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Aspect-Based Emotion Analysis and Multimodal Coreference: A Case Study of Customer Comments on Adidas Instagram Posts

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Abstract

While aspect-based sentiment analysis of user-generated content has received a lot of attention in the past years, emotion detection at the aspect level has been relatively unexplored. Moreover, given the rise of more visual content on social media platforms, we want to meet the ever-growing share of multimodal content. In this paper, we present a multimodal dataset for Aspect-Based Emotion Analysis (ABEA). Additionally, we take the first steps in investigating the utility of multimodal coreference resolution in an ABEA framework. The presented dataset consists of 4,900 comments on 175 images and is annotated with *aspect* and *emotion* categories and the emotional dimensions of *valence* and *arousal*. Our preliminary experiments suggest that ABEA does not benefit from multimodal coreference resolution, and that *aspect* and *emotion* classification only requires textual information. However, when more specific information about the aspects is desired, image recognition could be essential.

Keywords: ABSA, ABEA, Sentiment Analysis, Emotion Detection, Multimodal Coreference

1. Introduction

Nowadays, all large companies and brands own a designated page or channel on social media platforms which allows them to directly communicate with various stakeholders, most notably the general public. This rise of social media communication has also propagated research on automatically analysing user-generated content which is often full of opinions and emotions. As a consequence, research on sentiment and emotion analysis has thrived.

Since companies not only want to know which general opinions their stakeholders hold on their company or brand, but also want to learn which products or which features of their products are greatly appreciated or disliked by the online community, the research domain of sentiment analysis has started to focus more and more on fine-grained sentiment analysis (positive/negative/neutral) at the feature or aspect level (Liu, 2012). This is referred to as Aspect-Based Sentiment Analysis (ABSA), which focuses on the detection of all sentiment expressions within a given document and the concepts and aspects (or features) to which they refer. Following the task description in the SemEval 2015 shared task on this topic (Pontiki et al., 2015), aspect-based sentiment analysis can be decomposed into three subtasks: aspect term extraction, aspect category classification and aspect term polarity classification.

In its original sense, sentiment analysis involves classifying instances as one of the three classes *positive*, *negative*, and *neutral*, but more recently, many research objectives shifted to extracting more fine-grained emotional information like the emotional categories *anger*, *sadness*, and *joy* (Mohammad, 2016). When performing emotion detection at the aspect level, we can analogously refer to this as Aspect-Based Emotion Analysis (ABEA) (Padme and Kulkarni, 2018).

Given the rise of more visual content, which is illustrated by the popularity of platforms such as Instagram and TikTok, we want to investigate whether text-based models are sufficient to classify social media content which clearly exhibits both textual and visual information in terms of aspect and sentiment/emotion. Moreover, whenever images are presented, text is often used to pinpoint specific aspects of an image (e.g. "Love the color of these"). By closely analysing these instances, and especially those where anaphors are used, we wish to get more insights in whether it would be helpful to include visual information in the ABEA pipeline by means of multimodal coreference resolution.

We perform a case study using customer comments on the Adidas Instagram page by collecting 4,900 comments on 175 Instagram images, and annotating them with aspect categories and emotional information. Moreover, the annotators indicated for each comment whether the image was necessary for a full understanding of the comment. By comparing the performance of the aspect classification and emotion analysis models on both types of comments, we can assess whether comments that rely on visual information for a full understanding are more difficult to classify than comments that do not rely on visual information.

The contributions of this paper are twofold. Firstly, we present a multimodal dataset that can be used in the

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context of aspect-based sentiment and emotion detection, consisting of 4,900 comments on 175 images and annotated with both aspect and emotion labels. The dataset is freely available for further study[2]. Moreover, we assess the utility of multimodal coreference resolution in an ABEA framework.

The next section of this paper will be dedicated to the description of related work (Section 2). In Section 3, we describe the data collection and annotation process. The methodology of the experiments to assess the importance of visual content for ABEA and the results of these experiments are reported in Section 4. The results are further discussed in Section 5, followed by a conclusion in Section 6.

2. Related Work

In its original use, the goal of sentiment analysis was to classify text documents in terms of polarity, i.e. positive or negative (Pang et al., 2002). Through the years, the objective of sentiment analysis evolved to extracting more fine-grained insights about subjective information in texts and the need for sentiment analysis on the feature or aspect level was first expressed by Liu (2012). ABSA received a lot of attention in the context of a shared task at SemEval 2014 (Pontiki et al., 2014) and 2015 (Pontiki et al., 2015), which provided datasets of English reviews in two domains (laptops and restaurants), annotated with aspect terms, aspect categories and sentiment labels.

