**Understanding customers’ perceived value of emerging technology through content analysis: a case study of autonomous vehicle**

# **Abstract**

In an early stage of developing emerging technologies, there is often great uncertainty regarding their future success. Companies can reduce this uncertainty by listening to the voice of customers as the customer eventually decides to accept an emerging technology or not. We show that risk and benefit perceptions are central determinants of acceptance of emerging technologies. We present an analysis of risk and benefit perception of self-driving cars from June 2016 until January 2019. In this period, we analyzed 455,724 tweets using supervised machine learning for text classification. Furthermore, we implemented two key performance metrics, risk rate (RR) and benefit rate (BR), which allow analyzing risk and benefit perceptions on social media quantitatively. With our results, we provide impetus for further research on acceptance of autonomous vehicle and a methodological contribution to acceptance of emerging technologies research. Furthermore, we identify crucial issues in the public perception of autonomous vehicles and provide guidance for the management of such emerging technologies to increase the likelihood of their acceptance.

# **Keywords**

Technology acceptance, voice of customer, benefit perception, risk perception, autonomous vehicles, natural language processing, recurrent neural networks.

# **1)- Introduction**

The evolution of transportation has faced numerous trials as it has grown and expanded over time. It seems safe to assume that this steady chain of development of faster and safer vehicles with improved technological features continues (e.g., Burns 2013). Over the past decade, a vast amount of research has been conducted regarding the topic of autonomous vehicles (Fagnant and Kockelman 2015; Kyriakidis et al. 2015), which are being vigorously pursued by companies in the automotive, transport, data aggregation and related information technology industries. Even high competence IT companies such as Google are pursuing the development of autonomous vehicles (Spinrad 2014). However, for a technology to be successful, we must remember a significant key factor for the success of emerging technologies, technology acceptance by its customers (Davis et al. 1989).

In recent years, self-driving cars have become a controversially discussed topic. Ethical, regulatory, and liability concerns (Zmud and Sener 2017; Gogoll and Mül- ler 2017), centering on who is driving and who assumes responsibility for accidents, are issues of heated debates. Nevertheless, there are many industries exploring possibility of autonomous vehicles and these sectors seem convinced that self**‐**driving cars will be the future of mobility and may underestimate the public’s concerns and misconceptions related to this emerging technology (Piao et al. 2016) that often differ from the perceptions of experts (Blake 1995). With the first intelligent vehicle handling systems, a pre-stage of technologies that enable self-driving cars, Conover (1994) already discussed that risk and benefit perceptions could be an issue. Research regarding other technologies also shows that risk and benefit perceptions are central determinants of their public acceptance (Siegrist 2000; Butakov and Ioannou 2015). Public perceptions, therefore, eventually determine whether self-driving cars will be used and, thus, are a crucial factor that needs to be considered especially for initial acceptance of emerging technologies such as self-driving cars (Butakov and Ioannou 2015; Pendleton et al. 2015; Bansal et al. 2016).

However, studies addressing public perception and acceptance of this emerging technology, especially across several countries and its change over time, remain scarce. We address this paucity of research by first outlining the results of previous research on public perception and acceptance of self-driving cars. Second, we describe an approach to measure and react to public perceptions facilitating the voice of the customer (VOC). This approach gives us the opportunity to utilize the vast amounts of data publicly available in social media to anticipate acceptance of emerging technologies and answer the following research questions:

“How can we measure public perceptions of self-driving cars to anticipate acceptance? “

“How do events influence the public perception of self-driving cars? “

To address these research questions, we created an approach for automatically determining and monitoring perceived risks and benefits of emerging technologies from short 140-character text messages published on the social media platform Twitter. We build on scientific literature and text mining methods, which allow the extraction of knowledge from text documents (Tan 1999) and, more specifically, sentiment analysis (Hopkins and King 2010). We use the social media platform Twitter to collect a stream of opinions about self-driving cars, one instance of currently emerging technology. Based on the perceived risks and benefits of self-driving cars, we identify events and issues crucial for the future acceptance of this emerging technology and guide the management of emerging technologies.

The remainder of this paper is structured as follows: First, we provide an overview of current literature on technology acceptance i.e self-driving cars, and previous research on the acceptance of self-driving cars. Second, we describe the text data extraction from Twitter, the preprocessing of the data, and the model generation including its evaluation. Third, we describe and discuss the results of extracting the relevant data and applying our machine learning model to this data. We conclude with a summary of the results, limitations of our work, possibilities for further research, and the contributions to research and practice.

# **2)- Theoretical background**

In this section, we provide an overview of current literature disclosing the significance of acceptance towards self-driving cars from both an Information Systems (IS) and public acceptance perspective. An introduction to self-driving cars, the current scientific knowledge about them, and studies assessing the acceptance of self- driving cars are presented as well. We conclude this section by summarizing the theoretical background for our study.

## 2.1 Technology acceptance

Technology acceptance is one of the main research streams of IS research. The technology acceptance model (TAM) originates from this research stream and is a crucial source of numerous research endeavors (Venkatesh et al. 2007). TAM explains and predicts if and why a particular technology will be used by individuals using three basic constructs: perceived usefulness, perceived ease of use, and behavioral intention to use the given technology under consideration (Davis et al. 1989). Perceived usefulness is defined as the probability that a specific technology system increases the user’s performance for a given task. Perceived ease of use describes the effort a user expects when using the technology system to solve a given task. The main hypotheses of TAM are that perceived usefulness and perceived ease of use determine the strength of the behavioral intention of using a specific technology to solve a given task (Davis 1989). Behavioral intention then leads to actual use as described in the Theory of Reasoned Action (Fishbein and Ajzen 1975), an influential theory from social psychology on which TAM is based upon (Davis et al. 1989).

