective or adverb form (e.g. pretty, fun, joyful). The *Clarifai* API is recognized for its high accuracy of 89.3% (*Clarifai* Technology, 2016). An example of earlier work that conducted a visual content analysis based on such *Clarifai* word tags is Jaakonmäki et al (2017).

This research also makes use of such word tags to quantify visual content and correctly answer research question 1. This research, however, presents methodological approaches to transform these word tags into more suitable visual content features. This is further discussed in Chapter 3.

2.1.3 Visual Content Features and Engagement

Previous papers provide relevant precedents for linking visual content features and engagement in other, non-commercial contexts. They thereby prove the actual applicability and relevance of visual content features over visual content entities. An overview of the visual content features used in these researches and the effects found is given in Table 1 below.

Table 1: Overview of Established Effects for Visual Content Features in Other Contexts [1]

Visual Content Features	Found Effect	Research Source
babies, animals*, surprise-arousing*	• All increased engagement in a Youtube video context	Tellis, MacInnis, Tirunillai & Zhang (2019)
*human faces**	• Increased engagement in an Instagram photo context	Jaakonmäki, Müller & Vom Brocke (2017)
contemporary visual trends ("Memes" and "Internet Ugly)	• Increased engagement in an Instagram photo context	Highfield & Leaver (2016)
use of filters, use of light and low-saturated colours, use of red colour* versus *use of blue colours*, use of dominant colour* versus *wide range of dominant colours*	• *Use of filters*, *use of light and low-saturated colours* increased engagement over *vibrant dark colours* in an Instagram photo context • *Use of red colours* led to more engagement than *use of blue colours* • *Use of one dominant colour* led to more engagement compared to a *wide range of dominant colours*	Bakhshi, Shamma, Kennedy & Gilbert (2015)
human faces, duck-face selfies, 'real' people*, high number of stimuli, older people**	• *human faces*, *duck-face selfies*, *'real' people* rather than *models* increased engagement in an Instagram photo context • *high number of stimuli*, *older people* decreased engagement in an Instagram photo context	Bakhshi, Shamma & Gilbert (2014)

[1] *Visual content features indicated with * are also included in the empirical analysis in this research paper because the Clarifai algorithm has the potential to detect them or variants of them, see also section 3.1*

Tellis et al (2019) argued that visual content features such as babies and animals aroused emotions and therefore inspired high engagement. This indicates that such elements are more relevant to consider than the video as a whole because they locate where the sentimental value of such visual content is inspired. Sentimental value is captured by certain visual content elements, such as objects (babies, animals). Furthermore, Bakhshi et al (2014) and Bakhshi et al (2015) show that visual Instagram content features can be subdivided into substance features (the actual objects and ideas depicted, such as human face depictions) and presentational features (the manner in which these objects and ideas are depicted, such as the use of light).

Findings such as the ones in Table 1 may extrapolate to other marketing contexts (Jaakonmäki et al, 2017), such as the social media influencer one in this paper. Furthermore, there is extensively more relevant information to be collected regarding the relationship between visual content features and engagement, as there are infinitely more content features yet to be researched (Bakhshi et al, 2014).

The existing dominant theoretical basis that underlies how visual content features can cause engagement comprises the idea that high engagement is driven by the sentiment expressed by a particular visual content feature (Highfield & Leaver, 2016). In other words; visual content features can capture (and potentially induce) sentiment, in the form of an emotion or a valence. Sentiment captured by photos refers to the sentimental value expressed on that photo. An example hereof is the sentiment tied to a facial expression that is depicted on a photo. Lewinski, Fransen & Tan (2014) found that happy facial expressions on photos also led to a happy sentiment of the consumer viewing the photo in an advertising context. Therefore, it is plausible that sentiment expressed by a photo also induces sentiment in consumers. This induced sentiment is, in turn, a strong engagement predictor in social media (De Vries & Carlson, 2014). A similar effect was found by Highfield & Leaver (2016); pictures that express high-intensity arousal and strong emotions, of both positive and negative valence, are more likely to go viral than pictures that contain no emotional appeal. This is likely to elicit excitement sentiment in consumers, which drives their engagement (De Vries & Carlson, 2014).

Research by Ging and Garvey (2018), Warrick (2019) and Jaakonmäki et al (2017) shows further consonance with this theory. Specifically, they deliver concrete examples of how post engagement as a result of the visual content features of that post, is provoked by sentimental involvement. Ging and Garvey (2018) show by means of an analysis of pro-anorexia content on Instagram that differently characterized images, based on content, can elicit different emotions in young female social media users. The post engagement of anorexia-stimulating posts hereby could be explained by the emotional backlash Instagram users were experiencing as a result of the content substance of the post. Warrick (2019) presents empirical evidence that high-engaging travelling photos on Instagram inspired users to travel themselves, as a result of experiencing happy sentiment when looking at the content. Jaakonmäki et al (2017) show that visual content depicting people and emojis leads to significantly higher engagement when the expressions of these people and emojis represent positive emotions such as love, joy and relief, causing the users to assimilate with these emotions. This is in accordance with the theory of De Vries & Carlson (2014) that the extent to which content induces sentimental value is causal in explaining engagement.

These theories and precedents demonstrate that the sentiment expressed on visual content is a dominant cause for how people choose to engage with that content. This theory is likely to apply in the context of commercial research as well; sentiment is inherently linked to consumers and consumer behaviour and therefore, likely to play a role in both commercial settings and non-commercial settings. Furthermore, emotional appeal has been established to be the most dominant explanatory factor in the virality of textual online marketing content (Berger & Milkman, 2012). This effect could arguably extend to visual online content because the marketing goal of the content remains the same.

This research integrates the theory from the abovementioned insights through examining whether significant effects can be established between visual content features and engagement (research question 4). Furthermore, this research anticipates on the abovementioned theory by using sentiment to most accurately model research question 4, in order to isolate the correct effect for the visual content features and the role sentiment plays herein. It should be noted that sentiment hereby reflects the sentiment captured by the photos, based on sentiment analysis (see also section 4.3).

2.1.4 Insights from Other Content Types: The Importance of Unexpectedness

The current findings regarding the influence of visual content features on engagement are still relatively general (See Table 1), as a likely result of the complexity of researching visual content. However, in other content types more detailed content analyses have been conducted in the relevant context. Engagement has hereby proven to often be the result of more nuanced and distinct factors, such as the unexpected elements comprised by the content of interest.

Bruni, Francalanci & Giacomazzi (2012) present that in order for textual content to lead to virality on Twitter, a notion of 'meaning' is essential. Meaning is described as how content leads to a change of mind, and therefore a new insight, for the consumer. This presents the notion that engagement may sometimes be a result of the unexpected, rather than the expected, in terms of what is visually depicted. This theory is underlined by Antretter, Blohm, Grichnik & Wincent (2019), who present empirical evidence that 'buzzing' user-generated content on social media comprises elements of anomaly or unexpectedness. Tellis et al (2019) furthermore state that surprise ensures that content is not experienced as trivial and uninteresting in a Youtube video context. Surprise is hereby a proxy for the extent to which the content comprises unexpected elements. Tellis et al (2019) prove that unexpectedness leads to significantly more engagement, as a result of the drama and suspense that viewers experience upon unexpected elements, rather than expected ones. Pickering & Jordanous (2017) show the same results in a context of narrative content, by presenting that unexpectedness (the extent to which content deviates from prior expectations) is vital. Predictability namely leads to an unsatisfying experience for the reader. In a more visual-driven content form, Chen & Lai (2014) show that unexpectedness is a main driver of interest and therefore has better communication value in the context of artistic design. Furthermore, viewers perceive unexpected elements as more memorable (Chen & Lai, 2014), simply because they deviate from the usual.

These findings illustrate that underlying, sophisticated and nuanced content elements, such as unexpectedness, have the potential to impact the engagement of a content entity on social media. It seems intuitive that the massive volume of social media, especially in the influencer atmosphere, can be experienced as relatively uniform in its outings. The inclusion of something deviating from the usual in a post might have a positive influence on engagement.

This paper calculates and establishes the extent of unexpectedness present in influencer photos on Instagram (research question 3). Also, this paper examines the relationship between unexpectedness in Instagram influencer photos and engagement, in order to potentially extrapolate the abovementioned results to an influencer marketing context (research question 4).

3. Methodology

3.1 Research Approach

This paper aims to advance the current methodological approaches in visual content analysis through the research approach as illustrated in Figure 1.

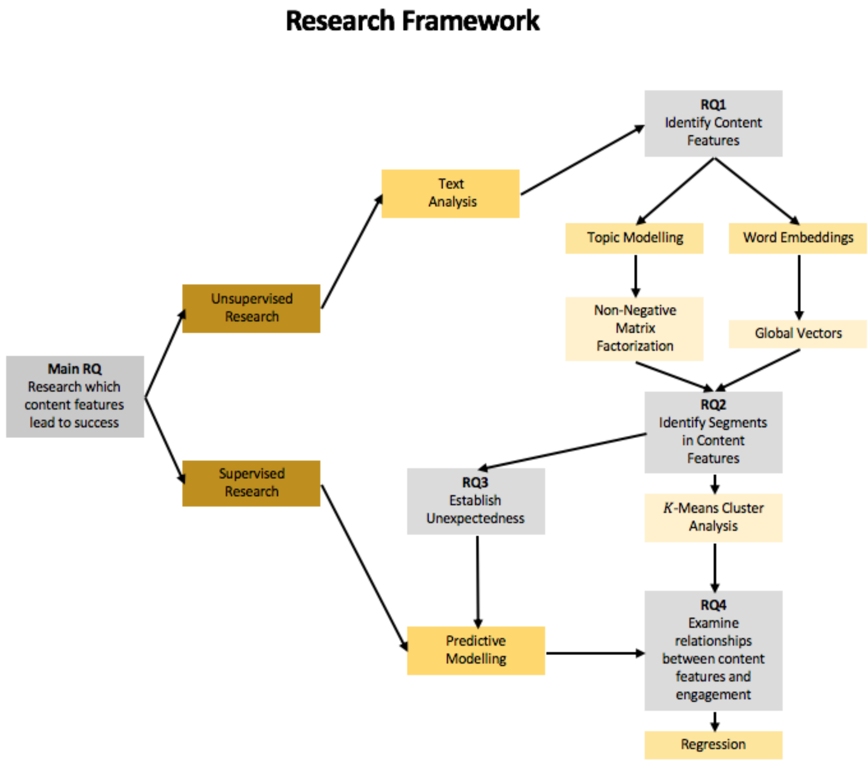

Figure 1: Illustration of Research Framework

Figure 1 shows that the research employed in this paper entails both unsupervised and supervised analyses to answer the main research question. First, an unsupervised content analysis (classified as text analysis) using topic modelling, word embeddings and cluster analysis, is employed. Underlying visual content features in the visual content are first identified to answer research question 1; *"Which visual content features can be detected in the photo content of influencer marketing campaigns on Instagram?".* Topic modelling is employed in the form of non-negative matrix factorization. Word embeddings are employed through global vectors for word representation.

Subsequently, cluster analysis is applied to distinguish underlying, larger structures in the photos based on these visual content features. This answers research question 2; *"Which groups or themes can be found in the photo content,* *and how can these groups be characterized?".* The K-Means algorithm is used to execute the cluster analysis.

These clusters as well as the visual content features are used to quantify the unexpected elements present in the photos. This answers research question 3; *"What is the extent of unexpectedness present in the photos?".*

Lastly, both the clusters and the unexpectedness are, amongst other control variables, used in the supervised research. This takes the form of predictive analysis, intending to examine the relationships between the identified visual content features and campaign success. Campaign success is measured by engagement. Hereby, an answer is provided to research question 4; *"Which content elements lead to the most campaign success, measured by post engagement within each group?".* Specifically, both linear regression and LASSO regression are employed as means of predictive modelling.

3.1.1 Text Analysis

Text analysis is used to identify and establish visual content features based on word tags that reflect the visual content data. The underlying idea is that engagement on influencer marketing campaign posts is driven by (consumer's attitude towards) the visual content features of the Instagram photos (the visual content). This makes the correct operationalization of such visual content features relevant and crucial. Since the word tags that reflect the visual content data entail textual data, text analysis is an integral part of the methodological approach in this paper. It is expected that visual content features can be more suitably epitomized using topics and word embeddings, compared to their original tag word format. This is based on a comparison of both methods by Qiang, Chen, Wang & Wu (2017), of which the applicability for this research is discussed below. It should be noted that for each method explanation in the remainder of this section, the letters used to indicate the parameters are specific for each method: similar letters may indicate different parameters for different methods.

The **topic modelling approach** views the visual content features that are to be established based on the visual content data, as topics. Topic modelling employs a global context scope to establish these topics. A global context reflects a document-level context, where a document entails one text unit in the corpus of text, reflecting all the tag words linked to one photo post. The text corpus refers to the aggregate of all documents.

Through this context scope, topic modelling examines which topics (visual content features) are prevailing over all the documents (Instagram photo posts) in the data set. This incorporates the use of the bag-of-words assumption; the location and order of words is not considered. As such, similar pictures throughout the entire corpus, as well as underlying themes over all the *Clarifai* tags, are detected.

Essentially, the employment of such a global scope and the bag-of-word assumption enables the identification of predominant underlying themes in the visual content of all the influencer marketing campaigns. Summarizing similar tag words into overarching themes hereby leads to more meaningful and distinct concepts compared to the extensive collection of tag words. These themes can then be viewed as viable visual content features. Engagement may be the result of such overarching concepts rather than individual tag words because individual tag words may take different forms to express the same meaning. In other words: dimension reduction, the process of reducing a set of variables to a smaller set of principal features, makes interpretation easier.

For example; if photos reflect images of hamburgers, fries and sodas the tag words associated with those photos are *hamburger*, *fries* and *sodas* respectively too. However, topic modelling would produce the underlying dimension "junkfood" to overarch these terms. This is more informative and meaningful about the actual content-wise interpretation that relates to the engagement of that post. Also, it is more practical with regards to the marketing recommendations that can be derived upon it. Topics are thus more descriptive and informative than single words, as they are not as sensitive to trends and specificities. If the manner of presentation varies over different entities, topics will still reflect the same underlying theme, while keywords remain somewhat arbitrary (Lau, Collier & Baldwin, 2012).

Topic modelling fits the structure of the data; topic models disregard the order of words in a text (photo), and tag words as produced by the *Clarifai* algorithm have no recognized structure.

Non-Negative Matrix Factorization (NMF), as proposed by Lee & Seung (2001), is employed as a topic modelling method. This technique has proven to be more suitable for textual data relating to visual content in a 'keywords-only' scenario (Chen, Bordes & Filliat, 2016), compared to other topic modelling approaches. This corresponds to the format of the dataset used for this research; the *Clarifai* algorithm produces a set of isolated words.

Furthermore, Non-Negative Matrix Factorization is recognized for its ability to simulate human-like data processing in order to arrive at practical recommendations.

This processing takes the form of identifying separate components that constitute an entity (Chen, Liu & Lin, 2019). This is a proper basis for this research because Instagram photos represent an overall entity of separate depictions (visual content features). Hereby, the whole entity, entailing a combination of all visual content features, must be considered.

Non-Negative Matrix Factorization is a predominant topic modeling technique that aims to detect underlying meaningful topics in text data. To do this, NMF employs the topical patterns carried by global context information under the bag-of-words assumption, to learn topic structures from a text corpus. NMF is a form of matrix factorization, which relies on the principle of reducing the dimensionality of a dataset by deconstructing it into smaller parts. The dataset can hereby be reconstructed through interpreting the sum of these parts.

This dataset that forms the input of the NMF analysis, takes the form of a term-document matrix: matrix V of dimensions $m \times n$, whereby m is the total number of terms across a set of documents and n is the number of documents in the data set. NMF decomposes this matrix into two smaller output matrices: a $n \times k$ matrix H and a $k \times m$ matrix W. k hereby represents the inner dimension of W and H (the number of topics to be determined) and should therefore suffice $k <$ min (m, n).

The product of the two matrices approximates V, such that $V \approx WH$. W is hereby called the basis matrix and reflects terms, H is called the coefficient matrix and reflects documents. Each i th column v of V can be calculated through the multiplication of each ith column h of H with W. Thus, one element of V is the dot product of a row and a column from W and H respectively. Columns hereby reflect terms and rows respectively reflect documents. Since $k < n$ and $k < m$, the dimensionality of the dataset is through this factorization reduced by detecting a smaller set of overarching components (the topics) in the term-document matrix.

Specific for NMF as a matrix factorization method is that it introduces non-negativity: it replaces all values < 0 in the matrices with 0, causing all elements of W and H to be ≥ 0.

The mathematical representation of this matrix factorization problem aims to establish W and H through minimizing the Euclidean distance between the V and the product of W and H. This representation includes the non-negativity constraint and is presented in equation 1:

$$\min_{W,H} \|V - WH\|_F = \sqrt{\sum_i \sum_I (V_{iI} - (WH)_{iI})^2}$$

subject to $W_{ij} \geq 0$, for $i = 1, \ldots, n; j = 1, \ldots, k$

$$H_{jI} \geq 0, \text{for } j = 1, \ldots, k; I = 1, \ldots, m. \quad (1)$$

Equation 1 is solved with Alternating Constrained Least Squares, which iteratively establishes W and H through alternatively solving the optimization of W and H conditionally on the other. This is illustrated by equation 2 and 3.

$$\min_{W} ||H^T W^T - A^T||_F^2, \text{subject to } W \geq 0 \quad (2)$$

fixes H and optimizes with respect to W, and

$$\min_{H} ||WH - A||_F^2, \text{subject to } H \geq 0 \quad (3)$$

fixes W and optimizes with respect to H.

After their creation, the matrices W and H can be interpreted respectively as factors and loadings; respectively the observed overarching topics and the representation of these topics in documents. Hereby, NMF succeeds in identifying underlying topics, as a result of learning a parts-based representation of a whole through which a grouping component is inherently introduced.

Interpretation of the NMF output relies on interpreting themes based on high-loading terms for these themes.

Word embedding models view the visual content features that are to be established as word embeddings. Word embedding models consider a local context scope. A local context refers to a word-level neighbourhood scope that covers a focal window: a focus word and its neighbouring words.

Through this scope, word embedding models establish word meanings reflected by word embeddings (visual content features) over the entire text corpus (all the word tags). The word meanings, and therefore embeddings, are hereby derived from the neighbouring words of each word. These local contexts contain syntactic and semantic properties of the words. In this manner, word embedding models capture the meaning, in the form of syntactic and semantic properties, of all individual *Clarifai* tags.

Essentially, word embeddings establish the meaning of a feature depicted on a photo, based on the other entities features on that Instagram photo. The relevance hereof lies in the notion that engagement of a photo post may not only be a result of the objects depicted upon that photo, but also synergies and contextual information of these objects. Consumers may like certain visual content subjects only in combination with other certain visual content subjects (Lin & He, 2009).

For example; the word “blue” may have a positive association for most people when presented in combination with “sky”, but a negative one when presented in combination with “face”. Word embedding models have the potential to shed light on such contextual or semantic differences in photos. Therefore, the added value of a word embedding model in the frame of this research is that it establishes a more subtle and detailed interpretation of visual content features in the visual content data. In comparison, the visual content features produced by topic models are rather general and robust. Word embeddings are more likely to capture the senses of ambiguous words, for which topic modelling employs too broad a context (Qiang et al, 2017).

It should be noted that word embedding models are at first sight not a likely choice with regards to the nature of the data used in this research. The *Clarifai* platform produces a set of isolated words rather than a structured text, in no recognized order. This essentially makes a local context of semantics and syntactic characteristics non-existent.

Through a comparison with the topic modelling approach, this research, therefore, aims to establish whether the established visual content feature interpretations substantially differ upon the text analysis approach used. This also demonstrates whether, for the word embeddings approach, the potential benefits can outweigh the potential unsuitability of the data set and still produce useful insight. An argument in favour of the latter is that word embedding models focus on interpreting meaningful words, such as keywords, based on surrounding words. Frequently-occurring adverbs, linking words, pronouns and prepositions (e.g. “the”, “I”, “an”) make up the better part of conventionally structured texts and therefore often occur in local contexts. However, such words are not necessarily meaningful to derive meaning upon. For the *Clarifai* tags used in this research, this is not an issue.

The **Global Vectors (GloVe)** model, as presented by Pennington, Socher & Manning (2014), is employed as a word embedding model to perform the desired analysis. GloVe is the only word embedding model that corrects for word repetition in textual data. Most earlier invented word embedding models define context by selecting a focal window around the word of which the meaning is to be predicted, not making use of the general descriptive statistic word repetition within the dataset. This leads to rather meaningless words being identified in the observed linguistic patterns (Pennington et al, 2014). This causes a certain shallowness of such models, which would in this research be expressed through objects with a very high occurrence frequency, such as a face on an image.

The GloVe model uses the general descriptive statistic word repetition as a basis for its model, thereby eliminating the aforementioned shallowness through analyzing the context on a deeper level. GloVe thus attains a higher probability of identifying (meaningful) details. As a result of this, the technique has proven to outperform other word embedding models on various evaluation metrics (Pennington et al, 2014).

Global Vectors is a word embedding technique that aims to use the idea of context to derive the meaning of a word. To do this, GloVe utilizes the semantical properties carried by local context information, to learn word embeddings from a text corpus. Local context hereby reflects a focal window of size z. Meaning is thus expressed in the form of word embeddings: vectors of words that carry meaning. Essentially, GloVe is thus a method to convert words into meaningful word embeddings.

This is basically executed by decomposing the input of the analysis; a $p \times q$ co-occurrence matrix X. A co-occurrence matrix contains all words present in the text corpus as rows and columns, whereby the entries indicate how often respective words appear together. For arbitrary words i and j, the matrix entries $X(i,j)$ should be bigger if word i appears in the context of word j often and vice versa. GloVe uses this co-occurrence matrix to establish co-occurrence probability ratios. These ratios of co-occurrence probabilities are more informative to distinguish between relevant and irrelevant words as well as relevant words and other relevant words compared to co-occurrence probabilities themselves.

