University of Sheffield

Identifying complaints in social media using deep learning with transformers



Nitin Sunny Mathew

Supervisor: Nikolaos Aletras

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Declaration

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Name: Nitin Sunny Mathew

Signature: Nitin Sunny Mathew

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Abstract

A complaint is a statement made by a person or an entity with the intent to indicate something is unacceptable or unsatisfactory. This is commonly used in various aspects of day-to-day life including when conducting business operations. With the proliferation of social media across our lives and the active enablement of such platforms by organisations for user engagement, it has become a common medium for users to raise complaints. With such complaints being publicly visible, it is imperative for organisations to identify, prioritise and respond to these complaints swiftly. Automatically identifying complaints in social media is an active area of research. In the past few years, the focus has been on using NLP approaches driven by developments in transfer learning and transformer-based models.

In this paper, the use of these approaches are extended by assessing 'lightweight' transformer based models such as DistillBERT, MobileBERT, BERT tiny/small which are meant to reduce the time required for fine-tuning as well as inference. The performance of these 'lightweight' models is compared with the traditional transformer models including BERT, ROBERTA, BERTweet for this particular task. The dataset used consists of anonymised and annotated(complaint or not) Twitter data utilized in previous research and currently available in the public domain. In addition, the act of complaining and the nature of complaints are analysed from a linguistic perspective along with discussions on state-of-the-art approaches for such NLP tasks.

^{**}Update with high level results**

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Introduction

1.1 Background

In the act of complaining, dissatisfaction or annoyance is expressed by a person or entity in response to a previous or ongoing event that has negatively impacted them [10]. It provides an avenue to direct dissatisfaction to the appropriate organisation or individual with the hope of rectification or redressal. The event or action could be concerning a product or service procured by the concerned person or entity. The need to recognise, acknowledge and act on complaints is of significant importance to businesses and organisations to retain their customers while maintaining their reputations.

Until the advent of online platforms and specifically social media, the impact of negative word-of-mouth was confined to a relatively limited audience. However, since then complaints posted online have the potential to rapidly go viral, reaching millions of individuals and significantly damaging a company's brand reputation and goodwill in a short period [14]. Customers are able to express their complaints directly, conveniently, and with enhanced effectiveness to organisations through multiple social media channels and platforms [2].

In addition to the timely addressing of customer complaints, automated detection of complaints in natural language has a number of other purposes. Linguists could gain a more detailed understanding of the context, intent, and various types of complaints on a larger scale while psychologists could utilise this information to identify the underlying human traits that drive the behaviour and expression of complaints. Developing downstream natural language processing (NLP) applications, such as dialogue systems is another use case of this task [11].

Attempting to identify complaints manually through the multitude of posts and streams coming through the various social media channels is neither practical nor scalable. Various approaches to automate this task have been explored. The traditional vector-space method utilizing dictionaries has been applied in other text classification tasks [8]. Latent Semantic Indexing based on Singular Value Decomposition along with linguistic style features has

been utilised to classify emails as complaints or not [5]. In recent years, we have seen the use of various Machine learning and Natural Language Processing (NLP) based approaches for similar classification problems. The performance of logistic regression over various types of feature spaces against neural-network based models like Multi-layer Perceptron (MLP) and Long Short Term Memory (LSTM) has been analysed by [11] on Twitter feeds. The use of more advanced approaches using transformer networks has shown to have better results as explored by [6]. As part of this paper, the use of the BERT and its many variants, including that of lightweight versions that have been created in the recent past will be assessed further on a publicly available Twitter dataset.

1.2 Aims and Objectives

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Literature Survey

2.1 The act of complaining

As per [10], the speech act of complaining in the traditional sense can be understood from the perspective of the speaker stating their displeasure or dissatisfaction to a target entity or individual. This is done as a reaction to an unfavourable event that is currently taking place or has already occurred. The authors believe a few preconditions have to be satisfied to result in a complaint being made. This includes the speaker's belief the entity or individual is responsible for the unfavourable outcome and that the speaker in question suffers from the consequences. The result is a verbally expressed complaint. The authors further delve into the intentions of the speaker in making the complaint. They argue this is carried out with either the hope of repair of the situation or as a 'Face Threatening Act' with the purpose being to damage the face of the individual or entity against whom the complaint is made.

While such complaints could be considered direct complaints as per [4], they additionally highlight the use of indirect complaining in speech. In the case of indirect complaints, the speaker does not attribute responsibility for the cause of the complaint to the individual or entity being addressed. The authors theorise, an indirect complaint is used to bring about 'solidarity' between speakers, which is contrary to the use of direct complaints. It can serve as a means to initiate conversations and establish temporary connections with others. The scope of the data for this project (described in the subsequent chapter) is primarily focused on direct complaints as they are selected based on tweets being addressed to a brand's customer service handle. But it is possible there are tweets which fall into the category of indirect complaints.

Analysing deeper into which types of customers complain more, [13] have looked at how personality traits like impulsivity and self-monitoring impact customer complaining behaviour. *Impulsivity*, as defined by [12], refers to a consistent inclination of customers to act spontaneously and immediately, without much reflection or careful consideration of available options or potential consequences. This trait remains relatively stable over time for such customers. [3]

defines self-monitoring as the propensity to adjust one's behaviour based on the actions or behaviour of others. High self-monitoring individuals are sensitive to others' expressions and behaviour, relying on social cues for their actions, while low self-monitoring individuals may be influenced by personal traits. From their experiments, [13] concluded that individuals with high impulsiveness tend to complain more than those with low impulsiveness, whereas individuals with high self-monitoring tend to complain less than those with low self-monitoring. However, these effects are more pronounced in situations where the level of dissatisfaction is high.