The evolution of extracting more and more fine-grained subjective information also caused a switch in focus from polarity to emotion (Mohammad, 2016). Instead of focusing on the positive/negative dichotomy, the goal in emotion analysis is to extract specific emotional states, such as the basic emotion categories of Ekman: *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise* (Ekman, 1992). Recently, various studies performed emotion detection based on emotional dimensions instead of categories, e.g. the work of Buechel and Hahn (2016) and Mohammad and Kiritchenko (2018). They follow the theory of Mehrabian and Russell (1974), who claim that every emotional state can be represented by the three dimensions *valence* (or pleasure–displeasure), *arousal* (or activation–deactivation) and *dominance* (dominance–submissiveness). Also the circumplex model of affect (Russell, 1980), which only focuses on the dimensions *valence* and *arousal*, has been used in emotion detection studies (Preoţiuc-Pietro et al., 2016).

Mostly, emotion detection is performed at the sentence or document level. Analogously to ABSA, one could analyse emotions at the aspect level as well, resulting in Aspect-Based Emotion Analysis (ABEA). Some studies have been carried out on this subject (Padme and Kulkarni, 2018), but there are no publicly available datasets that have specifically been made for ABEA.

A problem in aspect-based sentiment and emotion analysis is that aspect terms are often not explicitly mentioned. This can manifest itself in various ways, e.g. by an implicit aspect that can only be inferred from the contextual meaning (e.g. "My mouth is still watering!", which has a food-related but implicit aspect) or by an anaphor referring to an antecedent previously mentioned in the text (e.g. "*They* were absolutely horrible."). In an age where visual content is becoming more and more prevalent — see also the work on multimodal NLP (Kruk et al., 2019) — it is even possible that these implicit aspects can only be understood with the help of the image accompanying the text.

Looking at both ABSA and ABEA, the same first two subtasks can be defined: aspect term extraction and aspect category classification. Regarding the latter, one could hypothesize that this task might suffer from these implicit aspects and that coreference resolution is needed to overcome this. However, previous research has shown that coreference resolution does not necessarily improve aspect term classification (De Clercq and Hoste, 2020). When linking anaphors to their correct antecedent in restaurant reviews, this additional semantic information did not really help to better classify the aspects into predefined categories, suggesting that the models have enough with the contextual lexical information alone. However, in the context of multimodal coreference, where text and image appear together, this has not been investigated yet.

3. Dataset

3.1. Dataset Collection

The Adidas Instagram page (*@adidasoriginals*) has more than 37 million followers with a great number of comments on each post, which makes it a rich page for collecting opinions on the brand and its products. In order to scrape all the posts on the Instagram page, we first obtained their shortcodes, by which each unique post can be identified. This was done using the Selenium package and the Beautiful Soup library in Python. The Selenium package automates browsing and interacting with the web. We used it to automatically open the page and scroll down until all posts were visible. Then, using the Beautiful Soup library, we extracted the shortcode for each post from the HTML source code of the fully loaded page.

The next step was to open each post and click on the "Load more comments" button in order to acquire all the comments under each post. After all comments were loaded, once again using the HTML source code, we extracted the comments for individual posts. Since our objective was to annotate only the English comments, we used the *langdetect* library[3] to recognize the language of the comment and filter out the non-English ones. Our tool for downloading shortcodes and com-

[2]https://lt3.ugent.be/resources/multimodal-abea/

[3]https://pypi.org/project/langdetect

Main Category	Subcategories	Example
Company	General, reliability	Looks likes I'm Adidas fan now. Got to make daddy in law happy @jazminchristine_
Marcom	General, promotions	Thanks for the birthday coupon
Personnel	General, friendliness, service, reception, speed, information, availability, familiarity	Still no one reply to me of this wind jacket. As I've leave my phone number to your retail shop staff in Causewaybay! Even no stock or when will restock! But until now still no feedback. What the hell of customer services? Very disappointed
Product	General, price, quality, availability, variety	Hope it will be available in the philippines.
Social media	Content	I was 2013 in chicago...very nice and very nice picture ;) @adidasoriginals
Store/Office	General, parking, location, cleanliness, lay-out, opening hours	(no examples in the dataset)
Website	General, information, user-friendliness	What's wrong with the app? I've been trying to place an order 3 days already

Table 1: Aspect taxonomy and examples from the dataset for each main category.