Words often have a long tail distribution, causing the matrix to be sparse and to have large non-zero entries. GloVe therefore transforms the entries to logarithms, in order to scale down these large entries. Equation 4 mathematically represents how the logarithmically transformed entries of this matrix are used to establish meaningful word vectors, whereby w_i and reflects the word embedding for word i and $\widetilde{w}_k$ reflects the word embeddings of context words k. Equation 4 includes bias terms for the word- and context vectors; b_i for w_i and $\widetilde{b}_k$ for $\widetilde{w}_k$.

$$w_i^T \widetilde{w}_k + b_i + \tilde{b}_k = \log(X_{ik}) \ . \tag{4}$$

As the matrix entries causing sparseness are not actually missing, but equal to 0, and the logarithm of 0 does not exist, these entries are replaced by 1. This takes the mathematical form of equation 5:

$$w_i^T \widetilde{w}_k + b_i + \tilde{b}_k = \log(1 + X_{ik}) \ . \tag{5}$$

After this preparation of the co-occurrence matrix, matrix decomposition is applied through minimizing least squares, with the inclusion of an additional weighting function. This weighting function assigns estimation weights based on the occurrence frequency of words within the corpus, in order to ensure that less importance is assigned to very frequently as well as very infrequently occurring words.

Furthermore, context weights are assigned to the entries in the co-occurrence matrix, negatively dependent on the distance (number of words) between the words that co-occur within z.

The resulting minimizing least squares problem is depicted in equation 6, which uses the arbitrary words i and j and introduces parameter L for corpus size:

$$J = \sum_{i,j=1}^{L} f(X_{ij})(w_i^T \widetilde{w}_j + b_i + \tilde{b}_j - \log(1 + X_{ij}))^2 \ . \tag{6}$$

Weighting function $f(X_{ij})$ hereby takes the form of equation 7 below:

$$f(x) = \begin{cases} \left(\frac{x}{x_{\max}}\right)^{\alpha} & \text{if } x < x_{max} \\ 1 & \text{otherwise} \ . \end{cases} \tag{7}$$

The underlying idea of applying matrix decomposition is to extract meaning from the information that is compressed in the process of dimension reduction, which takes place as a result of the deconstruction of the co-occurrence matrix into smaller parts.

This matrix decomposition shows how the co-occurrence matrix is the product of two smaller matrices A and B, of which the entries in turn represent vectors of entries for one word in the co-occurrence matrix. These vectors are the word embeddings for that respective word, which are of length d. d hereby represents the rank, or inner dimension, of the co-occurrence matrix, if matrices A and B are respectively of dimension $p \times d$ and $d \times q$. The entries of the co-occurrence matrix therefore represent dot products of two entries in the smaller matrices, and therefore the likeliness of words to co-occur.

It follows that the differences and/or similarities between the word vectors, or word embeddings, extracted from the matrices as a product of the decomposition, inform about the differences and/or similarities in co-occurrence, and therefore context. These can therefore be used to interpret the meaning of the respective words, through which GloVe succeeds in establishing meaningful word embeddings.

Interpretation of the GloVe model thus relies on the matrix factorization principle that a whole is the sum of its parts, whereby the parts are reflected by meaningful word embeddings of length d. Since the vectors inform about the difference or similarity in context of two words, it follows that the word embedding of the word "king" should for example be really close to the word embedding of the word "man" subtracted from the word embedding of the word "queen". Hereby, meanings of words can be interpreted based on the word embeddings. Interpretation of performance is often done by interpreting cosine word similarities: the angel between two vectors as represented in a dimensional space. This reflects the extent to which the word represented by vectors are similar.

K-Means Cluster Analysis is conducted to establish underlying patterns in the photos, based on the outputs emulated by the NMF and GloVe analysis, respectively. The outputs, which respectively entail topic scores and word embedding vectors, thus function as segmentation data: data that serves as a basis for the identification of different segments.

The K-Means algorithm is used because of its scalability, as well as its suitability in similar approaches in previous literature. Examples hereof are Zhao, Chen, Perkins, Liu, Ge, Ding & Zou (2015) and Boltužić & Šnajder (2015). These authors applied K-Means cluster analysis for the establishment of contextual clusters in respectively topic model output and word embedding output.

The added value of the cluster analysis is to determine the role of context through the potential identification of contextual segments in the photos. The idea behind this is that this research aims to link visual content features in a photo to engagement, however, the effect hereof may be strongly dependent on the photo context (Schreiner et al, 2019 and Lin & He, 2009). A notion of context can be determined by identifying photos that have a similar topic score or word embedding vector distributions. Such a similar distribution may indicate inclusiveness in an overarching content-wise topic segment or embedding segment, which may be relevant for the engagement.

For example; pictures of scenery may result in high engagement in a travelling context, but not at all in a fashion context. Marketing campaigns are more effective when they are perceptually congruent (Kuo & Rice, 2015); they are in line with what consumers perceive to be suitable and expected, in terms of the context of the campaign. This is extendable to a social media context; situational factors influence the interpretation and experience of the absolute subject matter in a social media post (Lin & He, 2009). More importantly, these factors might have the potential to influence engagement.

Using cluster analysis to establish contextual clusters that are, by definition, more general than the visual content features can solve this problem. Examples of such contextual groups would entail fashion or travelling. A precedent for using cluster analysis for this objective is Hu, Manikonda & Kambhampati (2014).

This research uses photo hashtags and sentiment as descriptor data to describe the identified clusters. Hashtags are relevant to use for description because they express contextual and content-wise information regarding the respective posts they are placed in (Highfield & Leaver, 2015). Also, they are used to classify and highlight content around a topic of interest or inquire about a specific subject (MacArthur, 2018). Sentiment is relevant to use for description because it transfers the affective essence of visual content. The sentiment expressed on content is linked to the sentiment of the consumer upon viewing that content (Lewinski et al, 2014), which is in turn linked to engagement (De Vries & Carlson, 2014).

3.1.2 Predictive Modeling

The connection posed in research question 4 can best be examined by modelling the relationship between variables of interest that represent potential data patterns (visual content features of Instagram photos) and an outcome (the engagement of those photos). This will take the form of the predictive model as presented in Figure 2.

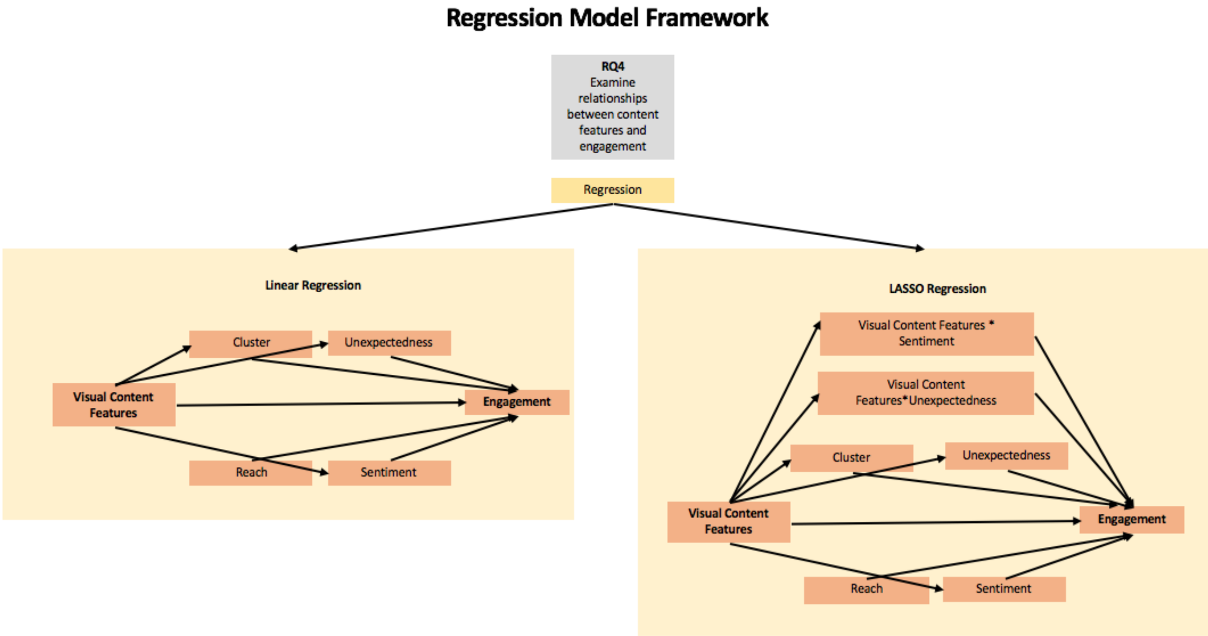

Figure 2: Research Framework of Predictive Modeling Approach

Figure 2 shows that two regression models are conducted in this research; a **Multiple Linear Regression** model and a **LASSO Regression** model. Both aim to examine the relationship between *Visual Content Features* and *Engagement.* The linear regression also includes *Cluster, Unexpectedness, Reach* and *Sentiment.* The LASSO model contains the same variables but adds two-way interaction terms of the visual content features with *Sentiment* and *Unexpectedness*.

Visual Content Features are in this analysis deemed a good manner of quantifying visual content itself, as they entail the actual elements of visual content that inspire emotions and therefore engagement, based on the theory of visual rhetoric, as presented in section 2.1.2. The visual content features in this research specifically take two forms; topics and word embeddings.

Topics are appropriate to use as an independent variable to explain engagement because sentiment is dependent on subject domains rather than keywords (Lin & He, 2009). Topics adequately summarise keywords in a subject domain and are more informative, due to not being trend-sensitive (Lau et al, 2012). Such topics, rather than keywords, influence how consumers form an opinion, summarise keywords in their head, and how their sentiment towards that content piece is formed (Lin & He, 2009). Since such sentiment is a major driver of engagement (Highfield & Leaver, 2016), topics are considered a proper quantification of visual content features to use as explanatory variables in predicting engagement.

Word embeddings are appropriate to use as an independent variable to explain engagement because they uncover the meaning of words (Taghipour & Ng, 2015). Meaning, in turn, affects how consumers intrinsically judge the respective content and also affects the sentiment that consumers develop as a result of that content (Melamud, McClosky, Patwardhan & Bansal, 2016). Keywords cannot capture this, because meaning is a natural result of context and context per definition consists of multiple words. A context can even drive the same word to have different meanings. Taghipour & Ng (2015) give the example of 'bank', which could be used as 'the bank of a river' or 'a bank loan'. Meaning is, therefore, relevant and sometimes even needed to operationalize a visual content feature appropriately. Thus, word embeddings are deemed a more appropriate manner of quantifying visual content features, compared to keywords themselves. It is difficult to hypothesize whether meaning is also established in this paper by word embeddings in its conventional manner, due to the absence of a local context. However, meaning can still be somewhat approximated by word embeddings. Word embeddings uncover lower dimensions of the words. The word vectors represent an underlying reflection of how visual content features can be defined, upon how they are depicted on the photos. This gives a lower-dimensional representation of each separate feature, where topics give a lower-dimensional representation of multiple features. Word embeddings are, therefore, more likely to capture a 'deeper' sense of meaning. Since both meaning (Bruni et al, 2012) and consumer sentiment towards content (Highfield & Leaver, 2016) are essential engagement drivers, word embeddings are also considered suitable explanatory variables for predicting engagement.

The visual rhetoric theory states that it is important to consider all features and elements in an image, as well as the connections between those features and elements. To account for this, the LASSO model includes two-way interaction effects between visual content features and other relevant visual content elements: sentiment and unexpectedness. Interactions between the topics themselves are not included, because this would require a very extensive analysis that is outside the scope of this research. The LASSO model is therefore conducted in an exploratory manner to examine whether such interaction effects do indeed have an impact on engagement as well, conforming the theory of visual rhetoric (Bulmer & Buchanan-Oliver, 2006). A LASSO model is suitable to do this because it decreases multicollinearity issues that are likely because of the intertwined relations of visual content features. Furthermore, it performs variable selection (Fonti & Belitser, 2017), which is essential because the number of variables might become very high.

Cluster is appropriate to include as an independent variable because it accounts for the context of the photo. Both Lin & He (2009) and Schreiner et al (2019) state that such contextual themes can influence the engagement caused by the visual content of that photo. Kuo & Rice (2015) present a potential explanation for this; perceptive congruence by consumers of a feature with an overall campaign is more likely to yield marketing success. Perceptive congruence reflects what a consumer expects to belong to a particular aspect or element, based on their beliefs. Depending on these beliefs, consumers might experience some features as more positive in different contexts, which could impact their engagement. For example; Ha, Kwon, Cha & Joo (2017) show that professional photo lighting and settings are somewhat less popular on Instagram than casual, spontaneous photos in the contextual theme fashion because the latter resonates more with the Instagram audience. Holmberg, Chaplin, Hillman & Berg (2016) present that professional photography within the contextual theme food was more popular than the opposite, because careful placement and lighting contributed to the appearance-wise palatability of the food. This difference shows how thematic context can impact engagement.

Unexpectedness is included as an independent variable, based on section 2.1.4. Bruni et al (2012) and Tellis et al (2019) both state that unexpectedness is an element of visual content, which can influence engagement, because it transfers a notion of surprise and suspense for the consumer.

Reach is included as an independent variable, from the intuition that it accounts for the ‘size’ of the influencer; influencers with more followers are more likely to receive more likes on their photo posts, simply because more people are exposed to this post. Earlier research established a significant positive relationship between influencer follower bases and engagement (Bakhshi et al, 2014).

Sentiment is included as an independent variable, based on the theory in section 2.1.3: engagement is driven by the sentiment expressed on the pictures. Therefore, this is a relevant variable to include in the model, as it is part of the manner in which visual content features cause engagement. Including this variable enables the isolation of the effect of visual content features themselves. Furthermore, sentiment itself is an interesting visual content element. It should again be noted that these variables capture the sentiment expressed on a picture. This is linked to the sentimental experience of the consumer of that content (Lewinski et al, 2014; Berger & Milkman, 2012), but not the same.

4. Data, Operationalization & Conceptualization

4.1 Data Description

The dataset used was provided by *TheCirqle*, a company that interlinks influencers and companies and supervises influencer marketing campaigns in fashion, lifestyle and travel sectors. *TheCirqle* offers an open platform for regular people to register as influencers; companies/brands can choose to hire an influencer for their influencer campaign based on the characteristics shown upon registering. The influencers are, therefore, in this research limited to influencers employed by *theCirqle*. The influencers in the dataset together have over 50 nationalities; however, the scope of the influencers and the campaign is global. The campaigns used for the analysis in this research all entail marketing for the lifestyle, fashion and travel sector and a global scope because that is the scope of the data. All the influencer marketing campaigns in the data were conducted on the social media platform Instagram.

Two points must be noted with regards to the dataset. In the first place, *TheCirqle* is an open-source platform on which all regular people can register. Therefore, not all influencers are of the same 'quality'. In the second place, it is assumed that all posts have a primary commercial purpose and that the dataset does not contain posts of influencers that do not have a commercial purpose, for the reason that there is no manner to make that distinction based on the data at hand. The dataset originally contained 355,188 observations and encompassed the variables specified in Table 2.

Table 2: Variable Description of Dataset

Variable	**Description**
ID	Influencer ID
Content	Complete textual subject-matter of the post
Reach	Number of followers of the respective influencer that posted the campaign at the moment of that particular campaign post

Hashtags	Complete textual content of the hashtags of the post
Mentions	Complete textual content of the mentions to other accounts the post contained
No_Comments	Number of comments by other social media users that were placed as a reaction to the post
No_Likes	Number of likes by other social media users that were generated as a reaction to the post
General	Textual *Clarifai* classifications of the images present in the post. The algorithm produces objects and presentational themes in noun form (e.g. *woman, fall*), actions in verb or noun form (e.g. *swimming, relaxation*) and expressions or feelings in adjective or adverb form (e.g. *pretty, fun, joyful*).

4.2 Data Pre-processing

The data pre-processing took a relatively different form compared to regular text analysis pre-processing. The *Clarifai* produced word tags had a clear 'keywords-only' structure and separation mannerism, contrarily to the conventional unstructured and disorganized form text data usually takes.

The needed pre-processing therefore entailed in the first place the removal of non-meaningful word separating interpunction, numbers and characters. In the second place, it involved the deletion of nonsensical *Clarifai* generated word type codifications. No decapitalization was applied because the *Clarifai* algorithm produces only lower case letters for the generated meaningful words. No stop words were removed because such words do typically not exist in the *Clarifai* output, and if they did, they would not be unmeaningful. Subsequently, stemming and lemmatization was applied to correct for differences in word types: the *Clarifai* algorithm produces nouns as well as verbs which leads to different word forms that have the same meaning. The Porter language was used for stemming because of its scalability. Usually, stemming and lemmatization would not be applied in the case of a GloVe analysis, because such a word embeddings approach relies on the local context. The exact interpretation and nuance of a word is thereby a vital piece of information. However, since this data is of a different nature and local context does theoretically not exist, stemming and lemmatization can be used to prepare the data for both analyses.

Based on the document frequency histogram in Appendix A1, it was decided to delete the word *email* from all the documents. Nearly all documents contained this word, which leads it to be not meaningful for the analysis. The high occurrence of *email* can be explained by the theory that the *Clarifai* algorithm recognizes the @ symbol as an indication of the occurrence of an email or email related concepts. However, in the Instagram environment, this symbol signifies the mentioning of another Instagram account, which is often textually displayed on a photo. In the case of influencers, this symbol will always occur for the respective brand the influencer is campaigning for. This theory supports the notion that this word is not meaningful in the further analysis of this paper.

Very uncommon words, defined as words of which the occurrence entailed less than 1% of the total word occurrence within the dataset, were also deleted because they are not informative enough due to their extremely low occurrence.

4.3 Operationalization & Conceptualization

For the sake of clarity and summarization, Table 3 presents an overview of the relevant concepts in this research. Furthermore, Table 3 shows how these concepts are operationalized in this research, based on the available data presented in section 4.1 and 4.2.

Table 3: Overview of Relevant Concepts and Operationalizations [2]

Concept	Conceptualization	Operationalization
Instagram Influencer Marketing Campaign	Marketing campaign whereby word-of-mouth and social media marketing are constructed using the authority of influencers for the promotion (Hinz, Skiera, Barrot & Becker, 2011; Kiss & Bichler, 2008; Bokunewisz & Shulman, 2017). In this research, specified on the platform Instagram.	**One commercial post** by an influencer on Instagram, which can in turn consist of one or multiple photos.
*Visual Photo Content**	Visual subject-matter on photos	**Tag words** that describe the visual subject-matter on photos, produced by the *Clarifai* algorithm
Visual Content Features	Visual elements of the visual photo content as well as the interactions hereof, entailing both substance and presentational features (Buchanan & Oliver, 2006; Bakhshi, Shamma & Gilbert, 2014)	**Topics** (underlying descriptive themes of the visual photo content tags) and **word embeddings** (meaningful vectors of words of the visual photo content tags)
*Unexpectedness**	Additional visual content element that comprises the extent to which a campaign is inconsistent with the viewers prior forecast of that content (Tellis, MacInnis, Tirunillai & Zang, 2019)	Extent to which a campaign contains **visual content features not conform the underlying theme of that visual content entity**
*Sentiment**	Sentiment expressed by the visual content of the photo (Schreiner, Fischer & Riedl, 2019; Yu, 2014).	**Valence and emotions** expressed by the visual content features on photos
*Success**	Marketing impact, or profitability, caused by influencer marketing campaigns. Engagement can be used as a proxy for this (Hughes, Swaminathan & Brooks, 2019).	**Likes and comments** received by a post, corrected for the scope of the influencer

For the purpose of clarity, an example of *visual photo content* is given in Figure 3. Figure 3 gives an example of some photo posts in the dataset, along with the *Clarifai* tags that belong to these pictures (after data pre-processing). It should be noted that these words are stemmed and lemmatized. However, in the rest of this paper words will be used and called by their original most general form, for the purpose of clarity.

[2] *Concepts indicated * require additional explanation, which is given in the rest of the section*

Clarifai tags:
drink, coffee, espresso, cappuccino, cup, dark, caffeine, chocolate, adult, indoor, foam, one, woman, hot, people, bar, mug, man, food, sugar

Clarifai tags:
woman, sexi, fun, summer, young, fashion, vacation, leisur, beach, pretti, girl, sunglass, friendship, enjoy, beauty, joi, recreat, outdoor, fit, bikini

Clarifai tags:
woman, fashion, portrait peopl, model, recreat, sexi, glamour, editori, summer, matern, pretty, girl, on, wear, actress, adult, movi, music, dress

Figure 3: Example of Instagram Photos and respective Clarifai tags

For *unexpectedness*, a few notes should be made with regards to the operationalization. The underlying theme reflects the clusters as identified through research question 2. The content that does not conform this theme can be extracted from the available data through calculating the variation not explained by the visual content features available in a visual content entity, which do not conform the cluster that entity belongs to.

The theory behind this operationalization is based on Bruni et al (2012), who present the idea that unexpectedness is implied by the extent to which content is different from the viewer's prior expectations. Assuming that these prior expectations are dependent on the theme of the photo, it is a reasonable measure to assume that the elements that do not conform this theme are unexpected. The implementation of this operationalization is based on Pickering & Jordanous (2017), who state that the expectedness can in computer science be quantified by the likeliness of a concept to occur. This likeliness is based on prior beliefs of the reader in the context of written stories. They specifically quantified this by creating a set of overarching story paradigms that had the same underlying structure, characterized by a vast set of agents and events. The variation in these stories that could not be explained by the vast paradigm was quantified as the degree of unexpectedness.