2.2 Complaining online

The act of complaining exists online in various forms and with varying degrees of intensity and this prevalence lead to the emergence of third-party organisations that provide online channels for customers' ease and convenience [14]. Notably, there are complaint websites like complaintsboard.com, review websites like trustpilot.com as well as consumer organisations' sites such as consumeraffairs.com, where customers can share their negative experiences and exchange information with others. The impact of negative word of mouth is quite high due to the ease with which negative reports can rapidly reach millions of people, potentially causing significant harm to a company's brand. Various user-generated content platforms such as YouTube, Twitter, and Facebook serve as spaces for expressing complaints. Brands use these platforms for user engagement and this provides the users with the required visibility to potentially raise or escalate an issue. With numerous such options available online, companies can experience significant repercussions arising from actions taken by dissatisfied customers [14].

Of the 431 online complaints assessed by [14], 96% followed what they call a double deviation. This occurs when customers experience both a product or service failure followed by multiple unsuccessful attempts to resolve the issue, resulting in them feeling they have been violated twice. Such customers then resort to online complaining. Their urge to complain online is driven by how they felt betrayed rather than simply being dissatisfied or with any form of malicious intentions to hinder business operations.

2.3 Complaining in social media

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2.4 Self-expression on Twitter

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2.5 Transformers

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2.6 Ongoing research

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Methodology

3.1 Data and pre-processing

The data used for the experiments is from Twitter. Twitter provides a good representation of social media text due to the direct connection consumers have with organisations and brands as well as the ability to express oneself [11]. **Add content on why Twitter**

The data set created by [11] and further used by [6] is utilised for this project. The original process for collection and annotation employed by them is breifly described below. The particular version ¹ used for the experiments is the one enhanced by [7] with the addition of labels for the severity of complaints. These additional labels are not used for the experiments in this project.

3.1.1 Domains and organisations

A cross-industry representative collection of 93 customer service handles of organisations on Twitter were identified manually. These handles were then categorised into 9 domains based on their industry type. Since an organisation could have business activities across domains, the assigned domain was based on the products or services receiving the most number of complaints. All the domains used in the experiments are listed in Table 3.1.

3.1.2 Collection

The data was extracted from Twitter via the Twitter API ². The most recent 3,200 tweets at the time of the collection exercise were extracted and the original tweets to which the customer service handles responded were identified. Then, random sampling equally for each handle, 1,971 tweets were identified where there was a response from the support's handle. To ensure a more balanced and diverse dataset, 1,478 randomly sampled tweets were added to the dataset. 739 tweets were replies to other handles (outside the 93 identified) and

¹The data can be found here - https://archive.org/details/complaint_severity_data

²https://developer.twitter.com/en

Domains	No. of Complaints	No. of Non-Complaints	Total Tweets
Food & Beverage	95 (73%)	35 (27%)	130 (7%)
Apparel	141 (55%)	117 (45%)	258 (13%)
Retail	124 (62%)	75 (38%)	199 (10%)
Cars	67 (73%)	25 (27%)	92 (4%)
Services	207 (61%)	130 (39%)	337 (17%)
Software & Online Services	189 (65%)	103 (35%)	292 (15%)
Transport	139 (56%)	109 (44%)	248 (12%)
Electronics	174 (61%)	112 (39%)	286 (15%)
Other	96 (79%)	33 (21%)	129 (7%)
Total	1232 (63%)	739 (37%)	1971

Table 3.1: The nine domains and the distribution of tweets that are complaints and those that are not. The percentages indicate how the splits are distributed.

the remaining 739 tweets were not addressed to any Twitter handle. Table 3.2 shows the breakdown of the total population of the tweets dataset. Tweets were filtered for English using langid.py [9]. Retweets were excluded and all usernames and URLs were anonymised and replaced with placeholder tokens.

Collection Criteria	No. of Tweets
Addressed to and replied by identified 93 customer service handles	1971 (58%)
Addressed to other customer service handles	739 (21%)
Not addressed to any Twitter handle	739 (21%)
Total	3449

Table 3.2: Selection of tweets based on random sampling and where they have received replies when addressed to the 93 customer service handles combined with random sampled tweets that are addressed to other handles and tweets that are not addressed to any handle

3.1.3 Annotation

A binary annotation task was setup to determine whether a tweet includes a complaint. Since tweets are concise and typically express a single idea, an entire tweet was classified as a complaint if it contained at least one speech act of complaining. To guide the annotation process, a complaint definition from [10], stating that a complaint portrays a situation that contradicts the writer's positive expectation was used. Two of the authors with extensive annotation experience in linguistics independently labelled the 1,971 tweets with Cohen's Kappa of $\kappa = 0.731$, indicating substantial agreement as per [1]. In the end, 1,232 tweets (63%) and 739 tweets (37%) were identified as complaints and non-complaints. Table 3.1 gives the breakdown of the complaint and non-complaint tweets for each domain.

3.2 Models and Libraries

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3.3 Nested cross validation

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3.4 Domain splits with nested cross validation

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3.5 Ethical, Professional and Legal Issues

Results and discussion

4.1 Risk Analysis

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4.2 Project Plan

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4.3 Another Section if You Need It

Conclusions

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Appendices

Appendix A

An Appendix of Some Kind

Appendix B

Another Appendix