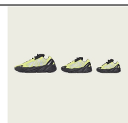
Comment	Emotion	Valence	Arousal	Aspect	Image needed?	
Hope it will be available in the philippines.	Longing	3	1	Product - availability	Yes (📷)	
Been rockin your shoes since the 90s! Sambas, Gazelles, Superstars, NMDs! Thank you!	Joy	4	3	Product - general	No (¶)	

Table 2: Examples of annotated comments.

ments is available on GitHub[4].
In order to download the Instagram images, we used the *scraper* software package[5]. This software contains a command line utility that takes as input a file containing a list of the shortcodes and the name of the directory in which we want to store the images. The shortcode is used to build an absolute path for the post. For each post, the web page is downloaded in HTML format and then the temporary image URL path is collected from the metadata. Subsequently, for each image URL, an HTTP request is made to download the image and save it on the hard disk.

3.2. Dataset Annotation

The comments of 175 Instagram images were annotated by two students who were enrolled in the final year of a Bachelor's program in Applied Linguistics. The annotators were provided with an Excel file containing the image and comment.
They were asked to view the comments from the perspective of the person who wrote them and to indicate whether an emotion was expressed. If that was the case, they were asked to specify this emotion. Initially, the emotions of interest were *anger*, *fear*, *joy*, *love*, and *sadness*, conforming to De Bruyne et al. (2020). However, after a trial annotation round, *fear* was removed from the label set as it was almost never indicated. However, the category *longing* was included instead to account for the emotion of desire, which was often expressed in the context of wanting the Adidas product that was represented in the Instagram post. Additionally, the annotators had to rate the emotional dimensions from the circumplex model of affect (Russell, 1980), namely *valence* (from low to high degree of pleasure) and *arousal* (from low to high degree of activation), on a 5-point scale. Note that *valence* is equivalent to *sentiment* or *polarity*, but that *arousal* is not equivalent to emotion *intensity*: when one is *depressed*, for example, the emotion has a high intensity but a low degree of arousal.
In the next step, the annotators had to indicate the aspect term associated with the emotion (or 'null' if the aspect was not mentioned explicitly in the text) and assign the appropriate aspect category (main and subcategory) for this aspect term. The aspect taxonomy is shown in Table 1. It was obtained in the framework of a larger project (SentEMO[6]) where aspect category tax-

[4]https://github.com/akkarimi/instascraper
[5]https://github.com/hachreak/scraper
[6]https://lt3.ugent.be/projects/multilingual-aspect-based-

Class	IAA
Aspect	0.598
Emotion	0.618
Valence	0.466
Arousal	0.337

Table 3: Inter-annotator agreement for aspect and emotion categories (Cohens's Kappa) and emotional dimensions (Krippendorff's alpha).

onomies for different domains (retail, hotel, ...) have been drawn up in close collaboration with representative partners from the industry and on the basis of which the more generic taxonomy as presented here was derived. When multiple emotions and aspects were present in an Instagram post, the sentence was split up according to the number of aspects. It is worth noting that these comments were not taken into account for the remainder of this paper. In the last step of the annotation process, the annotators were asked to indicate whether the image was necessary for a full understanding of the comment or not (e.g., in the case of "Love the color of these", the image is needed to know which color and what product is referred to).

In total, 5,140 comments were annotated in this manner. After filtering out the comments with multiple aspects or erroneous annotations, our final dataset comprises 4,900 comments, of which 2,615 were annotated as emotional and 2,285 were neutral. Two annotated examples are shown in Table 2.

The comments accompanying the first ten images were annotated by both annotators (trial annotation round consisting of 90 comments) in order to calculate inter-annotator agreement (in the final dataset, only Annotator 1's annotations of the first 90 comments were taken into account). For the emotion categories and aspect categories, Cohen's Kappa was calculated. For the emotional dimensions (*valence* and *arousal*), Krippendorff's alpha was used. The agreement scores are shown in Table 3 and reveal a moderate to substantial agreement for aspect and emotion categories, and a fair to moderate agreement for emotional dimensions.

After this initial trial annotation round, the annotators sat together to align their annotation method. The remaining comments were more or less equally divided among the annotators. The annotators were free to discuss the annotations with each other when necessary in order to further guarantee consistency.