For *sentiment*, the following should be noted: this research obtains the sentiment expressed by the content of the photos through applying sentiment analysis on the visual photo content. This epitomizes the sentiment captured by the photo. Previous literature has linked the sentiment expressed by content to the sentimental experience of the consumer of that content as well as the content engagement (Berger & Milkman, 2012). Sentiment analysis is applied according to a sentiment lexicon; the *NRC Dictionary*, chosen because of its scalability. This dictionary links words to emotions (*Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust*) and valences (*Positive, Negative).* Valences reflect the extent to which the content contains a favourable (positive) or unfavourable (negative) polarity (Mohammad & Turney, 2013). Emotions reflect the extent to which the content contains feelings or expressions that suggest a certain emotion (Mohammad & Turney, 2013). The lexicon contains for each word, a score of 1 upon being associated with an emotion or a valence. A score of 0 is assigned upon no association. For a collection of words such as the photos, the emotions and valences therefore reflect the total of the scores over all the words in the document, for each emotion and valence. The dictionary therefore captures sentiment, both expressed by the valence as well as the emotions expressed on the visual content. Mohammad & Turney (2013) show that valence types and emotion types are different category types that should both be used in natural language processing. The two may sometimes be interconnected, but many emotions (such as for example *surprise*) are ambiguous. They also present the example that a negative word is not the same as an angry word (even though one might associate angry as a negative emotion). Ulla, Amblee, Kim & Lee (2016) furthermore show that content with a very high negative valence often contains no emotions, explicable by strong disinterest. Therefore, words are assigned different scores upon ‘negative’ emotions and a negative valence. It is therefore relevant to include both in the analysis.

In line with Hughes et al (2019), *success* and therefore, *engagement* is operationalized through the likes and comments received by a post. However, this research introduces correcting for the scope of the influencer: the intuition that influencers with a higher number of followers are directly more likely to receive a higher number of likes and comments. This is implemented by separately correcting for the influencer reach, through dividing both the number of comments and the number of likes by the reach of the respective influencer.

Post comments reflect the number of individual reactions that consumers have placed underneath a photo post. The relevance of post comments was stressed in earlier research by Glucksman (20017), who stated that commenting is one of the crucial social media features that ensures the possibility of a personal conversation between the influencer who represents a brand and the consumer.

Post likes reflect the number of individual clicks the 'thumbs up' icon underneath a photo post has received. The relevance of post likes was underlined in earlier research by Jang, Han & Lee (2015): likes are a measure of popularity in the social media atmosphere. Furthermore, likes reflect the degree of interest with regards to a post (Jäakonmaki et al, 2017).

4.4 Data Preparation

For data preparation, the preprocessed dataset was subjected to the deletion of missing observations (campaigns for which no *Clarifai* output was presented or observations that remained empty after pre-processing). This produced a dataset of 221.547 remaining campaign observations with 221.229 unique influencers.

4.5 Data Exploration

For the sake of general data exploration, Table 4 below depicts descriptive statistics of the overall dataset.

Table 4: Descriptive Statistics in TheCirqle dataset after Data Preparation

Descriptive Statistic	**Result**
Total number of unique words	*4,737.0*
Mean number of words per document	*20.6*
Maximum number of words per document	50.0
Minimum number of words per document	*8.0*
Mean word occurrence	*12,363.0*
Maximum word occurrence	*153,433.0*
Minimum word occurrence	*2,229.0*
Mean number of post likes	*2,133.3*
Maximum number of post likes	*675198.0*
Minimum number of post likes	*0.0*
Mean number of post comments	*53.9*
Maximum number of post comments	*114694.0*
Minimum number of post comments	*0.0*
Mean reach	*85.769.1*

Maximum reach	*3.397.141.0*
Minimum reach	*1.0*

The total number of unique words in the dataset entailed 4.737, and the mean number of words per document entailed 22. These amounts are both considered high enough to provide a solid basis for the analyses. The topic modelling approach requires an extensive range of different words to establish well-defined topics over the whole dataset. For the word embedding modelling, commonly used context sizes are up to 20 words.

On average, a word occurred 12.363 times in the entire dataset, whereby the spread entailed a maximum of 153.433 and a minimum of 2.229 times. This range is considered large enough to offer sufficient variation within the dataset to employ the predictive analyses. A considerable variation provides a more distinct basis for the relationship to be drawn. The same applies to the vast range of likes and comments present in the dataset.

The reach, which reflects the influencers' follower base, entails a minimum of 1 and a maximum of 3.397.141. This range may seem significant, however, all the influencers in the dataset were selected by companies themselves to execute an influencer campaign. Therefore, they should all be included in the research because they provide crucial information on potential campaign success, whereby the number of followers will be corrected for in the analysis. A likely reason for companies to select influencers with a low following for their campaign is that the success of an influencer can often not be predicted prior to the campaign. It is wise to include a wide range of different influencers in a campaign because even low-following influencers may cause virality in the long run (Bakshy, Hofman, Mason & Watts, 2011).

For more in-depth data exploration and to understand the nature of the content data, the wordle and word cloud in Figure 5 below were produced based on the 200 most frequently-occurring words in the dataset.

The wordle in Figure 5 displays a visualization of the occurrence frequencies. The right figure shows a multi-dimensional scaling produced word cloud, which visualizes the extent to which words often occur together in the dataset by transforming the word co-occurrences to distances. Words positioned more closely to each other in the word cloud, therefore, more often co-occur.

Wordle (left) and Word Cloud (right) of *Clarifai* Tag Word Frequencies

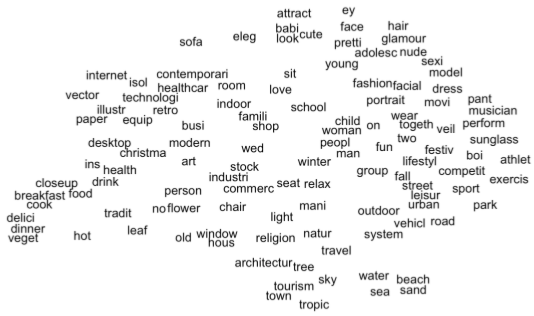

Figure 5: Wordle and Word Cloud of Clarifai tag word frequencies in TheCirqle dataset

Figure 5 shows that *woman* and *people* are the most frequent words, followed by, amongst others, *adult, person, portrait, wear, outdoor* and *fashion.* This indicates most photos display adult people, of which either the face or full body is depicted, in an outdoor orientation featuring fashionable clothing. These words are rather basic and have broad interpretations. However, the wordle also displays somewhat more specific surrounding, object or mood indicating words such as *summer*, *travel*, *leisure*, *model, young* and *pretty.* This suggests that many photos display recreational activities, nice weather as well as beautiful people or models. Less frequent words are even more specific of objects or depictions, which include, for example, *daylight, sunglass, table, landscape* and *horizon.* This suggests particular photo components such as the notion that photos are taken by day, display a landscape (background) or depict specific objects such as a table or sunglasses.

The word cloud shows several significant word-groups than can be interpreted as relatively distinct photo themes as a result of objects that often occur together. In the centre of the cloud, *family* often occurs in combination with *shop* and *indoor*. This suggests the dataset contains a prominent set of photos displaying families, or family-like groups engaging in indoor shopping. Furthermore, *child* occurs with *woman*, *people, man* and *one*. This reflects a collection of photos displaying one person or a small group of people as the primary display subject. The combination of *fall, street, leisure* and *urban* also occurs quite often, which suggests photos with an outdoor, city-like atmosphere.

5. Analysis & Results

5.1 Non-Negative Matrix Factorization

Non-negative matrix factorization was conducted as a first method to identify the visual content features present in the *Clarifai* tags. Visual content features hereby take the form of topics.

5.1.1 Model Specification

Due to the computational infeasibility of using cross-validation to establish k, this value was determined by looking at the number of factors resulting from regular matrix factorization without the non-negativity constraint (singular value decomposition). This is a popular alternative for determining the inner rank of the matrices of non-negative matrix factorization (Gillis, 2014). The number of topics resulting from this decomposition could be different from the optimal number of topics for NMF, because regular matrix factorization also produces some negative solutions (Gillis, 2014). However, this difference is not problematic, as Qiao (2015) and Golub & Van Loan (2012) established empirically that using this method to determine the number of factors for NMF led to similarly good results. Furthermore, sensible interpretation of the obtained factors provides a good metric to assess the feasibility of the topics as well, due to the unsupervised nature of the method. The plot in Appendix A2 denotes the sum of squares of the smaller matrices of which the dot product reflects the reconstruction of the matrix to be deconstructed, based on singular value decomposition. In other words, the plot denotes the explained variance on the vertical axis against the number of topics on the horizontal axis. Onwards from a value of $k = 25$, the added benefit of adding a topic compared to how well the matrix is reconstructed, is relatively very small. Therefore, this value was considered the most efficient topic number.

5.1.2 Interpretation, Discussion & Performance of the Model

Figures A3.1 until A3.5 in Appendix A3 depict for all 25 factors, the top 10 most high-loading and therefore dominant terms. Each factor can be interpreted as a topic, whereby the intuition and suitability of the terms and topics serve as a measure for model performance. It was chosen to provide an interpretation based on the top 10 most high-scoring terms because this was deemed sufficient to build a stable theme around. This interpretation is given in Table 5. Table 5 gives a topic number, name and characterization, based on the high-loading terms of the topic.

Table 5: Interpretation of Topics Produced by NMF

#	Topic Name	Topic Characterization
1	“Smiling Female”	• **Female** related terms *girl, adult, woman, people* • **Happy** related terms *happy, beauty, lifestyle*
2	“(Walk in) Outside Summer Environment”	• **Outside** related terms *nature, grass, park, outdoor, sky* • **Joyous** summer terms *summer, happy, fun.* • *Travel, people* suggest **walk** concept
3	“Interior Design”	• **Interior** related terms *room, furniture, table, indoor, chair, seat, interior* • **Design** related terms *design, luxury, contemporary*
4	“City Trip”	• **City** concept characterized by *street, outdoor, city, urban, road, pavement* • **Trip** concept characterized by *luggage, travel, portrait, people*
5	“Female Model”	• **Female** related term *woman* • **Modelesque** features reflected by *pretty, sexy, beauty, glamour, young, cute, hair, fashion*
6	“Graphic Design”	• **Graphic** reflected by *illustrate, art, symbol, vector, text, retro, color* • **Design** reflected by *desktop, design, person*
7	“Beach Vacation”	• **Beach** related words *sea, water, beach, ocean, seashore, sand, summer, sun* • **Vacation** related words *vacation, travel*
8	“(Office) Work”	• **Work** related words *business, paper, internet, computer, laptop* • **Office** elements *technology, finance, data, office*
9	“Food”	• **Food** related terms *meal, cook, plate, dinner, lunch, plate, table, delicious, traditional, food* • *Person* reflects **eating**
10	“Loving Family”	• **Children** related terms *little, girl, child, cute* • **Loving parental** terms *joy, love, together, family, fun, two*
11	“Domestic Coziness”	• *Sofa, furniture, room, indoor, sit* suggest **domiciliary** couch setting • **Coziness** and stay-at-home activities reflected by *people, woman, family, look, relax*
12	“Sports Contest”	• **Sports** related words *football, stadium, athlete, sport, action, people, wear* • **Contest** theme reflected by *competition, game, uniform*
13	“Outdoor Scenery”	• **Scenery** related words *landscape, weather, outdoor, scenic* • Nice **fall** scenery suggested by *fall, fair* • **Outdoor** related words *tree, nature, wood* • *Person* suggests presence of **human**
14	“Leisure”	• **Relax** related terms *recreation, relax, fun, enjoy, lifestyle* • *Fair* and *health* are common **leisure** occupations
15	“Pets and Animals”	• **Pet**-like terms *pet, dog, little, young, cute* • Broader sense of **animals** reflected by *mammal, animal, look portrait* • *Person* suggests presence of **human**
16	“Flowers”	• **Flower** related terms *flower, leaf, flora, nature, color, floral, décor, bouquet* • *Person* and *love* suggest use of flowers by people as **expression of love**
17	“(Power) Couple”	• **Couple** related terms *man, adult, woman, two, group, together, people, portrait* • **Power** element reflected by *wear, business*
18	“High Fashion”	• *Fashion, wear, dress* and *glamour* suggest **fashionable, expensive and trendy clothing** • **Model**- and/or **fashion-show** related terms *adult, model, girl, woman, people*
19	“Travelling”	• General **travelling** terms *travel, tourism, person* • Broader **travelling and trip** terms *architecture, building, city, town, sky, water, outdoor*
20	“Marketplace”	• *Market, commerce, sale, merchandise* reflect **selling environment** • *Business, stock* suggest **stock trading marketplace**

		• *Indoor, shopping* reflect **mall environment** • *Woman, people* suggest **presence of humans**
21	"Swimming Pool"	• **Swimming pool** related words *swim, pool* • Broader **vacation/leisure** related words *water, dugout, vacation, travel, recreation, summer, resort, bikini*
22	"Road Transport"	• **Road traffic vehicle** terms *vehicle, road, car, traffic, wheel, drive* • **Transport** related terms *system, transport, race, travel*
23	"Musical Performance"	• **Music** related words *music, festival, musician, singer, concert, movie* • *Recreation, perform, group, people* suggest **performance event**
24	"Portrait Photography"	• *Facial, expression, portrait* suggest **close-up photography** • **Typical portrait photography background setting** reflected by *room, together, furniture, two, happy, wear* • *Brunette* suggests **presence of brunettes**
25	"House Exterior Design"	• **House** related terms *house, family, doorway, window* • **Exterior** related terms *exterior, old, building* • **Design** related term *architecture* • *Person* suggests presence of **human**

Table 5 shows that overall, the topics as produced by NMF are well-defined and have clear interpretations. "Smiling Female", "Swimming Pool" and "Road Transport" suggest some concrete objects and actors depicted as visual content features; happy women, swimming pools and conventional transport methods. "Outside Summer Environment" and "Marketplace" suggest surrounding and background visual content features; shopping environments and beautiful outside summer weather. "Domestic Coziness", "Power Couple" and "High Fashion" suggest main activities that are depicted on the photos; people in cozy home surroundings, practicing their career or wearing couture fashion. "Portrait Photography" suggests a presentational visual content feature; the manner in which photos are taken is professionally centred towards one actor of interest, with suitable placement and lighting. The collection of these topics shows that the topic model picked up several types of visual content features in summarizing the *Clarifai* tags; objects, actors, activities, themes and a presentational characteristic. Overall, the topics are interpretable and quite general; they all reflect one clear theme with little detail or nuanced relationships. Furthermore, it is remarkable that the topics often contain the feature 'humans' or a relation to that, likely because the majority of photos contain people.

Figure 6 gives an example of the topics NMF produces for the Instagram photos earlier shown in Figure 3.

NMF produced topics:

"Food"
"Domestic Coziness"

"Marketplace", "Smiling Female", "(Power) Couple"

NMF produced topics:

"Female Model"
"Leisure"
"(Walk in) Outside Summer Environment"

"Smiling Female", "Beach Vacation", "Loving Family", "High Fashion", "Swimming Pool", "Musical Performance"

NMF produced topics:

"Female Model"
"High Fashion"
"Musical Performance"

"Smiling Female", "(Walk in) Outside Summer Environment", "Beach Vacation", "Leisure", "(Power) Couple", "Swimming Pool"

Figure 6: Example of NMF Produced Topics

As can be seen, these topics are an informative means of visual content features. They capture the essence of the photo, by adequately and more informatively summarizing a broad range of detail-driven keywords, that are more likely to relate to sentiment and therefore, engagement. For example; the topics "Food" and "Domestic Coziness" summarize a notion of consumption with a house-like comfortableness element. This fundamentally explains what the photo is about, without needing details like *cappuccino, foam, hot* and *indoor.* Furthermore, "Domestic Coziness" is robust to time-sensitive trends, as it captures an underlying ambience, of which the exact substance may differ upon different times and viewers. This is not the case for *indoor,* which only describes a part of this element and is not likely to relate to a certain feeling (and therefore engagement). The findings of the topic model are thus confirming the expectations in section 3.1.1; the model effectively summarizes terms in more meaningful topics to capture what the photo is about.

5.2 Global Vectors for Word Representation

Global Vectors for Word Representation was conducted as the second method to identify the visual content features present in the *Clarifai* tags. Visual content features hereby take the form of word embeddings.

5.2.1 Model Specification

Regular rules of thumb were adhered for the parameter selection of the GloVe model. The data was of an unconventional format, as local context does not exist, so no specific requirements needed to be met. Furthermore, it is interesting to see how the model performs upon being applied as usual. The context window entailed 2x5, which is a typical context size and is amongst other sizes used in Pennington et al (2014). This is a relatively small context size, which contributes to this model researching a more local context compared to the global context of topic modelling. The model thus considers within each document (photo), the 10 words around that word to be the local context.

Word vectors are of a length and therefore dimensionality $d = 50$. This is a standard low-dimensional value that can be used as a rule of thumb for GloVe, because no sufficient research has yet been conducted to establish decisive measures to determine the optimal dimensionality degree (Patel & Bhattacharyya, 2017).

5.2.2 Interpretation, Discussion & Performance of the Model

The GloVe-produced word embedding vectors were subjected to the calculation of cosine similarity between words so that an interpretation could be provided. Furthermore, interpretation-wise, it could be evaluated whether this similarity was intuitively correct. This therefore also showed whether the model performed well. A visualization of the similarity in a dimensional space, whereby similarity is transformed to distance (MDS), is given in Appendix A4. Appendix A4 provides a global overview of the substance of the word embeddings output but is challenging to use for evaluation. The words are difficult to read when plotted close together upon being very similar. However, a substantial amount of words needs to be plotted in order to interpret the patterns. Some similar groups of words are therefore projected as zoom-ins on the plot.

To evaluate and gain insight into the output in a more detailed manner, a selection of words, with the 22 most similar words in terms of cosine similarity, is depicted in Table 6. This selection includes words with different occurrence frequency levels, as deduced from Figure 5.

Table 6: Word Similarity Task for Selection of Words of Different Occurrence Frequencies

Woman	**Adult**	**Fashion**	**Travel**	**Leisure**	**Urban**	**Coffee**	**Health**
People (0.9710407)	People (0.9812451)	Model (0.9346825)	Outdoor (0.8835909)	Lifestyle (0.9217883)	City (0.9463096)	Tea (0.9338934)	Healthcare (0.7243858)
Adult (0.9639608)	Portrait (0.9673784)	Sexy (0.8948347)	Citi (0.8316259)	Relax (0.8875050)	Street (0.9273641)	Drink (0.8752269)	Healthy (0.6981838)
Girl (0.9489316)	Woman (0.9639608)	Pretty (0.8842239)	Water (0.8286630)	Enjoy (0.8740946)	Build (0.8133887)	Cup (0.8558988)	Medicine (0.6744224)
Man (0.9362878)	One (0.9527651)	Glamour (0.8715501)	Sky (0.8286579)	Fun (0.8453002)	Pavement (0.7967152)	Table (0.7800032)	Treatment (0.6383700)
Portrait (0.9281831)	Man (0.9448032)	Wear (0.8630755)	Architecture (0.7864353)	Recreation (0.8219044)	Road (0.7908510)	Mug (0.7536630)	Relax (0.5989902)
One (0.9017017)	Girl (0.9438995)	Dress (0.8535519)	Street (0.7655837)	Girl (0.8169912)	Outdoor (0.7888513)	Breakfast (0.7177996)	Closeup (0.5821712)
Wear (0.8867765)	Wear (0.9280525)	Beauty (0.8341780)	Build (0.7608880)	Happy (0.7999206)	Step (0.7814526)	Espresso (0.6819200)	Isolate (0.5776426)
Child (0.8759245)	Young (0.8462545)	Girl (0.8256447)	Daylight (0.7591427)	Summer (0.7984182)	Downtown (0.7722638)	Restaurant (0.6792594)	Care (0.5695942)
Two (0.8144717)	Child (0.8264895)	Sunglass (0.8251432)	Summer (0.7547528)	Young (0.7778614)	Architecture (0.7512542)	Milk (0.6602801)	Ingredient (0.5433689)
Young (0.8013943)	Sit (0.8171038)	Young (0.8112691)	Urban (0.7348131)	Child (0.7677331)	Travel (0.7348131)	Cappuccino (0.6310953)	Bottle (0.5361414)
Sit (0.7915681)	Two (0.8002605)	Adult (0.7626799)	Sea (0.7145047)	Adolescent (0.7626505)	Town (0.7040319)	Bar (0.6272030)	Clean (0.5358986)
Pretty (0.7740229)	Pretty (0.7858879)	Woman (0.7623794)	Landscape (0.7068947)	Joi (0.7574125)	Daylight (0.6871840)	Furniture (0.5978666)	Aromatherapy (0.5243852)
Fun (0.7666086)	Model (0.7812795)	Brunette (0.7599210)	Vacation (0.6890329)	Sit (0.7529145)	Door (0.6861772)	Shop (0.5973663)	Drink (0.5153225)
Fashion (0.7623794)	Indoor (0.7761928)	On (0.7581709)	People (0.6865354)	People (0.7516938)	Sky (0.6758575)	Laptop (0.5937609)	Nutrition (0.5136058)
Leisure (0.7465950)	Lifestyle (0.7701952)	Portrait (0.7327808)	Beach (0.6831508)	On (0.7468341)	Luggage (0.6662899)	Indoor (0.5895599)	Desktop (0.5072102)
Indoor (0.7367021)	Fashion (0.7626799)	Luggage (0.7276732)	On (0.6753484)	Woman (0.7465950)	Tourist (0.6634375)	Computer (0.5886102)	Summer (0.5020906)
Sexy (0.7308702)	Sexy (0.7388217)	Hair (0.7149250)	Recreation (0.6721303)	Two (0.7464546)	Window (0.6158070)	Telephone (0.5773887)	Plastic (0.4997606)
Model (0.7300326)	Fun (0.7343453)	People (0.7124932)	Woman (0.6673320)	Adult (0.7298326)	Wear (0.6061720)	Room (0.5510272)	Leisure (0.4990788)
Lifestyle (0.7191656)	Leisure (0.7298326)	Elegant (0.7009127)	Nature (0.6651879)	Pretty (0.7247051)	Traffic (0.6056429)	Food (0.5485498)	Soap (0.4841940)
Together (0.7159751)	Adolescent (0.7153210)	Casual (0.6952223)	Leisure (0.6578810)	Together (0.7140358)	Police (0.5947151)	Technology (0.5400174)	Cure (0.4750047)
Enjoy	Street	Bag	Road	Boy	Brick	Dawn	Fit

(0.6953876)	(0.7149234)	(0.6789840)	(0.6572963)	(0.7133123)	(0.5938278)	(0.5379420)	(0.4694540)

Table 6 shows that words classified as similar in general also share an intuitively similar relationship with the main word in the first row. For high-occurring words, such as *woman* and *adult,* words such as *model, child, portrait, girl* and *man* show a particularly clear similarity relationship in the sense that they are close to being synonyms or antonyms. Words such as *lifestyle, enjoy, together, pretty* and *sit* entail a more indirect but still relatively likely connection in the sense that they describe something about a woman or an adult.

The relatively least frequently occurring words *coffee* and *health* also entail suitable similar words. These are also somewhat more specific than the other words. The words similar to *coffee* include coffee types and variations such as *espresso, tea, milk* and *cappuccino* and likely locations, attributes and timeframes for drinking coffee; the *dawn*, for *breakfast*, out of a *cup* or a *mug* and *indoor* at a *bar* or *restaurant*. For health, there is a group of similar words that reflect health as the antonym of being sick; *treatment, medicine, cure, healthcare*, and *isolate*. Alternatively, other words such as *healthy, fit, nutrition, drink, aromatherapy* and *relax* relate to a more general sense of adopting a healthy lifestyle.

5.3 Comparison of GloVe and NMF

After carefully interpreting the output of both models, the outputs were compared, in terms of their advantages and disadvantages. These were used to derive the most suitable model and output to be used in the remainder of this research.

5.3.1 NMF and GloVe Model Comparison: Balancing the Outputs

Due to the inconsistency of both outputs, an inherent result of the different working mechanisms of GloVe and NMF, the GloVe output was subjected to an equalizing measure to be more comparable towards the NMF output. GloVe dimensions and NMF topics are inherently different and therefore, difficult to compare.

Since the NMF output entailed topics, essentially consisting of clusters of words that scored highly for the same factors, the GloVe similarity matrix was subjected to a cluster analysis. The similarity matrix entailed rows and columns consisting of all words in the dataset. The entries hereof reflected the cosine similarity scores between the respective words based on the word embeddings as identified by GloVe. The cluster analysis aimed to detect groups of words that had comparable cosine similarity score distributions over all the words in the dataset. The cluster analysis entailed K-Means as a clustering algorithm, whereby $K = 25$. This seemed the most suitable base for comparison, as more clusters lead to 'unfair' comparison; some clusters are likely to entail more detail if topics are spread over more clusters. Secondly, the plot in Appendix A5 shows that this is a suitable value as well, as a relatively low amount of information is lost upon $K = 25$.

The cluster analysis aimed to find distinct groups of similar words. The goal was to evaluate the performance of the model in terms of how intuitive these clusters worked out. This would aid in providing a more substantive comparison of both models in section 5.3.2. The results of this cluster analysis are given in Table 7. It should be noted that only terms were used to interpret the clusters in this analysis. No other use of descriptor variables was made. This was done because this analysis was purely conducted for the sake of a comparison measure with the NMF model and NMF clusters were based on terms as well. More terms (between 20 and 50) were, however, used to interpret the clusters, because it was expected that to identify more detail and relationships in the GloVe clusters, more terms were needed compared to the case of NMF.

Table 7: Output and Interpretation Cluster Analysis upon GloVe Output

#	Cluster Name	Cluster Characterization
1	"Business Man"	• **Business** related terms *serious, attitude, conference, friendly, telecommunication, intelligent, corporate, pedigree, headshot, success, ambition, writer, tie, profession* • **Man** related terms *beard, bald, moustache, suit, individual* • **Apparel** related terms *suit, formal, menswear, formalwear, fine look, shirt, boxer, look, apparel*
2	"Fresh Cooking"	• **Fresh food** reflected by *potato, ham, sausage, broccoli, chicken, basil, carrot, egg, beef, seed, tomato, deep, bacon, rice, lettuce, sauce, pork, barbecue, slice, sandwich, mushroom, honey, root, sushi, onion, bun, macaroni, steak, spice* • **Fresh cooking** terms *appetite, seafood, dish, cuisine, tasty, meat, dinner, cooking, ecological, fresh*
3	"High Fashion"	• **Specific fashion objects and elements** such as *pants, skirt, dress, sunglass, bag, jacket, purse, hairdo, lip, eye, necklace, sweater, smile, blouse, lipstick* • **General fashion terms** *glamour, hair, trendy, lady, fashion, model, attractive, footwear, style, sexy, casual, face, denim, luggage, knitwear, beauty, jewelry*
4	"Family and Fun"	• **Family** related terms *girl, family, one, adult, people, woman, young, child, man, lifestyle, two, leisure, adolescent, cute, group, person, together, boy* • **Fun** related terms *joy, love, relax, express, enjoy, leisure, smile, recreation* • **Locations, features and related actions:** *festival, nature, house, school, indoor, outdoor, urban, seat, daylight, winter, fall, sit, portrait, furniture*
5	"Health"	• **Healthcare** related terms *cure, pharmacist, ill, chemistry, treatment, medicine, hospital, laboratory, detail, medicine, healthcare, pharmacology, drug, pain, biology, influenza, patient, research, science, chemicals, disease, pill* • **Hygiene** related words *hygiene, soap, shower, clean, tube towel, bath, toiletry, shampoo, lotion, purity, perfume, sterile* • **Wellness** related terms *massage, therapy, care, oil, moisture, stress*

6	"Monuments"	• **Monuments and landmarks** reflected by *pagoda, capitol, minaret, archeological, dome, grave, gondola, fortress, courtyard, arch, fountain, kremlin, pyramid, heritage, landmark, port, monument, history* • **Religious associations** reflected by *shrine, religion, monastery, worship, sacrifice, prayer, Buddha, destiny, cathedral* • **Related materials and associations** reflected by *cement, written, panorama, picturesque, tramway, sightsee, gothic, column, pedestrian, venetian, water, narrow, marble, mosaic, baroque*
7	"Eating (Out)"	• **Eating and food** related words *homemade, bread, nutrition, sugar, bake, chocolate, fruit, cream, milk, lunch, cake, vegetable, cooking, meat, food, dairy* • **Eating** related words *knife, fork, cutlery, indulgent, plate, bowl, delicious, sweet, tasty, meal* • **Eating out** related words *chef, restaurant, cuisine, dinner, lunch, breakfast, dish*
8	"Transport"	• **Road transport** related words *drive, driver, traffic, truck, automotive, car, system, wheel, highway, vehicle, engine, auto, bike, cross, motorbike, dashboard, cyclist,* • **Public transport** related words *bus, train, railway, station* • **Air transport** related words *airport, airplane, aircraft* • **General traffic** terms *hurry, asphalt, transport, pavement, speed, safety, race, commute, departure, journey*
9	"Show"	• **Spectacle and art events** reflected by *jazz, pageant, opera, couture, trophy, piano, song, charity, gala, convention, journalist, theatre, cinema, author* • **Props, attributes and features** of shows: *zombie, bat, scare, mystery, skull, bizarre, monster, clown, strange, fear, magic, princess, spotlight, mask, horror, crazy, eerie, funky, bald, moustache, kimono, tribal, feather* • **Presentational features** *monochromatic, sepia*
10	"Children and Pets"	• **Children** related terms *innocent, baby, toddler, newborn, son, offspring, little, sibling, infant, mama, parent, affect, laugh, blanket, birth, bed, preschool, tiny, pajama, kindergarten, maternal, daddy, bathtub, toy* • **Pet** related terms *pet, puppy, dog, mammal, terrier, cat, fur, kitten, animal* • **Love and affection** associations: *affect, adorable, curiosity, sleep, domestic, precious, funny, play, sofa, intimacy, love, dream, together, anticipate*
11	"Text and Figures"	• **Text** reflected by *typography, tag, letter, alphabet, write, font, type* • **Numbers** reflected by *data, number* • **Figures** reflected by *graphic, diagram, vector, graph, image, spherical, symbol* • **Design and reporting** reflected by *fact, organize, plan, info, element, template, online, strategy, cover, document, network, blank, banner, abstract, entity* • **Usage in office** reflected by *manager, company, future, inspire, internet, improvisation, community, procedure, world*
12	"Fitness and Sports"	• **Sports** related words *football, stadium, athlete, sport, action, people, wear, dancer, run, marathon, Pilates, trainer, coach, game plan, gymnastics, jogger* • **Fitness** related words *body build, weightlift, thorax, effort, weight, biceps, masculine, dumbbell, barbell* • **General exercise** terms *strong, fit, effort, strength, active, exercise, endurance, flexible, motion, energetic, vital, skill, determination, balance* • **Body** related terms *muscle, naked, shirtless, body, torso, underwear, body, fine look, slender, thin, abdomen, brawny*
13	"City Trip and Urban Scenery"	• **Scenery** related words *façade, sight, skyline, skyscraper, panorama, river, sky* • **Urban** related words *cityscape, town, architecture, city, urban, exterior, marble, brick* • **City-Trip** terms *church, castle, build, tower, landmark, ancient, tourism, monument, cathedral, arch, sightsee, fountain, canal, culture, entrance, dome, sight, roof, tourist, temple, bridge, balcony, square, capitol* • **Presentational feature** *dusk*
14	"Handmade Clothing and Make-up"	• **Materials and textures** reflected by *yarn, textile, fabric, weave, cotton, ink, silk, surface, canvas, strand* • **Tools** reflected by *brush, scissor, paintbrush, tool, needle* • **Make-up** reflected by e*ye shadow, blush, rouge, makeup, polish, mascara, powder, lipstick*

		• **Clothing** reflected by *garment, apparel, belt, buckle, pocket, accessory* • **Handmade** also reflected by *handmade*
15	"Nature Scenery"	• **Nature** reflected by *volcano, geology, horizon, valley, frosty, evergreen, cliff, feather, lush, hill, mountain, place, lakes, dune, deer, wave, shore, blue, sandstone, grassland, erosion, snowstorm, rock, storm, canyon, wild, glacier, cactus, rainforest, snowdrift, desert, soil, ecology, wasteland, mist, air, place, dust, fog* • **Scenery** reflected by *scenic, scenery, silhouette, seascape, heaven* • **Voyage** reflected by *solitude, safari, trunk, lighthouse, submarine, pinnacle*
16	"Marketplace and Shopping"	• **Marketplace** reflected by *supermarket, mall, marketplace, boutique, bazaar, merchant, counter, aisle, rack, mannequin, hanger, stall, shelf, cart, warehouse, market, stock, bookstore, bistro, pub* • **Shopping** related terms *bargain, choose, option, sell, shopper, aisle, buyer, purchase, sale, wholesale, souvenir, price, discount, billboard, variation, pay, commerce* • **Merchandise** reflected by *merchandise, wardrobe, retail, bartend, service*
17	"Vacation and Travelling"	• **Tropical vacation** related terms *seashore, ocean, sun, tropic, sand, island, beach, sea, sunset pier, surf, wave, bay, turquoise, exotic, shore, swim, bikini, bronze, coconut, pool, swimsuit, palm* • **Active travelling & vacation** related terms *lake, water, rock, sky, scenic, seascape, mountain, fair, landscape, tree, adventure, desert, hike, boat, river, solitude, nature, environment, hayfield, backlit, watercraft, grass, countryside, fog, park, hill, cliff, fisherman, maple, climb, valley* • **General vacation** terms *vacation, freedom, resort, paradise, summer, carefree, travel, sunny*
18	"Competition"	• **Competition** terms *championship, competition, perform, battle, league, war, action, game* • **Different disciplines for competitions** reflected by *football, soccer, concert, election, rugby, rap, rally, race, music, basketball, movie, theatre, track, exhibit, dance* • **Competitors** reflected by *singer, musician, politician, leader, athlete, group, squad, band* • **Competition apparel** reflected by *uniform, outfit, helmet, flag* • **Notions of praise and victory** reflected by *festive, audience, fan, spectator, popular, parade, victory, award, ceremony, energy* • **Trouble and law enforcement** reflected by *military, police, offence, weapon, army, rebellion*
19	"Water Activities and Transport"	• **Water transport means** reflected by *kayak, sailboat, yacht, motorboat, ship, gondola, sail, submarine, boat, deck, ferry* • **Water activities and scenes** reflected by *paddle, snorkel, aerobics, cruise, goggle, swim, coral, reef, binocular* • **Harbor** reflected by *port, marine* • **Transport means** reflected by *horse, wheelchair, car, motorcycle, camper, bike, sleigh* • **Drivers** reflected by *venetian, fisherman, equestrian*
20	"Treasures of Nature"	• **Adventure and treasure hunt** reflected by *adventure, event, vibrant, fire, wicker, treasure* • **Natural materials** reflected by *clay, crustal, violet, grape, honey, botanic, ceramic, platinum, pine, evergreen, husk, bone, haut, sunflower, snowflake, gem, pottery* • **Treasure activities** reflected by *glisten, carve, luminesce* • **Treasure related** terms *cornet, pendant, bangle*
21	"House Interior Design"	• **Interior elements** reflected by *rug, lamp, faucet, cabinet, fireplace, cushion, curtain, stool, wash closet, cupboard, headboard, mirror, armchair, refrigerator, stove, chandelier, drawer, oven, bathtub, blanket, vase, bookcase* • **House** related words *apartment, ceiling, patio, floor, porch, balcony, villa, bungalow, property, backyard, home, suburb, bathroom* • **Interior style** related words *interior, cosy, easy, minimalist*

22	"Time"	• **Planning related** *planner, timepiece, wristwatch, organize, deadline, date, schedule* • **Time related** *late, annual, future, capsule, monthly, daily, moment, occur* • **Terms relating to time limits/restrictions:** *prescription, waste, shipment, repair, justice, chip, report, commerce, move, trash, solar, notice* • **Unrelated terms**: *garage, junk, row, cartography, rudiment, curve, duck, reason*
23	"Elderly and Care"	• **Elderly** related terms *elder, grey* • **Physique and physical evaluation** related terms *teeth, mouth, stomach, cleavage, fingernail, eyebrow, abdomen, eyeball, finger, freckle, topless, stubble* • **Sleep and care** related terms *dream, sleepy, daydream, fatigue, worry, bedtime, stress* • **Caretakers:** *dentist, nurse* • **Cat** related terms*: tabby, whisker, furry* • **Family- and handling** related terms: *relationship, parent, desire, infancy, loyalty, obedient,* • **Presentational features** *sepia, monochromatic*
24	"Design and Digitalization"	• **Textual design** reflected by *text, fact, document, typography, write* • **Graphical design** reflected by *illustrate, symbol, sign, graphic, image, vector, creative, banner, abstract, design, retro, vertical, picture, pattern* • **Presentation means and tools** reflected by *paper, communicate, conceptual, entity, signalize, disjunction, blank, page, display, template, element, inform, screen, electronic* • **Usage in business** reflected by *busy, bill, money, technology, achieve, desktop, computer, internet, data, laptop, currency, financial, bank*
25	"(Formal) Celebration"	• **Celebration** reflected by *celebrate, drink, wine, table, champagne, glass, bouquet, flower, décor, gift, color, food, rose, candle, beer, person, golden, family, chocolate, love, fruit, luxury, alcohol, bottle, vase, cup, tableware, food* • **Festive events, times and locations** reflected by *Christmas, marriage, reception, anniversary, birthday, party, tradition, wedding, romance, breakfast, dinner, restaurant, garden* • **Presentational feature** *bright*

Table 7 shows that in general, the clusters derived from the GloVe output are relatively well-defined and interpretable. The exception is Cluster 22, "Time", which shows a set of words that seem unrelated, and for which no clear relationship can be established.

For the others, most striking is that the clusters generally entail very detailed and nuanced clusters. For example, cluster 19 ("Water Activities and Transport") lays a connection between different kind of water-related terms, including activities, scenes and transport. Another example is cluster 18 ("Competition"); a very detailed collection of terms that relate to competition is distinguished, under which competitors, apparel, award notions and even law enforcement infringement. Even if the terms in a cluster are topically similar, a very precise description of the cluster is provided through detailed house-related words, interior objects and interior styles. An example is cluster 21 ("House Interior Design"), whereby the terms all comparatively strongly and directly relate to house interior design. This nuance also is apparent from cluster 14 ("Hand-Made Clothing and Make-up") and cluster 2 ("Fresh Cooking"); both clusters enrich a rather general topic (respectively "clothing and make-up” and “cooking”) with another more specific dimension, respectively “hand-made” and “fresh”.

Overall, the detail in the topical clusters leads to the depiction of different types of visual content features; concrete objects, actors, activities, themes and presentational characteristics. For the latter, it is remarkable that several topics contain a presentational feature as part of the topical cluster (topics 9, 13, 23, 25). Furthermore, the clusters seem to be depicted elements, rather than topical subjects; they are detailed matters that are more likely to describe the essence of what is happening, than what the photos are generally about. For example; it is likely that “Eating (Out)” and “Fresh Cooking” are important elements of what is happening on a picture, whereas the essence of the photo would be “Food”.

Figure 8 exemplifies the dominant topical clusters that are detected upon the pictures shown in Figure 6, 7 and 3.

Topical Clusters (GloVe): *“Family & Fun”* *“Eating Out”* *“(Formal) Celebration”*	**Topical Clusters (GloVe):** *“Family & Fun”* *“Travelling & Vacation”* *“Fitness & Sports”*	**Topical Clusters (GloVe):** *“High Fashion”* *“Family & Fun”* *“Competition”*

Figure 8: Example of Instagram Photos and respective GloVe produced dimensions

As can be seen in Figure 8, this interpretation of visual content features is relatively successful in capturing word meaning. “Eating (Out)” for example captures the essence of *coffee, bar* and *indoor,* in a more effective and meaningful manner than these keywords separately. This is also the case for “High Fashion”, in relation to *wear, dress* and *glamour. A* meaningful component, trendy clothing, shows the context of *wearing* a *dress* in a *glamorous* manner. Disadvantageous about this interpretation is, however, that it seems to be partially incorrect; “Family and Fun”, “Competition” and “Fitness & Sports” for example, seem relatively far-fetched for the respective photos. They entail relationships that are very small components of the pictures, but do not capture the main essences.

The findings of the NMF and GloVe analysis in this chapter provide an answer to research question 1.

5.3.2 NMF and GloVe Model Comparison: Discussion

Upon comparing the visual content features as produced by NMF and GloVe based on Table 5 and Table 7 and the interpretations thereof, several important remarks can be made.

In the first place, the most significant difference between the two results is the level of detail and nuance. The topics resulting from NMF are universal and comprehensive, whereas the topical clusters resulting from GloVe are relatively precise, refined and require more interpretation. For example; NMF produces the topic “City Trip”, characterized by generic words *urban, city* and *travel.* Glove delivers the comparable topic “City Trip and Urban Scenery”, characterized by relatively refined scenery terms *panorama, skyline, skyscraper,* urban terms *cityscape, town, brick* and trip terms *tourism, landmark.* The latter provides more detail and subtlety to what themes and connections are displayed upon city-trip like photos but also requires a more detailed interpretation to link the concepts together. This is in line with the previous expectations and a likely result of the different working mechanisms of both methods. GloVe uses a local context to identify word meaning and therefore is more likely to establish subtleties and characteristics that often occur with words. NMF, however, detects global themes that are often present on photos in the dataset. The latter is more likely to produce universal themes.

In the second place, a significant distinction that can be made is the extent of interpretation enabled upon the identified visual content features by both methods. The visual content features produced by NMF analysis demonstrate what the photos in the dataset are about, the visual content features created by the GloVe analysis exhibit, to a certain extent, what is happening on the pictures in the data set. A good example hereof is the comparison between topic 12 (“Sports Contest”, NMF) and cluster 18 (“Competition”, GloVe). Hereby, “Sports Contest” reflects the most common type of competition, sports, throughout all the photos. “Competition” reflects the entire theme of competition and shows that this occurs in different forms, such as sports, music and politics. It also detects that such competition elements often occur in the proximity of a victory element, and even that law enforcement can have an intervention in competition proceeding. The latter demonstrates more what is happening in the sense of competition settings on photos. The former illustrates that competition, in the context of sports, is a well-reflected theme on many images. This is an inherent proceeding of point 1; GloVe produces more detailed visual content features because it looks at the local surroundings of words and thereby considers with which objects other objects occur on photos.

In third place, NMF produces high-performing terms as important components of topics and topics themselves, whereas GloVe does not. The most general topic produced by NMF, “Smiling Female”, is not returned upon the cluster analysis applied to the GloVe output. This is a likely result of GloVe’s ability to correct for extremely high-occurring words, whereby (smiling) females are inclined to be present on the majority of the photos (as is also projected in Figure 5). This point is also apparent from the fact that human- and people like terms are often important terms that define topics in the NMF produced topics, but not in GloVe inspired topical clusters.

Furthermore, the form in which presentational visual content features are detected differs per method. NMF detects one topic, and therefore one visual content feature that reflects a dominant presentational characteristic; a portrait photography setting (topic 24). GloVe, however, relates presentational characteristics, such as dusk, monochromatic, bright and sepia to certain topics (topics 9, 13, 23, 25). This is a likely result of the different working mechanisms of both methods. GloVe detects embeddings that represent context and meaning. Hereby, a presentational characteristic, such as the aforementioned filters, can relate to the interpretation of a theme when it often occurs in the context of that theme. NMF, however, detects overarching themes often present on many different photos, therefore reflecting a strong topic.