A summary of the data annotations can be found in Tables 4 and 5. Out of the 2,615 emotional comments, *joy* is the most dominant category (1,198 comments), followed by *anger* and *longing* (593 and 589 comments, respectively). As regards the aspect categories, the *product* category was clearly most prevalent. We therefore decided to only keep the subcategories for this particular category, but work with the main categories for the other aspect classes. The *store/office* class was omitted, as there were no instances annotated with this category.

A notable part of the instances contained an implicit aspect term: for 695 out of 2,615 emotional comments, it was not possible to indicate the aspect term associated with the emotion and they received the *null* tag as aspect term. Moreover, 883 of the instances where an aspect term could be indicated, contained an anaphoric pronoun (*this, that, these, those* and *it*). We can thus say that 1,578 instances (i.e. 60%) contained an implicit aspect term. Moreover, for the vast majority of emotional instances, the image was needed to completely understand the comment (2,317 out of 2,615 instances).

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Emotion (#)		Valence (#)		Arousal (#)	
Neutral	2,285	1	167	1	696
Anger	593	2	456	2	1,258
Joy	1,198	3	644	3	500
Longing	589	4	1,079	4	138
Love	191	5	269	5	23
Sadness	44				
📷	2,317	📷	2,317	📷	2,317
¶	2,583	¶	298	¶	298
Total	4,900	Total	2,615	Total	2,615

Table 4: Number of comments per emotion category / emotional rating. 📷 means that the image was needed for understanding the comment, ¶means that the image was not needed and the text alone was sufficient.

Aspect (#)	
Company	94
Marcom	20
Personnel	12
Product - availability	225
Product - general	1,650
Product - price	32
Product - quality	35
Product - variety	117
Social media	401
Website	29
📷	2,317
¶	298
Total	2,615

Table 5: Number of comments per aspect category. 📷 means that the image was needed for understanding the comment, ¶ means that the image was not needed and the text alone was sufficient.

4. Experiments & Results

In order to investigate the influence of visual content on the first two subtasks of aspect-based emotion analysis (aspect category classification and emotion analysis), we applied RoBERTa models (Liu et al., 2019) to our data and compared the performance on the comments for which the annotators indicated that no visual

Task	All	📷	¶
Aspect	0.784	0.815	0.544
Emotion	0.675	0.838*	0.849*
Valence	0.559	0.574	0.450
Arousal	0.614	0.611	0.638

Table 6: Accuracy of aspect and emotion classification for the complete dataset (All), and for subsets of the data containing either only instances where visual information was needed for full understanding (📷) or instances where visual information was not needed (¶). *For emotion classification, the neutral instances were filtered out from the subsets, as it was not indicated whether visual information was needed for neutral instances.

information was needed for a complete understanding versus the comments where the text alone sufficed. As we are dealing with short social media texts, we use the RoBERTa-based language model trained on Twitter data from Barbieri et al. (2020). For aspect classification, we use the base model (twitter-roberta-base[7]) and for emotion, valence and arousal classification, we use the twitter-roberta-emotion model[8].

For emotion classification, all instances were used (4,900 comments), while for valence, arousal and aspect classification only the non-neutral tweets were taken into account (2,615 comments). We used 10-fold cross validation to finetune the RoBERTa models for 3 epochs, with a dropout of 0.2, maximum sequence length and batch size of 64 and learning rate of 5e-05.

Table 6 shows the accuracy of these models. We report the performance on the full subsets, but also calculate the accuracy after filtering the instances based on whether visual information was required for full understanding. On the full dataset, aspect classification is 78% accurate. For emotion classification, accuracy is 68%, and for valence and arousal classification it amounts to 56% and 61%, respectively. Emotion classification results per emotion category are shown in Table 7, which reveals a high performance for the categories *anger, joy, love* and *longing* (between 78% and 88% accuracy), but a notably lower performance for *sadness* (43%) and the *neutral* category (49%).

Contrary to what we expected, the aspect and valence classification models perform better on comments where visual information is needed, compared to comments where the text alone suffices. Especially for aspect, the difference is substantial (82% versus 54%). This is counter-intuitive, as the models do not actually have access to that visual information. In the next section, this will be examined in closer detail.