Moreover, the topical clusters of both methods substantially differ; GloVe produced visual content features reflect, again as an inherent following of the first point, topical clusters that NMF does not find and vice versa. Examples of the former are “Text and Figures”, “Treasures of Nature” and “Formal Celebration”. In comparison, NMF produces “Leisure”, “Domestic Coziness” and “(Walk in) Outside Summer Environment”. The difference between the two is that the NMF topics are broad and likely frequently-occurring. This is also why they are not reflected by the topical clusters upon the GloVe visual content features.

These remarks are in line with the expectations upon the different working mechanisms of the methods. Overall, the main advantage of NMF is that it provides more information as to what the photos are essentially about, whereas GloVe provides more information as to what elements are depicted in the photos, or rather what is happening in them. The main disadvantage of NMF is that it allows for relatively obvious information, as a result of not accounting for extremely frequently-occurring words. The main disadvantage of GloVe is that it is more difficult to interpret because it contains complicated subtleties and details. Both methods prove to be suitable means for visual content analysis in their own way, and the preferred method depends on the objective of the study. In terms of pure interpretation and identification of visual content features in photos, NMF takes preference if one wants to know what the photos are about, whereas GloVe takes preference if one wants to know what is happening in the photos.

In the case of this research, the NMF produced topics take preference in the continuance of this research. For the cluster analysis, the choice was made to conduct this analysis upon the NMF output, because the goal of this analysis was to establish substantially different, very broad themes, in order to correct for underlying topical differences that lead to context-wise interpretational issues for the predictive analysis. Since the visual content features produced by NMF were expected and proved to be more generic and broad compared to those produced by GloVe, NMF was deemed more suitable for this.

For the predictive analysis, the choice was also made to include the topics generated by NMF in the analysis, instead of the GloVe inspired clusters. This research aims to establish visual content features as potential engagement drivers, and the essential topics of the photos produced by NMF are hereby considered more relevant than the actual occurring elements as produced by GloVe. The latter seems too complex and too detailed to capture a relevant meaning as well as too difficult to interpret with enough certainty. Since the GloVe analysis does definitely have the comparative advantage of showing relations, subtleties and essentially, the "story" on a photo, it is strongly encouraged for further research to explore the possibilities of using the GloVe output. For this research, however, this is outside the scope and the choice was made to first explore the "frame", or essence of the "stories" on the photo as a first step. The NMF topics apprehend and transfer a deeper essence of what the photo is about, which is more informative and too crucial to disregard upon predicting engagement. Furthermore, the NMF produced topics are clear and interpretable and leave less room for uncertainty in interpretation, whilst still being detailed enough to consider different types of entities, objects and other features. To establish correct relationships and derive practical recommendations, the correct establishment of visual content features is vital. Lastly, unexpectedness was expected to be more easily establishable upon NMF topics. The GloVe dimensions were so broad that they already contained too many links, ambiguities and contradictions to be able to extract such contradictions in a meaningful sense as a measure for unexpected features. The fact that the NMF has also produced rather arbitrary, dominant topics, such as “Smiling Female”, is not necessarily a problem. The effects for such visual content features can also be isolated and estimated correctly as a result of their existence.

5.4 K-Means Cluster Analysis

K-Means cluster analysis was executed on the photos, upon the visual content features established by the NMF topic model of section 5.1. Hereby, the goal was to determine whether there were underlying subject-wise themes in the photos.

5.4.1 Model Specification

The matrix containing the document scores, H, was used as the input dataset for this analysis. Hereby, the variables used for the actual clustering (from now on: the segmentation variables) entailed the 25 topics as established by NMF. The rows entailed for each word, the score of the term for the respective topic. The idea behind this was that the clustering algorithm found patterns in this dataset through establishing clusters of photos that scored similarly on the set of 25 topics. Since no different units were used in the segmentation variables, this dataset was not standardized.

K was established at a value of 7, based on the plot in Appendix A6, which shows an elbow at a cluster value of 7.

5.4.2 Interpretation & Discussion of the Model

The resulting clusters are graphically depicted in Appendix A7. The segmentation variables entailed the visual content features as produced by NMF. The descriptor variables entailed for each cluster, the predominantly used hashtags and the dominant sentiment valences and emotions. Based on this, an interpretation of the clusters is given in Table 8. Table 8 depicts the most dominant three topics of the segmentation variables. The results indicated relatively stronger mean scores for the dominant three topics, compared to the rest of the included topics.

Table 8: Cluster Segmentation and Description

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Name	***"Goals & Achievements"***	***"Urban Life"***	***"Well-being"***	***"Travel & Vacation"***	***"Architecture"***	***"Appearance"***	***"Love"***
Topics	• (Power) Couple • Smiling Female • High Fashion	• City Trip • Outside Summer Environment • Travelling	• Food • (Office) Work • Graphic Design	• Beach Vacation • Travelling • Swimming Pool	• Interior Design • Domestic Cosiness • House Exterior Design	• Female Model • High Fashion • Smiling Female	• Leisure • Portrait • Loving Family
Dominant Hashtags	• **Career-related** #success #entrepreneur #marketing #business #strategy #workflow #interviews #coffeeenclothes #busydays #press #campaign • **Fashion-related** #coffeeencl	• **Urban/City related** #cityscape #skyline #urbanjungle #bohostyle #london #italy #newyork #berlin #vegas #festival #streetstyle #urban #trip #manhatten #brooklyn • **Fashion-related**	• **Food-related** #ilovefood #foodgasm #foodphotography #dessertgram #coffee #breakfast #homecook #cheatday • **Fitness-related** #workout #training #fitnessmotivation #gym #fitness #pilates #yoga	• **Travel-related** #travel #travelgram #travellover #travelblogger #view #traveldreams #seetheworld #girlswhotravel #travelholic #naturelover • **Vacation-related** #sunsetgoals #beach #bikinibody #summerstay #beachlife #swim	• **Interior-related** #interiorsgoals #loftstyle #decor #walldecor #homedecor #livingroom #home #luxurystyle #interior #roominspo • **Exterior-related** #london #newyork	• **Make-up/Care** #beautytrends2018 #beautyroutine #beauty #makeup #tutorial #skincare #makeuplooks • **Perfume** #perfumes #fragrances • **Fashion-related** #fallfashion #fashionblogger #beautyinfluenc	• **Family-related** #familylove #family #motherhood #familyfirst • **Self-love/Female empowerment** #believeinyourself #workthatbody #movingforward #dreams #girlpower #empowerwomen • **Friend-related**

	othes #watch • **Couple-related** #couple #anniversary #wedding • **Goal achievement** #womenempowerment #goals	#fashiongoals #fashiontrends #fashion #streetstylefashion #styleinspiration #streetwear #lookoftheday #streetfashion • **Weather-related** #weather #summer #fall #weekend	• **Planning-related** #plannerjunkie #planner • **Social-related** #halloween #christmas #party #event • **Health-related** #naturemadehearthealth #positivevibes #wellness #healthylife #spa #healthyliving	#summerstyle #ocean	#lasvegas #chicago #marrakech #hotels #restaurants #sunrise	er #outfitoftheday #instafashion #personalstyle #fashionista #whattowear #sunglasses • **Lingerie** #lingeriemodel #lingerieoftheday • **Hair** #naturalhair#hairtutorial	#friendgoals #bestfriendsforlife • **Couple-related** #happycouple #relationshipgoals #love
Emotional Sentiment	• Trust	• None	• Anger • Anticipation • Disgust • Fear • Joy (+) • Sadness • Surprise (+) • Trust (+)	• Anticipation • Joy (+) • Surprise • Trust	• Disgust • Joy (+) • Surprise (+)	• Anticipation • Joy • Surprise	• Anticipation • Joy (+) • Trust
Sentiment Valence	• Negative	• None	• Positive	• Positive	• Positive	• Positive	• Positive

Cluster 1 is most likely to contain photos in professional settings of empowered, smiling men and women in classy business attire, as well as couple photos of relationship milestones. The sentiment expressed by visual content in this cluster suggests a notion of stress or fearful aspiration with regards to the milestones on the pictures.

Cluster 2 likely contains the depiction of street- and metropolitan fashion worn by women, who are located in urban environments such as world cities. Furthermore, the visual content likely contains skylines, skyscrapers and city-trip photos. The visual content in this cluster does not express sentiment. This suggests that urban features do not necessarily capture sentiment, which seems intuitive.

Popular hashtags in cluster 3 are either food-, fitness-, social- or health-related. Upon broadly interpreting "(Office) Work" and "Graphic Design", which seem relatively out of place, this suggests visual content featuring food pictures, as well as people engaging in exercise, social events or wellness activities. Visual content in this cluster expresses a broad range of sentiment, with a dominantly positive valence. This is intuitive; a balanced lifestyle and wellness is difficult to achieve and acquires inconveniences. Therefore, corresponding terms might be associated with several emotional states. However, it leads to overall positive results and sentiments.

Cluster 4 mainly reflects hashtags that entail either travel-related phrases or vacation-related phrases. The visual content is likely to contain beautiful views of landscapes and backpacking people, as well as beaches and ocean depictions with people in a bikini. The photos in this cluster capture positive emotions, with joy as the most important one. Furthermore, anticipation, trust and surprise are expressed on these photos. This might reflect excitement and amusement with regards to the experience of travelling.

Cluster 5 is mainly characterized by hashtags with interior- and exterior-related formulations. Therefore, the visual content in this cluster probably displays interior décor scenes and buildings, such as restaurants and hotels, in metropolitan cities. The sentiment expressed by this content entails a combination of disgust, joy and surprise, with a positive valence. This might capture regular, diverse sentimental expressions of people in these locations.

Cluster 6 is described by primarily beauty-, perfume-, fashion-, lingerie- and hair- related hashtags. These all suggest appearance-related photos that include models. The positive valence and joyous, anticipation and surprising emotions are likely expressions of and associations with the models or people on photos.

Cluster 7 entails family-related, self-love and female empowerment-related, friend related and couple-related hashtag phrases. All these relationships suggest a kind of love relation, which is likely to be characterized by portrait photos in leisure activities or relaxed settings. The sentiment expressed by photos in this cluster predominantly entails the emotion joy, along with anticipation and trust. The valence of these emotions is positive. These are intuitive associations for the depiction of love relations.

Since the clusters are relatively well-defined and overall make sense, this method can be evaluated as well-performing. Striking is that the themes contain a mix of rather intangible, aspirational themes, such as “Goals & Achievements”, “Well-being” and “Love” on one hand, and rather tangible, relatively more superficial aspects such as “Architecture”, “Appearance”, “Travel & Vacation” and “Urban Life”. For the latter tangible aspects, mainly joy and surprise are expressed as sentiment. For the intangible themes, the sentiment that is captured seems more complicated; it is either of negative valence, a mix of many emotions or containing anticipation and trust.

These clusters can be used in the predictive models in section 5.6, to correct for the general contextual theme in which the photo is published. An example hereof is given in Figure 9.

Cluster 3:
“Well-Being”

Cluster 4:
“Travelling & Vacation”

Figure 9: Example of Instagram Photos and respective Clusters of K-Means Cluster Analysis

Figure 9 exemplifies how the cluster analysis classifies these two photos in their correct contextual theme. This is likely to aid the analysis since context matters for how people interpret and engage with a photo (Lin & He, 2009). Some objects and colour use may be interpreted as positive upon a food-context, while not relevant on a beach-context. In the context of Figure 9, for example; *feet* may be a well-engaging feature in the context of travelling, but not in the context of food.

The findings established by the analysis in this section provide an answer to research question 2.

5.5 Calculating Unexpectedness

Upon completing the analyses presented in the previous sections, the *unexpectedness* could be calculated and established for each photo. This was measured as the extent to which the main topics represented on a photo deviated from the main topics that constructed the thematic cluster of that photo. This was assumed a proxy for the presence of unexpected topics in a picture, based on the intuition that prior expectations are aligned with the contextual theme of that photo. The main topics in this calculation reflect the top three topics that define the cluster of that photo. This was based on Pickering & Jordanous, (2017) upon whom this operationalization was based. They state that the foundational 'predictable' elements must be very general to be a fitting measure for a wide range of inputs. Since the clusters were based on the three most dominant topics in that cluster and the other topics generally were of substantially lesser presence, these three dominant topics were considered the most appropriate to consider as a general foundation.

Essentially, the unexpectedness of a photo observation n in cluster c was equal to the maximum possible document factor scores total, subtracted by the sum of the document factor scores on the three most dominant topics that constructed the cluster that document belonged to. This is mathematically represented in equation 8 below. It should be noted that for the unexpectedness calculations, the document factor scores were normalized so that they added up to 1, in order to make them universally comparable against each other. Therefore, the maximum variation explained by the clusters also entailed 1.

$$unexpectedness = 1 - \left(\sum_{i_c=1}^{3} s_{i_c} \right) \qquad (8)$$

Hereby, s entails the topic score for topic i, which in this calculation takes a range between 1 and 3. This refers to the top three topics that define the cluster of that photo. Topic i in turn depends on c; the cluster of photo n, ranging from 1 to 7. This is based on the 7 clusters as presented in Table 8.

In order to illustrate this measure, Figure 10 exemplifies two photos that scored very high on this operationalization of unexpectedness.

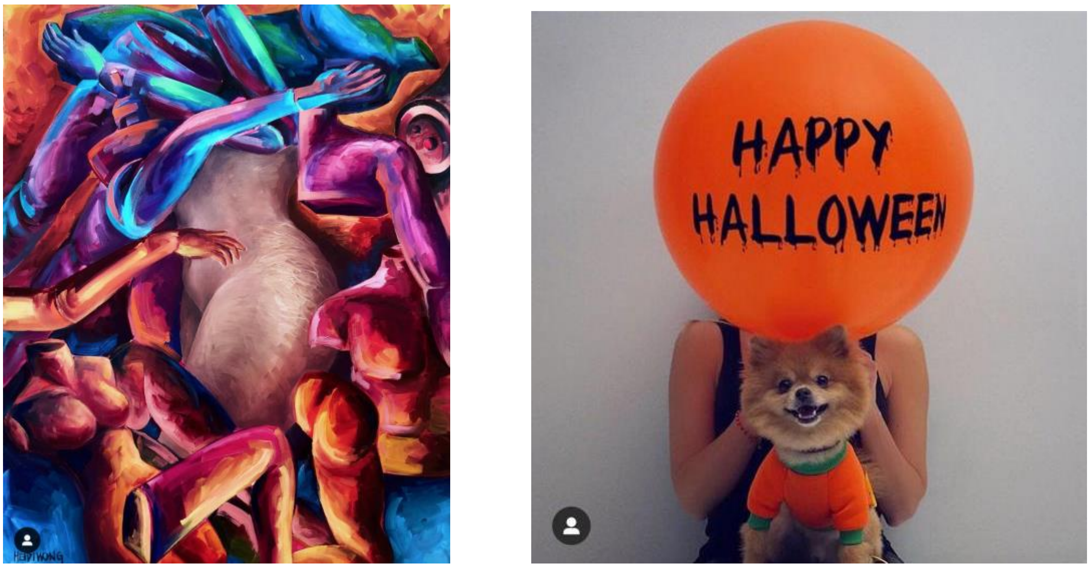

Figure 10: Example of Instagram Photos and that score high on Unexpectedness

The pictures in Figure 10 suggest a relatively well-working mechanism of the unexpectedness measure. The photo on the left shows a rather abstract, artistic depiction of different naked bodies. This is rather absurd and is likely to be unexpected for many viewers. The photo on the right shows a combination of a cute puppy, with a bright colourful top and a Halloween-themed balloon. This combination of freaky and cute is also likely to be different from prior expectations for many viewers.

The findings established by the analysis presented in this chapter provide an answer to research question 3.

5.6 Regression

In order to establish the connection between the identified visual content and the post engagement, a multiple linear regression model was conducted. To more specifically research interaction effects, a LASSO regression model was conducted.

For the linear regression (for which two models were conducted), the two dependent variables entail the number of likes and the number of comments, both divided by the reach, respectively. Since this produced very small numbers, the number of likes and comments per 1000 followers was adhered for interpretation.

It should be noted that the independent variables were standardized before performing the regressions, to ensure that the effect sizes of the variables were universally comparable against each other. The topic scores were hereby thus not normalized so that they added up to 1 but divided by their standard deviation. This was done to make interpretation easier: coefficients described the effect size as a result of one standard deviation increase in the document score of a photo on a topic.

Upon including the clusters from Table 8, Cluster 6 (*Appearance*) was left out as a reference category to avoid multicollinearity. This cluster was chosen because it was expected to be the most dominating and common based on Lee et al (2017). It was deemed most informative to interpret the effects of all clusters relative to the most dominant cluster, which is least informative by itself due to its commonness.

5.6.1 Multiple Linear Regression: Interpretation & Discussion

A summary of both models is given in Table 9 below.

*Table 9: Summary of Multiple Linear Regression Model on Likes and Comments per 1000 Followers, whereby a 5% significance level is denoted with **

	Variable	**Coefficient on *Likes per 1000 Followers***	**Coefficient on *Comments per 1000 Followers***
	Intercept	1.46E+01	6.67E+04
Topics	*Smiling Female*	1.46E+00*	2.77E+04
	Outside Summer Environment	-3.26E-02	-4.85E-02
	Interior Design	-9.38E-01	-8.12E-02
	City Trip	8.15E-01*	5.66E-02
	Female Model	6.30E-01	1.97E-01*
	Graphic Design	-9.24E-01*	2.77E-02
	Beach Vacation	-1.61E-01	-3.58E-02
	Office Work	-1.92E+03	-3.76E-02
	Food	-3.07E-02	1.02E-02
	Loving Family	-8.09E-02	2.02E-01*
	Domestic Coziness	-3.80E-01	-2.65E-02
	Sports Contest	-1.20E+00*	-3.00E-02
	Outdoor Scenery	-2.24E+00*	-8.54E-02
	Leisure	1.37E+00*	1.64E-01*
	Pets and Animals	-1.30E+00*	1.77E-02
	Flowers	-6.87E-01*	2.61E-02

	Power Couple	4.19E-01	6.50E-02
	High Fashion	1.94E+00*	4.09E-01*
	Travelling	1.44E-01	7.70E-02
	Marketplace	-2.14E-01	1.39E-02
	Swimming Pool	9.07E-01*	-6.61E-03
	Road Transport	-1.42E-01	-4.52E-02
	Musical Performance	-8.14E-01*	-2.12E-02
	Portrait Photography	-8.63E-01*	-3.21E-02
	House Exterior Design	-2.09E-01*	1.45E-02*
Sentiment	*Anger*	2.01E-01	1.45E-02
	Anticipation	-5.69E-01	-6.58E-02
	Disgust	1.09E+00*	2.71E-02
	Fear	-1.47E-01	4.87E-02
	Joy	-2.50E+00*	-3.11E-01*
	Sadness	9.87E-01*	2.54E-02
	Surprise	-7.66E-01*	-2.30E-02
	Trust	-6.41E-01*	-2.32E-02
	Negative	-6.34E-01*	-1.40E-01*
	Positive	3.40E+00*	2.72E-01*
Additional	*Unexpectedness*	1.04E+00*	2.70E-01*
	Reach	1.53E-05*	-8.19E-10*
Clusters	*Goals & Achievements*	-1.81E+00*	-2.65E-01*
	Urban Life	2.42E+00*	3.08E-01
	Well-being	-1.34E+00*	2.72E-02
	Travel & Vacation	-1.54E+03	5.23E-03
	Architecture	2.22E-01	1.22E-02
	Appearance	NA	NA
	Love	-3.02E-01	-5.77E-02
R-Squared		39.41E-03	30.11E-03

Table 9 shows the coefficients that denote the increase (or decrease when preceded with '-') of the engagement per 1000 followers in likes as well as comments, upon the increase of the corresponding variable with one standard deviation. For topic variables, this denotes the effect on engagement per 1000 followers, upon increasing the topic score of a photo for that topic with one standard deviation. For sentiment variables, the coefficients reflect the effect on engagement per 1000 followers, upon increasing the score of a photo for a valence or an emotion with one standard deviation. For *Unexpectedness*, the coefficients reflect the effect on engagement per 1000 followers, upon increasing the photo variation unexplained by the cluster analysis with one standard deviation. *Reach* provides the effect of increasing the number of followers with one standard deviation, on the likes and comments per 1000 followers. *Cluster* gives the effect on engagement upon inclusion in a cluster, compared to inclusion in Cluster 6. All the effects are established at a 5% significance level.

Smiling Female, City Trip, *Leisure, High Fashion,* and *Swimming Pool* have a significant positive effect on likes. For comments, *Female Model* and *Loving Family* additionally have a significant positive effect and *Swimming Pool* and *City Trip* contrastingly have no significant positive effect. These topics all suggest the presence of humans, and common relaxation and pleasure activities (laying by the pool, fashion, city tripping, leisure). *Graphic Design, Sports Contest, Outdoor Scenery, Pets and Animals, Flowers, Musical Performance, Portrait Photography* and *House Exterior Design* have a significant negative effect on likes. *House Exterior Design* is the only significant negative effect on comments. These topics all suggest no presence of humans, except for performance-related and effort-involving activities (musical performance, sports).

These findings suggest that even though people, especially women, are very dominantly depicted on influencer photos in Instagram, their presence on photos significantly leads to engagement, whereas their absence does not. This is in line with and extends the findings from Bakhshi et al (2014), who presented empirical evidence that the presence of faces (which implies the presence of people) on photos in a non-influencer context caused more likes and comments. A potential reason for this is that they inspire a sense of identification. Pérez-Vega, Taheri, Farrington & O'Gorman (2018) present that the presence of humans contributes to the identity attractiveness of the content: the degree to which individuals show attraction, identification, preference and relationship support for something. It is more likely that humans have this for other humans than for objects, as a result of being able to identify with them. Animals, flowers, graphic designs and exterior designs are things that plausibly do not invoke identification or relationship support.

The discrepancy between the pleasure-oriented activities and performance-oriented activities herein could be explained by Ha et al (2017). They found that facial expressions of happiness significantly lead to more advertising efficacy. Happiness expressions are more likely to occur in the context of low-involvement activities such as shopping or leisure, than for singing before a crowd or participating in a sports contest. These latter are more likely to contain facial expressions of exertion.

The emotion sentiment variables show relatively counterintuitive effects, which is remarkable. *Disgust, Anticipation* and *Sadness* have a positive effect on engagement, whereas *Joy, Surprise* and *Trust* have a negative effect. Berger & Milkman (2012) found a negative effect of low-arousal emotions such as *Sadness* on engagement, and positive effects of high-arousal emotions such as *Anticipation* and *Surprise.* Furthermore, positive oriented emotions like *Joy* and *Trust* would intuitively be expected to lead to more engagement. This is based on the theory that cues of positivity and amusement on content drive engagement (De Vries & Carlson, 2014). The positive effect of *Disgust* also seems counterintuitive, based on research that states that attractiveness and esthetics on photos leads to more engagement (Jaakonmäki et al, 2017).

The observed effect for *Surprise,* however, can be consolidated by Lindgreen & Vanhamme (2003). Their work presents that surprise is a complicated emotion; it is not necessarily positive or negative on its own, but becomes either of the two upon combination with other emotions. As such, pleasant as well as unpleasant surprises can arise. Unpleasant surprise is dangerous in marketing, because it is associated with consumer disappointment and outrage, which is detrimental to consumer relationships. Lindgreen & Vanhamme (2003) also present that surprise often unintentionally is experienced as negative by consumers, as divergence from reality is difficult to process for people. This might be the case for the content used in this research, which gives a potential explanation for the observed negative effect of *Surprise*. A comparable effect may be in place for *Anticipation*; this is also a rather ambiguous emotion that can be experienced as both positive and negative depending on the context. If the content used in this research predominantly contains a context that expresses unpleasant anticipation, this might an underlying reason for the observed effect.

A potential explanation for the observed effect for *Sadness* may be that content that contains sad emotions invokes compassion. Compassion, which induces people to sympathize with the pain of others, has been proven to positively impact behaviours of social conformity (Abreu, Laureano, da Silva & Dionísio, 2015). Liking the content may hereby be a form of social conformity or a manner of expressing compassion.

For *Sadness, Surprise* and *Anticipation* however, it is especially important to carefully inspect whether the LASSO model presents interaction effects that can still consolidate these confounding findings with previous literature.

The observed effect for *Joy* might be potentially underlaid by appearance of joyful content on already very positive content. This may cause a positivity overload, which was found in earlier research to decrease engagement because it threatens the perceived authenticity of content (Heimbach & Hinz, 2016).

The negative effect of *Trust* can be explained by the theory that many words associated with trust reflect concepts of extremeness. This was manually checked; extreme words such as *abundance* or *celebrity* are associated with trust in the lexicon, likely because they transfer a sense of acquiescence. Such extremeness however, may not necessarily lead to engagement on Instagram, because it may be considered less identifiable, genuine and authentic. Authenticity is, amongst other things, very important for engagement because it is in compliance with the unprompted nature of Instagram (Ha et al, 2017).

For *Disgust*, a potential explanation could lay in the nature of the data. The sentiment analysis produces emotional sentiment based on common associations of the word tags with certain emotions. Cwynar-Horta (2016) states that on photos, disgust is often related to imperfect and unconventional content. Cwynar-Horta (2016) however also states that currently, such content is becoming more and more popular on social media because it has increased identifiability for consumers. The 'body positive' movement, which presents the acceptance and idealization of bodies that would conventionally be called imperfect, is a good example hereof. Words like *scar, fat* and *stretchmark* are for example likely to be associated with *Disgust,* however their visual depiction acts as an engagement driver in the current social media atmosphere (Cwynar-Horta, 2016). This presents an explanation why content with higher scores on *Disgust* might increase engagement.

The interaction effects of *Disgust, Trust* and *Joy* are also important to identify, to potentially explain the counter intuitiveness of these observed effects.

The confoundedness and counter intuitiveness of these emotional sentiment variables may also be a result of data and research limitations. Emotions are often expressed by facial expressions upon photos (Mohammad & Turney, 2013), which was the input for the sentiment analysis. Ha et al (2017 state, however, that facial expressions are often complicated to capture and interpret by algorithms correctly. Contemporary visual trends, such as ‘model-chic’ (somewhat neutral, non-smiling facial expressions used in high fashion) is a good example of such difficultly interpretable contradictions in facial expressions and sentiment. This raises the question as to whether the emotional sentiments are divergent and counterintuitive because of the high presence of such contemporary trends. Such trends are likely to dominate Instagram, as this is a contemporary and trendy medium. This could lead to expressions and therefore sentiment not being correctly deducted, leading to confounding results.

The sentiment polarities do present intuitive effects that are in agreement with findings of previous literature. *Positive* has a significant positive effect, and *Negative* has a significant negative effect. Berger & Milkman (2012) state that positive content is likely to transfer a positive state of mind over to the consumer. For negative, the opposite effect is in place.

The significant positive effect of *unexpectedness* on engagement extends earlier findings of Bruni et al (2012), Pickering & Jordanous (2014) and Chen & Lai (2017) to an influencer social media context. These all presented the idea that unexpected features are likely to inspire more engagement. This can, through the findings in this research, be extended to an Influencer Instagram context. The working mechanism of *unexpectedness* is further elaborated on through the interaction effects in the LASSO model.

Cluster 2 (*Urban Life)* has a significant positive effect, Cluster 1 (*Goals & Achievements),* Cluster 3 (*Well-being)* and Cluster 4 (*Travelling & Vacation)* have a significant negative effect on likes per 1000 followers. Only Cluster 1 has a significant negative effect on comments per 1000 followers. This means that inclusion in these clusters leads to significantly more and less engagement, respectively.

Slater, Varsani & Diedrichs (2017) stated that appearance neutral images, such as interior- or exterior design images, as well as outside sceneries, often led to a more positive mood compared to appearance-centred images. The reason for this was that the latter caused body dissatisfaction issues. Leisure activities on Instagram photos were associated with pleasantness, according to Ferwerda & Tkalcic (2018). This suggests that overall, architecture-themed photos combined with leisure activities, which somewhat describes the urban life theme, led to a more pleasant experience of that photo. This could positively drive engagement (De Vries & Carlson, 2014). This is a potential explanation for the comparatively positive effect of *Urban Life* against *Appearance*.

The comparative negative effect of Cluster 4 against Cluster 6 can be explained by the effects of picturesque and filtered images. Ha et al (2017) state that Instagram is, as a result of being a contemporary spontaneous social media platform, subject to a growing trend of casual photos. These casual photos are less 'perfectly' oriented and are aimed to depict more genuineness, compared to traditional marketing photos. Man (2016), however, presents that travelling photos in Instagram often represent rather picturesque, heavily-filtered photos with edited colours and lighting. If Instagram is indeed experienced as having a spontaneous and casual essence, this provides a suitable explanation for travelling photos leading to less engagement compared to appearance photos.

This same effect could extend to the observed effect for *Well-being* (Cluster 3), encompassing food, amongst other themes. Holmberg et al (2016) presented that professionally photographed food pictures were prevailing on social media because such a presentation contributed to a 'tasty' experience of the photo in cookbooks.

A comparable theory may underly the observed effect for *Goals & Achievements.* This theme may itself be subject to a less authentic or genuine experience because of its inherent 'show-casing' characteristic. This may especially be the case when the fashion (and thereby also *Appearance*) segment on Instagram is becoming more and more centred towards the topic of authenticity. A good example is given by O'Donnell & Willoughby (2017), who declare that social media engagement is positively driven by authentic-appearing love relations and couple photos. Couple milestones and photos are a substantial part of Cluster 1.

Overall, all the effect sizes are slightly smaller in the second model; the visual content features overall have less of an impact on comments than they do on likes. This can be reconciled with the theory that visual content is more likely to invoke likes than comments. Bakhshi et al (2014) state that likes and comments are both measures of engagement, whereby likes measure the degree of interest of users for the content and comments measure the degree of discussion of users for the content. De Vries, Genser & Leeflang (2012) find that commenting is often increased when the content includes an engaging question, for which the only option to answer is to provide a comment. These findings both suggest that comments are often the result of some sense of controversy or discussion-invoking content, which is less likely to be the case for visual content because it cannot do this as explicitly as textual content.

Reach is significant in both models. Upon having more followers, the probability of more likes for an influencer photo is larger, whereas the probability of more comments is smaller. For likes, these findings are in line with the expectations, based on Bakhshi et al (2014), who established a positive relationship between the follower base and engagement on social media. The reason for this was simply that a larger follower base meant a higher exposure, which increased the likelihood of people liking a photo. For comments, this finding can be explained by another intuition proposed by Bakhshi et al (2014). Upon having more photo posts, all photos individually have a lower likeliness of being commented on. This explanation could extend to the finding in this paper. Upon having more followers, which is also a measure for the 'size' of the influencer, any individual follower has a lower likeliness of commenting.

The adjusted R-Squared of both models indicates that the explanatory power of these models is relatively low. Essentially, the engagement per follower in the form of likes can for a proportion of 0.03941 be explained by the variables in the model and for the engagement per follower in comments this holds for a proportion of 0.003011. It seems reasonable that the visual content characteristics as operationalized in this research do not explain a very large extent of the engagement. They are very specific parts of the content and many other potentially influential variables have not been taken into account in the model. However, given the immense volume of influencer marketing and the potential profitability thereof, the small proportion of explained variance still represents a meaningful impact that can be made through using visual content features and elements based on the established relationships.

The discrepancy in R-squared also confirms that visual content features are more explanatory for likes than for comments, which can be explained by the theory as mentioned above about discussion- and question invoking characteristics of visual content. For this reason, the LASSO model, conducted to further research potentially interesting interaction effects, is only conducted with likes per 1000 followers as a dependent variable. The model was also conducted with comments per 1000 followers as a dependent variable, but this produced only four non-zero coefficients.

5.6.2 LASSO Regression: Interpretation & Discussion

The LASSO model was conducted with a small regularization factor, of which the value was cross-validated. This led to relatively few variable coefficients being shrunk to 0. For space constraints, only the most remarkable effects are discussed in an exploratory manner, to meaningfully complement the previous analyses.

Table 10 below shows the coefficients of the feature-selected variables on the likes per 1000 followers for the variables of the general model. The table also provides remarks regarding the observed findings, to compare them to those of the linear regression model.

Table 11 below shows the coefficients of the feature-selected interaction effects with the sentiment variables on the likes per 1000 followers. These are ordered and discussed based on the sentiment variables, because this seemed most intuitive. Table 12 below shows the coefficients of the feature-selected interaction effects with *Unexpectedness* on the likes per 1000 followers. The coefficients hereby denote the effect change of the main effect of either of the two variables that participate in the interaction effect, upon interacting with the other. The tables 11 and 12 also provides a set of remarks and discussions for the most striking findings.

Table 10: Summary of LASSO Regression Model - General Model

Variables	Coefficient	Discussion
Intercept	1,60E+00	• For the **non-interaction variables**, the LASSO model produces roughly similar results to the linear regression model but selects additional variables that are of meaningful impact. *Smiling Female, City Trip, High Fashion, Swimming Pool, Graphic Design, Office Work* and *Pets and Animals* were feature-selected by the LASSO model with similar effect directions, next to being significant in the linear regression model. *Female Model, Leisure, Flowers, Power Couple, Marketplace* and *Musical Performance* were furthermore feature-selected by the LASSO regression model, with positive effect sizes. *Domestic Coziness, Outdoor Scenery, Portrait Photography* were estimated by the LASSO regression model to entail negative effect sizes. Underlining the theory presented to explain the findings of the multiple linear regression, the additionally selected features with positive effects mostly suggest the presence of humans or leisure activities. • The **exception** for this is *Musical Performance,* which had a contrasting effect direction in the linear regression model. An explanation for this is found by examining the interactions of *Musical Performance* as presented in Table 11. • For the **sentiment variables**, the same effect directions are in place as well. *Joy* and *Negative* however, were not feature-selected to have a main effect on engagement by the LASSO model. Contrarily, these sentiments did prove significant in the linear regression model. Therefore, their interaction effects are examined in Table 11. For the rest of the
Smiling Female (Topic 1)	7,00E-01	
(Walk in) Outside Summer Environment (Topic 2)	1,98E-01	
City Trip (Topic 4)	1,13E+00	
*Female Model (*Topic 5)	5,24E-01	
Graphic Design (Topic 6)	-9,22E-01	
(Office) Work (Topic 8)	-2,22E+06	
Domestic Coziness (Topic 11)	-1,24E-01	
Outdoor Scenery (Topic 13)	-5,58E-01	
Leisure (Topic 14)	4,21E-01	
Pets & Animals (Topic 15)	-2,10E-01	
Flowers (Topic 18)	1,88E-01	
Marketplace (Topic 19)	1,72E-01	

Swimming Pool (Topic 21)	1,36E+00
Musical Performance (Topic 23)	1,09E-02
Portrait Photography (Topic 24)	-5,81E-01
Anticipation	-2,93E-02
Disgust	6,72E-01
Sadness	5,08E-01
Surprise	-1,59E+00
Trust	-3,14E-01
Positive	1,46E+00
Goals & Achievements (Cluster 1)	-1,28E+00
Urban Life (Cluster 2)	1,92E+00
Travel & Vacation (Cluster 4)	-1,16E+00

sentiment variables in this model, the explanations as presented in the discussion of the linear regression model for the main effects are assumed to hold in this model as well. The interaction effects in Table 11 for these variables elucidate how these effects may differ upon interaction with different topics.

- ***Unexpectedness*** was not selected by the LASSO model as a singular variable, even though it was significant in the linear regression model. The selected interaction effects with *unexpectednes*s are discussed in Table 12. The selection hereof by the LASSO model essentially means that unexpected elements are only engagement drivers in combination with specific topics.

Table 11: Summary of LASSO Regression Model - Sentiment Interaction Variables

Sentiment	Topic Variables	Coefficient	Discussion
*Anger **	*City Trip*	2,57E-01	• The negative interaction effects of *Sadness* and *Anticipation* with ***Portrait Photography*** suggest a new interesting insight regarding this topic. The negative main effect of *Portrait Photography* could be explained by the theory that it reflects a professional photography setting. Ha et al (2017) state that in the context of fashion photos, marketing shots with professional elements such as lighting might not correspond to the spontaneous nature of Instagram. Casual, non-professional shots with a more authentic vibe perform better on this medium. Portrait Photography suggests however, among other things, the careful depiction of faces. The negative interaction effects with *Anticipation* and *Sadness* suggest that high-intensity facial expressions lead to even less engagement. An explanation for this is that such high-intensity emotional facial expressions are unconfirm a dominant current Instagram trend on facial expressions; “cool-chic” (Ha et al, 2017). This is a somewhat neutral, non-smiling facial expression that surpasses a notion of luxury and high fashion. Being unneutral, carefully depicted expressions of anticipation and sadness could be experienced as both less authentic and untrendy. This could cause the negative impact on engagement.
	Power Couple	2,49E-01	
	Marketplace	2,10E-01	
	Flowers	1,32E-01	
	Beach Vacation	9,34E-02	
	Smiling Female	3,83E-02	
	Female Model	2,29E-02	
	Road Transport	5,95E-03	
	Travelling	-5,71E-01	
	Interior Design	-4,93E-01	
	(Walk in) Outside Summer Environment	-2,77E-01	
	High Fashion	-1,63E-01	

	Domestic Coziness	-1,09E-01
	(Office) Work	-1,89E-02
	House Exterior Design	-1,10E+00
Anticipation *	*Pets & Animals*	8,77E-01
	Sports Contest	6,14E-01
	Musical Performance	3,25E-01
	(Office) Work	2,68E-01
	(Walk in) Outside Summer Environment	3,85E-02
	Marketplace	3,95E-03
	Food	-2,10E-01
	Domestic Coziness	-2,15E-01
	Power Couple	-2,65E-01
	Loving Family	-2,70E-01
	High Fashion	-3,42E-01

Furthermore, the positive interactions of *Portrait Photography* with both *Positive* and *Negative* can be explained by the theory that high content sentiment polarities are positively connected to perceived brand authenticity (Shirdastian, Laroche, Richard, 2019). Portrait Photography generally has a negative effect on engagement, which can be explained by the theory that it reflects a professional photography setting. Ha et al (2017) state that in the context of fashion photos, marketing shots with professional elements such as lighting might not correspond to the spontaneous nature of Instagram. Casual, non-professional shots with a more authentic vibe perform better on this medium. This could explain why photos with high sentiment polarities do have positive effects on engagement upon being combined with *Portrait Photography;* they are experienced as more authentic and do therefore better correspond with the nature of Instagram.

- For ***Anticipation**,* positive interaction effects seem to appear upon many topics that are intuitively high-arousal and performance oriented (*Sports Contest, Musical Performance, (Office) Work, Marketplace).* Thereby, the findings can be consolidated with the confoundedness with previous findings by Berger & Milkman (2012). Berger and Milkman state that high-arousal emotions lead to more engagement because they are more likely to inspire (physical) action, such as

	Travelling	-5,03E-01
	Graphic Design	-6,15E-01
	Portrait Photography	-8,19E-01
	Outdoor Scenery	-8,69E-01
	Smiling Female	-1,37E+00
*Disgust **	*Power Couple*	4,58E-01
	Food	1,35E-01
	Graphic Design	1,42E-02
	Travelling	6,46E-03
	Swimming Pool	-8,48E-03
	Leisure	-1,40E-02
	High Fashion	-1,53E-01
	Sports Contest	-2,37E-01
	Loving Family	-5,91E-01

liking. The positive interaction effects with high-arousal topics suggests that the positive effect of high-arousing content on engagement is still in place. The negative interaction effects with *Anticipation* also intuitively belong to low-arousal and less performance-oriented topics (*Domestic Coziness, Loving Family, Travelling, Outdoor Scenery).* The main negative effect of *anticipation* was earlier explained by appearance with negative topics, leading to unpleasant anticipation. This does however not seem the case upon considering the interaction effects: negative interaction effects appear upon topics that are intuitively positive (*Loving Family, Power Couple).* The working mechanism hereof therefore remains an interesting direction for further research. A possibility for the inexplicability of these results is that not all interactions between all elements were used in this model. To correctly isolate all the effects of interest such as the proposed one above, also interactions between different sentiments should be considered. This may present a limitation of this research that could explain the confoundedness of these results with previous research.

- The discrepancy between the different interaction effects for ***Disgust*** with the different topics might lay in the age of the audience that engages with these topics. George (2012) found that older audiences are less likely to be negatively influenced by disgust than younger

*Fear **	*(Walk in) Outside Summer Environment*	5,74E-01	audiences. Swimming Pool, Leisure, High Fashion, Sports Contest and Loving Family have negative interaction effects with *Disgust,* which indicates that these topics may thus be more liked or viewed by younger audiences. The topics that entail a positive interaction effects (*Power Couple, Food, Graphic Design, Travelling*) may therefore be predominantly viewed by older audiences. Cwynar-Horta (2016) also states that older women tend to be more adoptive of the current imperfection trend compared to younger women, which is presented as an explanation for the positive main effect of disgust. This underlines the theory that topics viewed by people who are comparatively more adoptive of this trend, are likely to engage with such content more. People who are comparably less accepting of this trend therefore engage less with such content. It is however difficult to link the topics to age groups, so the underlying reasons behind these effects remain somewhat inconclusive and this provides an interesting direction for further research.
	Power Couple	3,85E-01	
	Interior Design	3,30E-01	
	Outdoor Scenery	2,32E-01	
	Food	1,38E-01	
	Sports Contest	-2,74E-03	
	Graphic Design	-2,70E-02	
	High Fashion	-1,71E-01	
	Marketplace	-2,78E-01	
	House Exterior Design	-5,76E-01	
*Joy **	*House Exterior Design*	1,44E+00	• The observed interaction effects *with* ***Joy*** seem to underline the aforementioned theory. Heimbach & Hinz (2016) presented that positive content leads to more engagement up to a certain point, from which onwards it can decrease engagement. A reason for this is that it threatens the perception of genuineness of the content. With the intuition that joy has a similar working mechanism as positive content,
	Sports Contest	8,38E-01	
	Interior Design	4,93E-01	
	Beach Vacation	3,47E-01	

	Road Transport	3,40E-01	this effect could apply here as well. Negative interaction effects with *Joy* appear upon many topics that singularly have a positive effect on engagement as well as intuitively reflect happiness (*Smiling Female, Loving Family, Flowers*). Positive interaction effects are observed for topics that singularly were not feature-selected by the model and that do not directly reflect notions of happiness (*House Exterior Design, Interior Design, Road Transport*). It is therefore plausible and consistent with the theory that topics that already display a certain state of positivity, experience less engagement than usual upon being combined with a more positive emotion. Topics that did not yet reflect a lot of positivity, can have a more positive effect on engagement upon combination with a positive emotion than usual.
	Swimming Pool	-7,79E-03	
	Flowers	-7,49E-02	
	Female Model	-1,12E-01	
	High Fashion	-1,27E-01	
	Loving Family	-2,04E-01	
	City Trip	-1,01E+00	
	Smiling Female	-1,16E+00	
*Sadness **	*Outdoor Scenery*	5,83E-01	• ***Sadness*** has positive interaction effects with topics that predominantly suggest types of environments and surroundings (*Outdoor Scenery, Travelling, Marketplace, Domestic Coziness, House Exterior Design).* Gibbs, Meese, Arnold, Nansen & Carter (2015) present that sadness-containing, funeral-oriented posts on Instagram often displayed landscapes, locations, places and buildings*.* These surroundings transfer a sense of melancholy through natural elements and architecture. This is a plausible explanation for why the main positive effect of *Sadness*, with compassion as a potential explanation, leads to even more engagement upon capturing melancholy in a natural
	Travelling	4,77E-01	
	Marketplace	3,61E-01	
	Domestic Coziness	2,26E-01	
	House Exterior Design	1,03E-01	
	Female Model	8,41E-02	

<table>
<tr><td rowspan="11"></td><td>Swimming Pool</td><td>-9,39E-03</td><td rowspan="14">manner. The negative interaction effects appear upon topics that are intuitively positive or bright and rather artificial (Swimming Pool, Graphic Design, Smiling Female, Pets & Animals). These topics are less likely to transfer this melancholic natural sense and it makes sense they therefore comparatively lead to less engagement. Furthermore, they are intuitively less likely to evoke compassion, because of their naturally positive orientation.