[7] https://huggingface.co/cardiffnlp/twitter-roberta-base

[8] https://huggingface.co/cardiffnlp/twitter-roberta-base-emotion

Emotion	All	📷	¶
Neutral	0.487	–	–
Anger	0.789	0.776	0.836
Joy	0.866	0.868	0.843
Love	0.881	0.873	0.963
Longing	0.785	0.777	0.875
Sadness	0.432	0.424	0.455

Table 7: Accuracy per emotion category for the complete dataset (All), and for subsets of the data containing either only instances where visual information was needed for full understanding (📷) or instances where visual information was not needed (¶).

Comment	Aspect	📷/ ¶	F/C
Super super in love with this work of art	Product - general	📷	C
where can I get these same ones	Product - availability	📷	C
The same in black and I will buy this zxflux !!!	Product - variety	📷	C
@_6079 this pic is awesome	Social media	📷	F

Table 8: Examples of comments that include an anaphor. 📷 means that the image was needed for understanding the comment, ¶ means that the image was not needed and text alone was sufficient. When the classifier made a correct prediction, it is indicated with a C; when a false prediction was made, it is indicated with an F.

5. Discussion

We take a closer look at the comments and predictions to get more insights into the importance of visual information for classification. More specifically, we investigate implicit aspect mentions in the comments. The pronouns *this, that, these, those* and *it* appear in the aspect term of 883 of the 2,615 non-neutral comments, and 695 comments have the *null* tag as aspect term. The vast majority of these comments are indicated by the annotators as needing the image for full understanding (869 of the comments with pronouns and 622 of the comments with *null*, i.e. 1,491 out of 1,578 or 94%). However, given the results shown in Table 6, it does not seem that these implicit aspects cause problems for the classifier, as the performance of aspect classification is even higher for these instances. This suggests that aspect-based sentiment and emotion analysis would not benefit from multimodal coreference resolution.

However, a lot depends on the aspect labels of interest. In our case, the aspect labels seem broad enough to only rely on the text for extracting the aspects. Some examples are shown in Table 8. In the sentence "where can I get these same ones" for example, one does need the image to know to what specific entity is being referred, but the text alone is enough to know that

Emotion	Pred.	📷	¶	χ^2, p
Anger	True	361	107	$\chi^2 = 2.14$,
	False	104	21	$p = 0.143$
Joy	True	963	75	$\chi^2 = 0.47$,
	False	146	14	$p = 0.494$
Love	True	467	52	$\chi^2 = 3.80$,
	False	68	2	$p = 0.051$
Longing	True	136	14	$\chi^2 = 0.83$,
	False	39	2	$p = 0.361$
Sadness	True	14	5	$\chi^2 = 0.03$,
	False	19	6	$p = 0.861$
All	True	1941	253	$\chi^2 = 0.248$,
	False	376	45	$p = 0.618$

Table 9: Number of true and false predictions (i.e., true positives and false negatives) per emotion category for subsets of the data containing either only instances where visual information was needed for full understanding (📷) or instances where visual information was not needed (¶).

this comment is about a product (and the availability thereof). However, when one needs to know which specific product the comment is about, image recognition is still needed.

Most of the aspects in the dataset are subcategories of the *product* category (cfr. Table 5). When we look at the top three aspects in the comments with implicit aspect, *product - general* is dominant as well (1,123 comments) followed by the *social media* (244 comments) and *product - availability* category (130 comments). The majority of the *product - general* and *product - availability* instances with implicit aspect are correctly classified (1,165 out of 1,253, i.e. 93%). For the *social media* category however, only 102 out of 244 instances are correctly classified (42%) and are often misclassified as *product - general*.

For emotion classification, one would expect that there is no difference in performance between the 📷 subset and the ¶ subset, as emotional information (contrary to aspect information) is probably only present in the textual comment and not in the originally posted picture. As shown in Table 6, there is only little difference between the subsets. When performing χ^2 tests, we indeed find no significant difference at a 5% significance level between the performance on the subsets, neither when taking into account all emotional instances, nor when looking at the individual emotion categories (see Table 9).

6. Conclusion

We presented a multimodal dataset that can be used in the context of aspect-based sentiment and emotion detection, consisting of 4,900 comments on 175 images and annotated with both aspect and emotion labels. We assessed the utility of multimodal coreference resolution in an ABEA framework. Based on these preliminary experiments, we can assume that ABEA does not benefit from multimodal coreference resolution. However, when more specific information is needed than broad aspect categories (e.g. product type, product color, etc), computer vision techniques will become necessary.

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