Another remarkable insight is presented by the negative interaction effect with Musical Performance. This effect underlines the theory that the facial expressions depicted upon musical performances might often not be happy or joyous, but rather display a sense of exertion or effort. This effect may be captured by sadness, as sad facial expressions also present a notion of tension. It is therefore likely this effect was captured in the coefficient for Musical Performance as a singular predictor in the linear regression model, whereas the LASSO model isolated a relevant interaction. Without the notion of tension and facial expressions based hereupon, Musical Performance entails a positive effect as stated in Table 10, likely due to the presence of humans.

• The positive interaction effect of surprise with Interior Design can be explained by Lindgreen & Vanhamme (2003). Usage of a surprise element in marketing often creates an augmented product for the</td></tr>
<tr><td>Graphic Design</td><td>-3,40E-02</td></tr>
<tr><td>City Trip</td><td>-3,83E-02</td></tr>
<tr><td>Food</td><td>-9,59E-02</td></tr>
<tr><td>(Walk in) Outside Summer Environment</td><td>-1,39E-01</td></tr>
<tr><td>Smiling Female</td><td>-2,44E-01</td></tr>
<tr><td>Portrait Photography</td><td>-2,44E-01</td></tr>
<tr><td>Musical Performance</td><td>-2,93E-01</td></tr>
<tr><td>(Office) Work</td><td>-3,20E-01</td></tr>
<tr><td>Pets & Animals</td><td>-3,26E-01</td></tr>
<tr><td>Road Transport</td><td>-5,75E-01</td></tr>
<tr><td rowspan="3">Surprise *</td><td>Interior Design</td><td>1,51E+00</td></tr>
<tr><td>Power Couple</td><td>5,60E-01</td></tr>
<tr><td>Leisure</td><td>3,48E-01</td></tr>
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<table>
<tr><td rowspan="8"></td><td>Loving Family</td><td>1,22E-02</td><td rowspan="14">consumer; a new dimension of the product that makes it more desirable. Since singularly it has a negative effect, surprise is in combination with the interior design topic (which reflects actual products) expected to not lead to disappointment but desirability. The other positive interaction effects with the topics Power Couple, Leisure, Loving Family, High Fashion and Portrait Photography can also be consolidated with Lindgreen & Vanhamme (2003). Their work presents that dynamics reflected an interesting surprise element in fashion-like and photographic images that activated consumer minds. These topics are therefore expected to contain interesting dynamic features, more so than other topics. The presence of interesting dynamics also presents a potential consolidation with the confounding main effect of Surprise compared to Berger & Milkman (2012). Berger and Milkman considered high-arousing emotions in content to be positively impacting engagement because arousal is more likely to inspire (physical) action, such as liking. Dynamics are intuitively associated with high-arousal content. Therefore, it could be stated that Surprise, upon appearing in a high-arousal context positively impacts engagement even if its main effect is negative.

• The observed interaction effects for Trust underline the presented theory on extremeness and authenticity as an explanation for the main negative effect of Trust. The most positive interaction effects belong to</td></tr>
<tr><td>High Fashion</td><td>9,29E-03</td></tr>
<tr><td>Portrait Photography</td><td>4,04E-03</td></tr>
<tr><td>Road Transport</td><td>-3,93E-03</td></tr>
<tr><td>Smiling Female</td><td>-5,91E-02</td></tr>
<tr><td>Beach Vacation</td><td>-3,37E-01</td></tr>
<tr><td>City Trip</td><td>-5,38E-01</td></tr>
<tr><td>Outdoor Scenery</td><td>-7,00E-01</td></tr>
<tr><td rowspan="6">Trust *</td><td>Pets & Animals</td><td>1,53E+00</td></tr>
<tr><td>Domestic Coziness</td><td>4,63E-01</td></tr>
<tr><td>Marketplace</td><td>4,17E-01</td></tr>
<tr><td>(Office) Work</td><td>3,71E-01</td></tr>
<tr><td>Portrait Photography</td><td>3,22E-01</td></tr>
<tr><td>Female Model</td><td>2,90E-01</td></tr>
</table>

	Graphic Design	2,48E-01	topics that are intuitively authentic. *Pets & Animals, Domestic Coziness, Marketplace and (Office) Work* reflect rather “real” aspects of life and not necessarily extreme luxurious or perfection cues. It can therefore be stated that upon displaying authenticity, trust can positively affect engagement. Golbeck & Fleishmann (2010) found that trust on photographs had a positive relationship with empathy and personal connection of the viewer, which underlines this theory. • ***Positive*** has a positive interaction with topics that in a lesser sense reflect a sense of luxury and suggest more authenticity (*Smiling Female, Travelling, Domestic Coziness).* Heimbach & Hinz (2016) state that a very high positive sentiment of content has a negative relationship with engagement, because it threatens the perception of genuineness of the content. This could apply here as well: compared to generally positive content, only relatively authentic content (reflected by relatively authentic topics) leads to more engagement because it is perceived as more genuine. This theory can still be reconciled with the aforementioned discussion of the main positive effect of *Positive* based on Berger & Milkman (2012). Generally, positive content leads to more engagement. The interaction effects however thus shed light on the note that this effect only exists up to a certain point and therefore depends on the authenticity of the topics in that content as well.
	Musical Performance	1,01E-01	
	Swimming Pool	8,56E-03	
	City Trip	-6,95E-03	
	(Walk in) Outside Summer Environment	-9,45E-03	
	Food	-2,85E-02	
	Leisure	-9,50E-02	
	Power Couple	-9,75E-02	
	High Fashion	-1,89E-01	
	House Exterior Design	-6,82E-01	
*Positive **	*Smiling Female*	1,75E+00	
	Travelling	1,46E+00	
	Outdoor Scenery	1,03E+00	
	City Trip	9,85E-01	

	Portrait Photography	6,49E-01	• ***Negative*** has a positive interaction with topics that reflect a sense of luxury (swimming pools, cars, beach vacation, models), and negative interactions with relatively authentic-oriented topics (domestic coziness, loving family, smiling female and office work). Pentina, Guilloux & Micu (2018) state that in the marketing of luxury goods, the sense of inclusivity and social connection evoked by the content is an important engagement driver. The reason for this is that consumers of luxury goods are sensitive to social status and belonging. Galtung & Ruge (1965) show that negative content is often comparatively socially conform, because it is rather explicit and consistent with dominant trends. This provides a plausible explanation for the observed positive interaction effects between luxury-oriented topics and negative sentiment.
	High Fashion	4,02E-01	
	Domestic Coziness	4,67E-03	
	Graphic Design	-2,59E-03	
	Flowers	-7,08E-02	
	Beach Vacation	-2,59E-01	
	Pets & Animals	-2,03E+00	
*Negative **	*Swimming Pool*	1,03E+00	
	Road Transport	4,71E-01	
	(Walk in) Outside Summer Environment	2,91E-01	
	House Exterior Design	2,74E-01	
	Female Model	1,49E-01	
	Beach Vacation	1,38E-01	
	Portrait Photography	3,30E-03	

	Domestic Coziness	-1,41E-01	
	Loving Family	-1,59E-01	
	Travelling	-2,19E-01	
	High Fashion	-2,41E-01	
	Sports Contest	-3,82E-01	
	Leisure	-5,94E-01	
	Smiling Female	-8,69E-01	
	City Trip	-9,75E-01	
	(Office) Work	-1,09E+00	

Table 12: Summary of LASSO Regression Model - Unexpectedness Interactions

Unexpectedness	Topic Variables	Coefficient	Discussion
*Unexpectedness **	*Female Model*	9,63E-01	• Positive interaction effects occurred with *(Walk in) Outside Summer Environment, Female Model, Beach Vacation, Leisure, Power Couple, Travelling* and *Marketplace.* Negative interaction effects with *unexpectedness* are reported for *Smiling Female, Loving Family, Outdoor Scenery, Pets & Animals, Flowers, House Exterior Design.* Upon comparing these two groups, it seems that the positive effects relate to happy leisure activities that depict favourable elements of a relatively young audience, such as millennials. The negative effects seem to describe elements of a suburban existence, relating to issues of a slightly older audience. Smit (2011) reports that millennials respond to advertising very differently compared to other age groups because they enjoyed a digital, advertising-saturated upbringing. Specifically, they respond to advertisements that surpass a notion of feeling special, unstructuredness, free expression and authenticity. These elements align with unexpectedness, which provides a suitable explanation for the interaction effects of *unexpectedness* in this model.
	Marketplace	6,99E-01	
	(Walk in) Outside Summer Environment	4,31E-01	
	Leisure	2,99E-01	
	Travelling	1,35E-01	
	Beach Vacation	1,11E-01	
	Power Couple	3,04E-03	
	Loving Family	-2,59E-01	
	House Exterior Design	-6,49E-01	
	Outdoor Scenery	-6,57E-01	
	Flowers	-7,06E-01	
	Smiling Female	-1,03E+00	
	Pets & Animals	-2,03E+00	

The analyses, findings and discussions in this section provide an answer to research question 4.

7. Conclusion and Marketing Recommendations

The findings in section 6 can be summarized into a concluding set of remarks that outline which features most clearly drive the success of influencer marketing campaigns.

In the first place, it can be stated that influencer marketing campaign engagement on Instagram is driven by features that include humans and low-performance activities. This research presents smiling females, city trips, high fashion, swimming pools, leisure activities, female models and loving families as features of such a type. Unexpected elements also drive campaign success, when being combined with millennial trendy features. This research presents the millennial trendy features outside summer environments, female models, beach vacations, leisure activities, power couple shots, travelling photos and marketplace depictions. This research also presents a set of feature combinations that drive success. Portrait photography features lead to more engagement upon being combined with photos of a relatively high negative or positive sentiment valence. Visual content that includes joy sentiment enjoys more engagement upon being combined with features that are naturally not too positively oriented. The depiction of sadness sentimental content drives engagement upon being combined with environments and surroundings-oriented features. This research presents the features outdoor sceneries, travelling, marketplace depictions, domestic coziness or house exterior design as surroundings-oriented content. Surprise sentimental content leads to more engagement upon interaction with interior design or dynamic content features. This research presents power couples, leisure activities, loving families, portrait photography presentation as features with dynamic properties. Trust sentimental content drives engagement in combination with authenticity reflecting features. This research presents the authentic features pets and animals, domestic coziness, marketplace depictions and office work. Content with sentiment of a positive valence leads to engagement in combination with relatively non-luxury and authenticity reflecting features. This research presents the following features for this: smiling females, travelling and domestic coziness. Content with sentiment of a negative valence leads to engagement in combination with luxury features. This research presents the luxury features swimming pools, cars, beach vacation depictions and female models.

Marketing recommendations, therefore, include for influencer marketing campaigns to primarily depict humans on photos, preferably engaging in low-performance leisure activities, such as swimming or fashion. A portrait setting should be combined with a strong positive or negative sentiment. Positive content features however should be combined with relatively non-luxury and authentic features such as smiling females, travelling or domestic coziness. Negative content features should in turn be combined with luxury-inspired content features such as swimming pools, cars, beach vacations and models. Photos are however, generally recommended to depict positively sentimental content. When depicting joyful sentimental content features, the other content features should not be too positive. Moreover, surprising content features are recommended to be combined with interior design features or features with dynamic properties. Examples of the latter are leisure, power couples or loving families. Trust-associated content features are recommended to be combined with authenticity reflecting features such as pets, domestic coziness and office work. It is moreover recommended to include unexpected elements in photos, but only in combination with millennial-trendy topics. Examples hereof are outside summer environments, female models, beach vacations, leisure activities, power couple shots, travelling photos and marketplace depictions.

It is also recommended to note that in an influencer marketing context on Instagram, urban and appearance themed photos are relatively more effective than photos that display an underlying theme of goals and achievements as well as travelling. Lastly, it is also recommended to note that influencers with a large follower base are more effective in inspiring marketing impact.

8. Limitations and Recommendations for Further Research

A set of limitations must be noted with regards to this research, of which the most important and influential ones are outlined below. Naturally, these limitations have implications for further research.

The internal validity of the research should be considered with caution because the analyses are prone to a set of methodological limitations.

The most substantial limitation for the internal validity lays in the explanatory power of the predictive models, which is a likely result of the omission of relevant variables. The model included, for the reason of data limitations, for example, no creator-related and context-related features such as influencer demographics and follower identity, and day and time of posting. Such variables did prove significant in earlier studies (Jaakonmäki et al, 2017), which may cause the effect sizes and relationships estimated in this paper to be distorted as a result of not including all relevant control variables. It follows naturally that this may be the case for other relevant variables, potentially also ones that have not been researched previously. It is, however, difficult to assess the predictive power of the models; even though it is low, there are no other comparable models in the current literature to use as a base of comparison. Nonetheless, further research would, therefore, be recommended to include more relevant variables such as creator and context variables in the predictive model. This would also potentially increase the R-squared.

Furthermore, the measure of unexpectedness used in this paper is based on the notion that elements are unexpected upon not conforming the general theme of that photo. Through some manual checks, this proved intuitive in several cases. However, this might not always be an accurate manner to measure unexpectedness. Unexpectedness may also be a result of things that are rather surprising, but still within the general theme of the photo. Furthermore, the conformity against the general theme is based on the three main topics of that theme, as well as the three main topics of that photo. This is a relatively arbitrary benchmark, that may not always suffice to capture the correct elements and act as a base of comparison. Further research is therefore recommended to explore other manners of measuring unexpectedness on visual content. Alternatively, it is recommended to establish a manner to obtain the validity of the measure as calculated in this paper.

The results may also not be externally generalizable because of several main data limitations.

In the first place, the data is prone to selection bias; the influencers in the dataset all voluntarily subscribed to work for *TheCirqle*, which may have an impact on the manner in which they do their work as an influencer and therefore, their photos.

Furthermore, no information is known about the influencers themselves, such as age, nationality and cultural background. Such properties may also impact the content that they publish and the engagement hereof. Since the proportions of different influencer backgrounds are unknown, the extent to which the research is generalizable to other types of influencers is questionable. Moreover, the data represents engagement as static information, even though in practice, engagement is of a continuous nature. Engagement can increase over time, depending on when a photo was posted.

Even though the *Clarifai* algorithm has a high reported accuracy, which was confirmed by manual data exploration in this research, some eyeball checks confirmed that it sometimes produces incorrect results. This may damage the internal validity of the analysis, as it could cause the visual content features as produced in this research not to be based on the correct content descriptions. A notable example hereof is the ability of the algorithm to derive correct facial expressions and thereby sentiment, which has a high impact on the analyses conducted and conclusions drawn in this paper.

Further research would, therefore, be recommended to obtain a more randomized sampling form of an influencer population and explore other manners or algorithms of representing visual data. Further research is especially recommended to explore the role of sentiment in the relationship of interest, as this research was in some cases not able to establish satisfactory explanations for the observed results.

Some relevant practical implications and recommendations for marketing could be derived from the results obtained in this paper. However, the risk exists that the implementation of the recommendations might potentially be liable to 'user fatigue'. This is a phenomenon described by Jaakonmäki et al (2017), which describes how posts that are all similar, even though containing the correct content to inspire engagement, spike disinterest because of that similarity.

Further research is, therefore, recommended to explore different types of marketing recommendations that can overcome this phenomenon.

This research is, despite its limitations, a good starting point for future research on the contemporary topic of influencer marketing. The following interesting points also arose in this research as exciting directions for future research.

In the first place, it might be interesting for further research to further explore the possibilities of the word embeddings model. This model can be used to interpret more nuanced photo elements and to capture photo ambiguities and happenings that are too general for the topic model to capture.

Furthermore, a relevant direction for further research is extending the research regarding the interaction effects within photos. In line with the theory of visual rhetoric, also including interactions between the topics would help isolate the correct effects for all the visual content features and elements and provide useful additional insight. This research provides only an exploratory basis for the relevance of interaction effects.

Moreover, this research is relatively limited in the extent to which it researches comments; the emphasis lies on likes as a measure of engagement. Further research could examine the differences between these two measures and further study whether there are proper manners to drive engagement in the form of comments using photos.

In this paper, several interesting notions arose upon the discussion of the found effects. The findings for *Musical Performance, Anticipation and Disgust* as visual content features were somewhat inconclusive, because they could not be reconciled with previous literature sufficiently. Furthermore, a further exploration of unexpected elements in visual content and the link thereof to engagement is an interesting direction for further research. Future research could for example aim to research the connection between a millennial audience and unexpectedness in photos in a supervised manner.

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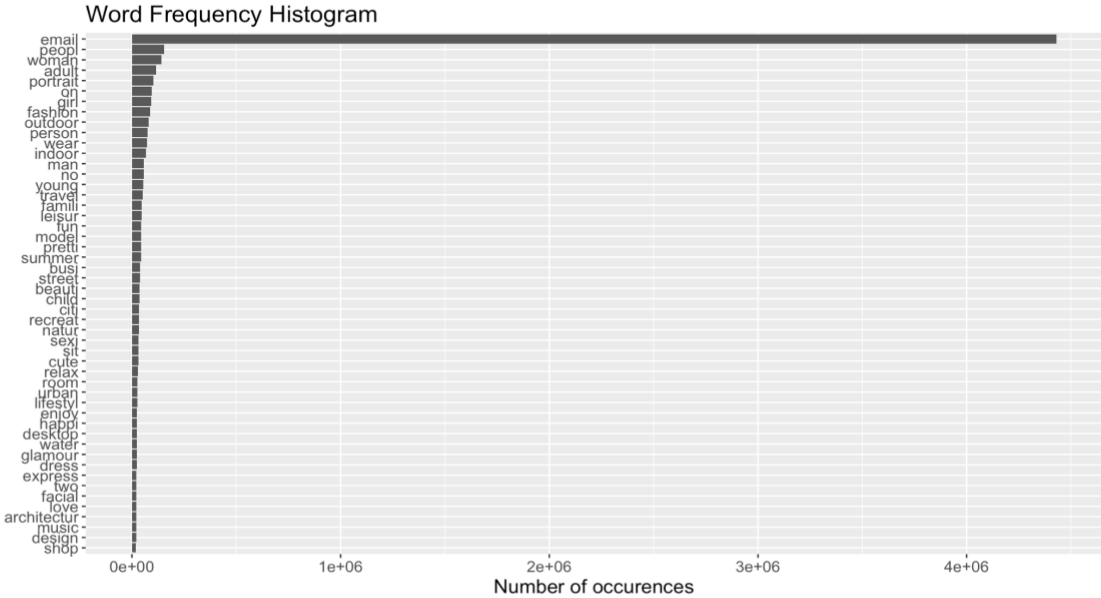
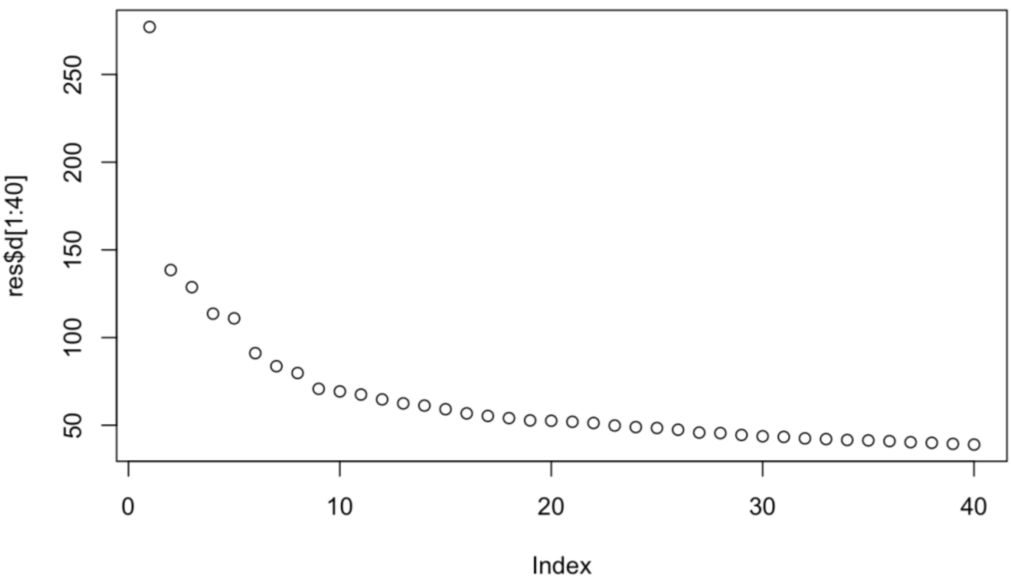
11. Appendix

Appendix A1: Document frequency histogram of words in dataset



Appendix A2: Variance explained (vertical axis) by matrix reconstruction upon the number of factors k (horizontal axis)



Appendix A3: Top 10 most high-loading terms for all 25 factors of NMF Topic Model, for readability reasons displayed per 5 in Figure A3.1 until A3.5.

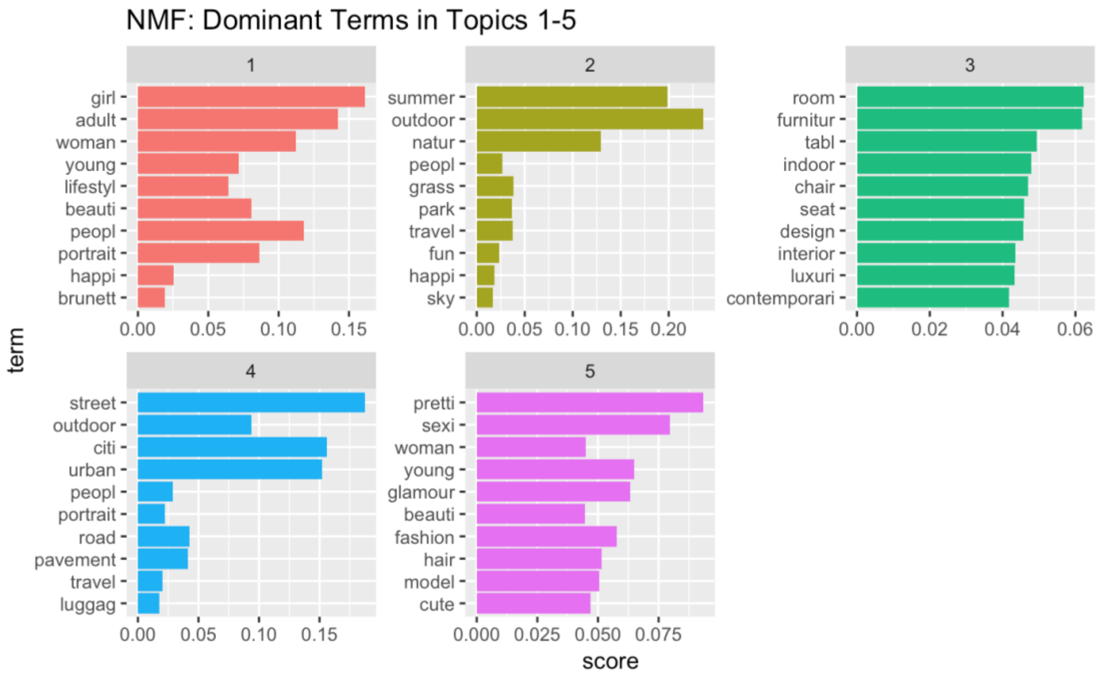


Figure A3.1: Dominant Terms in first 5 Topics generated by NMF

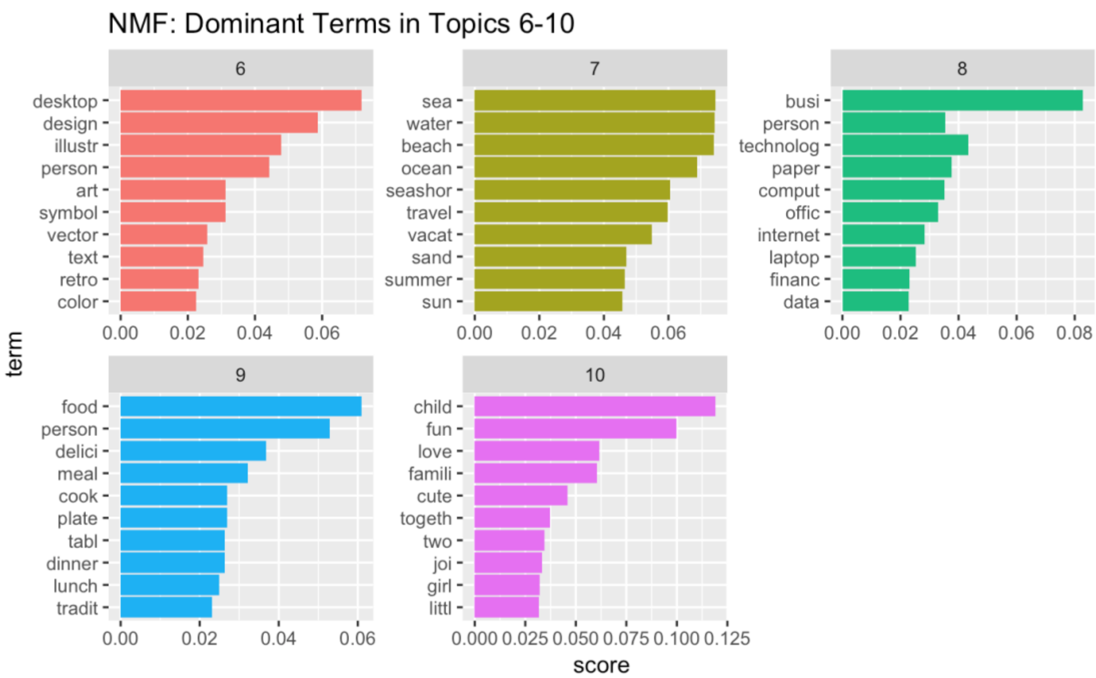


Figure A3.2: Dominant Terms in Topics 6-10 generated by NMF

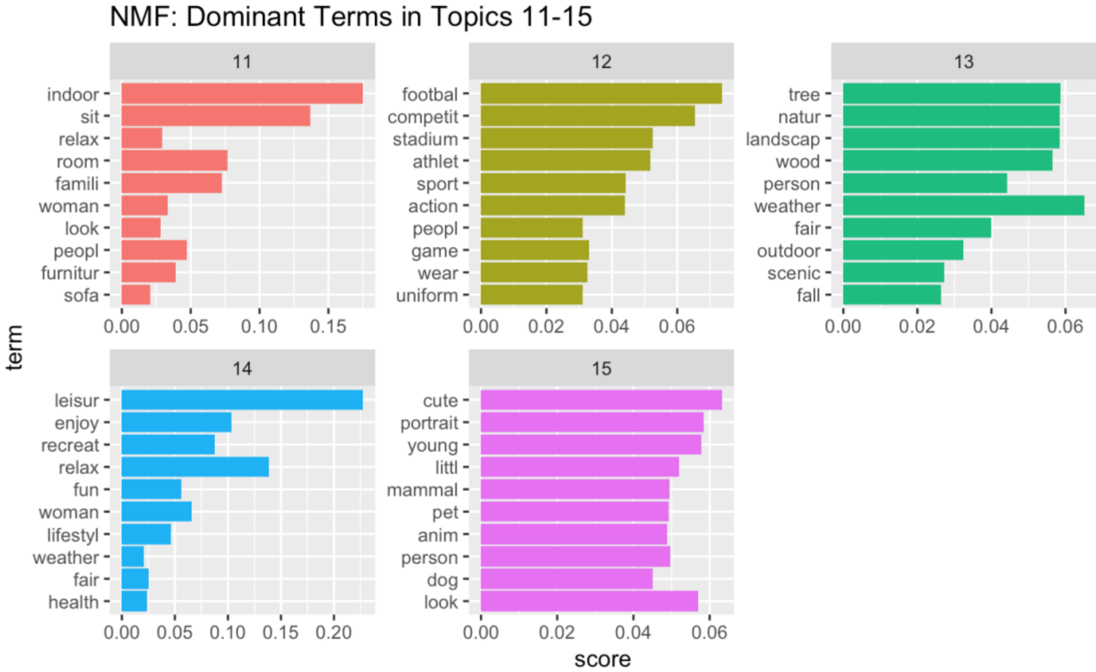


Figure A3.3: Dominant Terms in Topics 11-15 generated by NMF

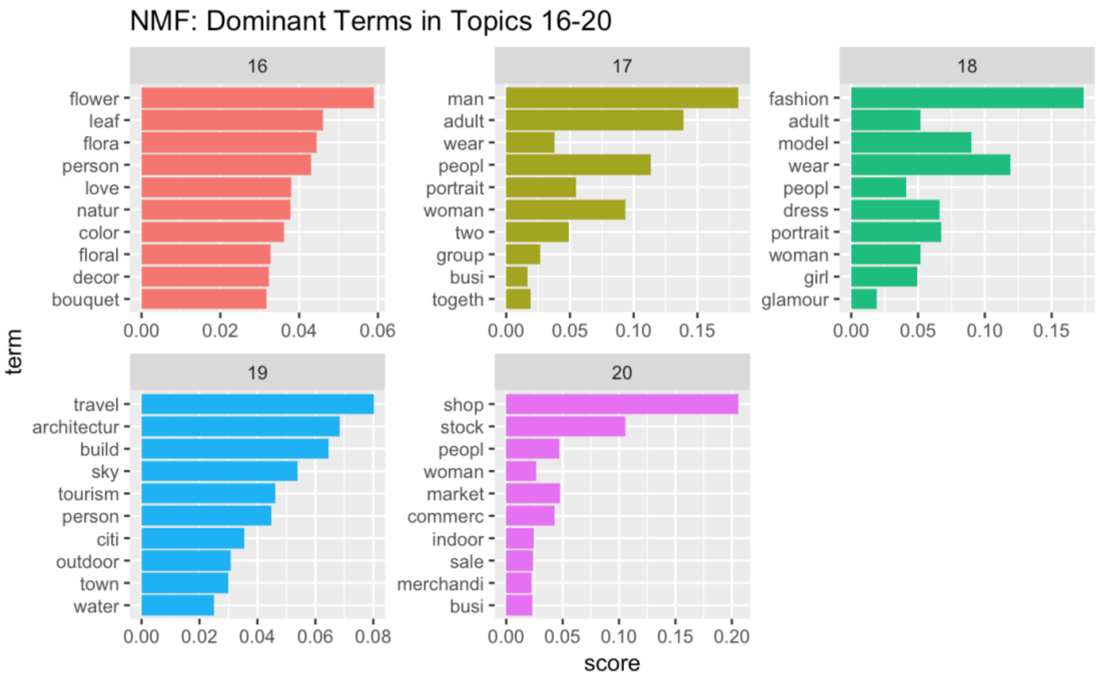


Figure A3.4: Dominant Terms in Topics 15-20 generated by NMF

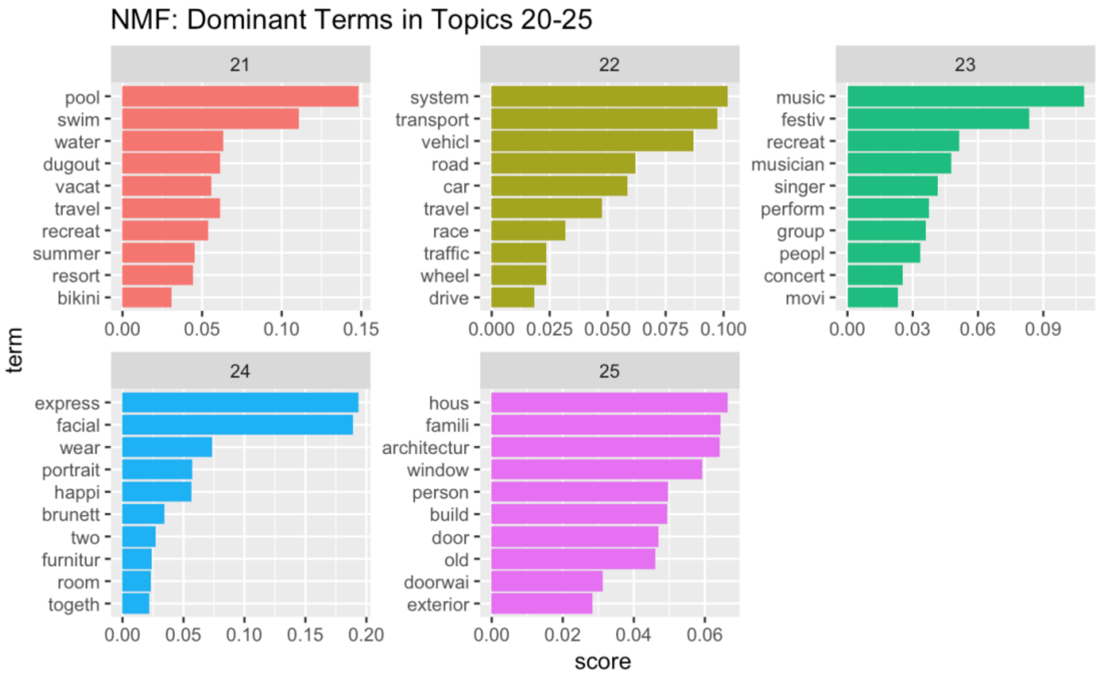
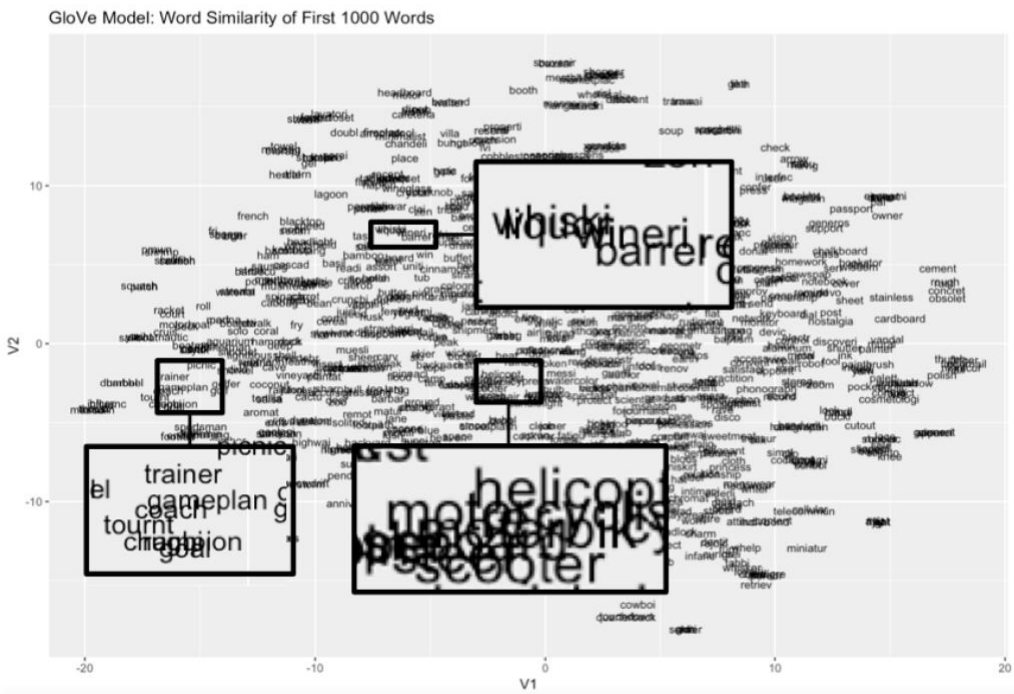
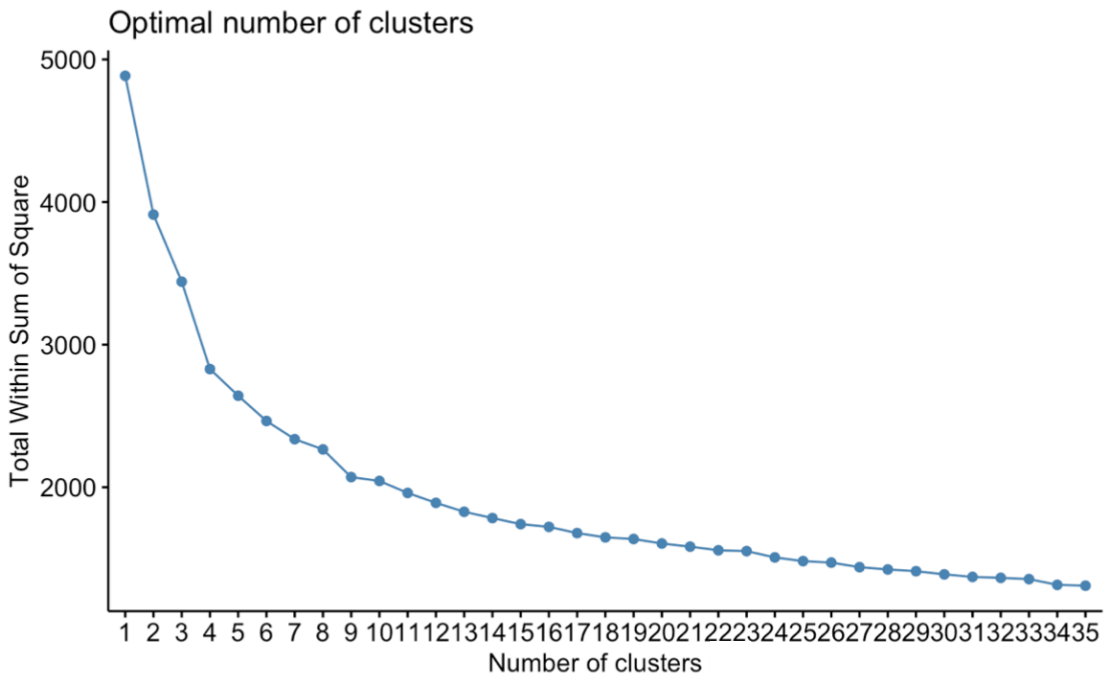


Figure A3.5: Dominant Terms in Topics 20-25 generated by NMF

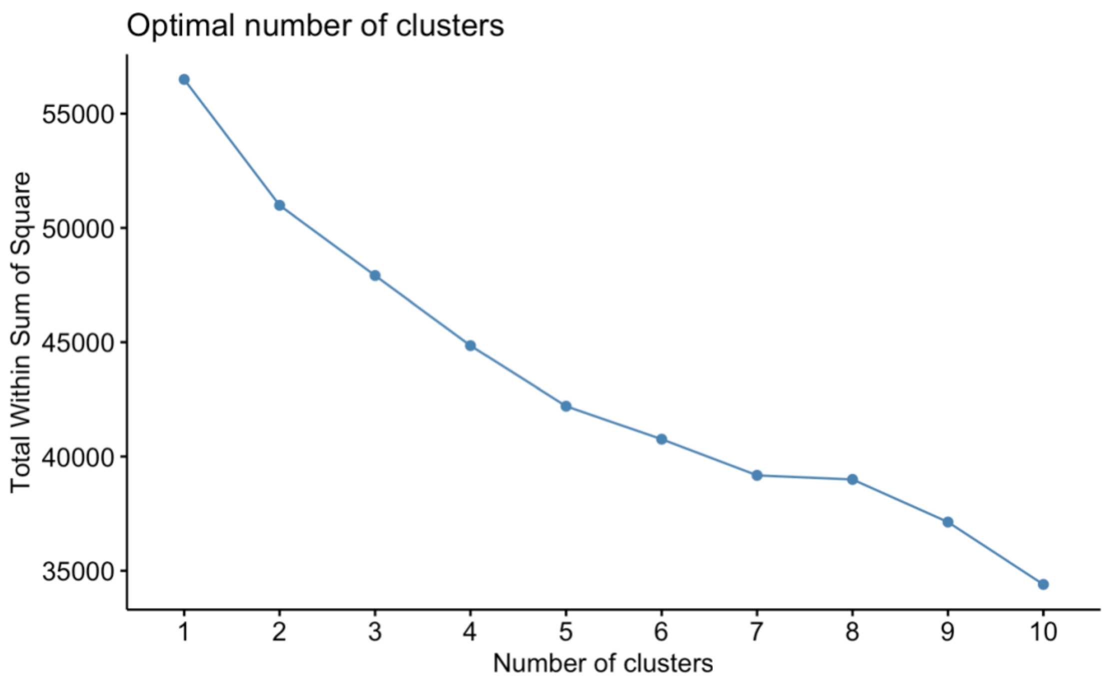
Appendix A4: MDS Visualization of Similarity Task for GloVe. It should be noted that only 1000 words of the dataset are displayed, for visual space constraint reasons.

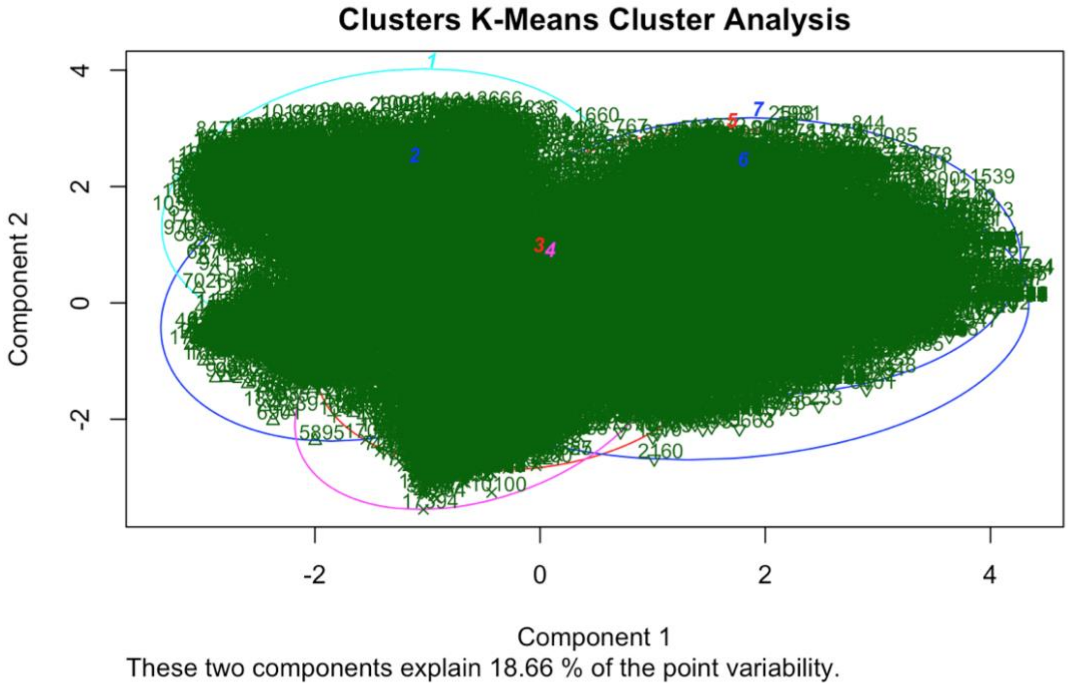


Appendix A5: Within-sum of squares (vertical axis) in relation to number of clusters (horizontal axis) for K-Means cluster analysis upon GoVe Output



Appendix A6: Within-sum of squares (vertical axis) in relation to number of clusters (horizontal axis) for K-Means cluster analysis upon NMF output





Appendix A7: Graphical depiction K-Means cluster analysis, whereby K=7