Several researchers have extended TAM to consider the importance of risk perception for user acceptance (Venkatesh et al. 2016). For example, Martins et al. (2014) study internet banking adoption and conclude that risk perception is an important factor. They found that privacy risk and the risk of being subject to Internet banking fraud are important for Internet banking acceptance. Lance- lot Miltgen et al. (2013) study end-user acceptance of biometrics and find that privacy risk is important for acceptance of biometrics. These studies show that assessing risk perception requires domain knowledge to identify risks that are relevant to a certain technology. However, despite some studies including risk perception as an additional factor, it has not been included in any of the central technology acceptance models (Venkatesh et al. 2016). Risk perception depends on the emerging technology itself and, therefore, is difficult to determine with standardized questionnaire items, as it is usually the case with TAM-based acceptance research.

Public acceptance research recognizes the central role of risk perception for acceptance. Previous research shows that many technologies have been rejected by people because of societal controversies, causing negative consequences for the commercialization of technologies (Gupta et al. 2012). Considering the vast investments in research and development of autonomous vehicles and the potential benefits of this technology for society, rejection of this technology could have severe consequences. The events and accidents that were recently reported with self-driving cars, such as recent Google self-driving car accident (Salon, 2020), could lead to fear and reluctance to accept, let alone try out this new technology (Hohenberger et al. 2016, 2017). Even traditional automotive companies, who are investing in research and development of autonomous vehicles, may suffer serious damage. If the technology failed to find wide acceptance, they would not get sufficient return on their investments.

Besides the research in the IS field, there is an influential model of technology acceptance in the public acceptance field proposed by Siegrist (2000). It specifically focuses on the relationship between perceptions of risks and benefits, trust, and public acceptance. Siegrist (2000) found that trust influences perceptions of risks and benefits, which in turn directly influence technology acceptance. To understand their model, it is important to differentiate between actual risks and benefits and their perceptions. The seminal work of Slovic (1987) describes the perception of risks associated with emerging technologies that are unfamiliar and incomprehensible to most people. People rely on intuitive judgments based on media reports rather than personal testing or technologically sophisticated analyses to assess the risks more objectively. These judgments are often prone to biases caused by heuristics that may not lead to optimal or rational decisions as described in prospect theory (Kahneman and Tversky 1979). Furthermore, the perception of risk and benefits is confounded (Alhakami and Slovic 1994), which means that people do not differentiate between risks and benefits when evaluating new technology. Thus, we cannot expect people to make rational decisions based on facts but rather consider their perceptions when anticipating their behavior. These perceptions are also influenced by trust, which helps people reduce cognitive complexity when evaluating new technologies (Earle and Cvetkovich 1995). Instead of their evaluation, people trust other entities to evaluate and apply emerging technologies correctly. In the case of autonomous vehicles, this could be the trust of people in regulatory authorities and the law to ensure that autonomous vehicles are safe to used (Choi and Ji 2015).

Risks and benefits of an emerging technology perceived by non-technical personnel may vary significantly from the risks and benefits determined by technology experts. Emerging technologies and products, in particular, may cause anxiety and resistance in using them (Bongaerts et al. 2016; Zmud et al. 2016). In recent past, emerging technologies such as nanotechnology and genetically modified food struggle for acceptance, even if the benefits outweigh the risks from a scientific perspective, because of subjective (mis)perceptions (Gupta et al. 2012, 2015). Identifying perceived risks and benefits in an early product development stage, as it currently is the case with autonomous vehicles, allows companies to act ambidextrously (Duncan, 1976); that is, to adjust their key technologies to align with current business demand so as to analyzing perceived risks and to exploit perceived benefits.

For anticipating and explaining technology acceptance, both IS and public acceptance research mainly rely on questionnaires. A questionnaire usually consists of several items for each construct (e.g., behavioral intention to use new technology), which were validated in prior research and adapted to the domain of application (e.g., telecommunication, banking) (Venkatesh et al. 2003). The questionnaire is then administered to a sample of the population and analyzed using regression or structural equation modeling after the data collection. This time-consuming and laborious approach comes with limitations. For example, an artifactual covariance between measures is caused by common methods, which can cause inflation of observed correlations (Sharma et al. 2009). Artifactual covariance is a major validity threat for IS acceptance as well as general social sciences research, which is often based on surveys (Sharma et al. 2009).

## 2.2 Self‐driving cars

Driving automation, as in the case of self-driving cars, can be categorized into different levels of automation. There are three commonly used definitions of these levels. The German Federal Highway Research Institute (BASt) defines five levels of driving automation (Gasser and Westhoff 2012), the US National Highway Traffic Safety Administration (NHTSA) defines five levels of automation (NHTSA 2013), and the Society of Automotive Engineers (SAE) defines six levels of automation (SAE International 2014). Besides the different number of levels of automation, the definitions are similar. Kyriakidis et al. (2015) provide a comparison of the three definitions. We use the BASt definition to elaborate the different levels of automation exemplarily.

The idea of all definitions is to differentiate between driving automation systems providing driver only, assisted, partially automated, highly automated and fully automated. Table 1 summarizes the levels of driving automation.

|  |  |  |
| --- | --- | --- |
| Level | Nomenclature | Description |
| 1 | Driver only | The driver continuously (throughout the complete trip) accomplishes longitudinal (accelerating/braking) and lateral(steering) control. |
| 2 | Assisted | The driver continuously accomplishes either lateral or longitudinal control. The remaining task is accomplished by the automating system to a certain level.   * The driver must permanently monitor the system. * The driver must at any time be prepared to take over complete control of vehicle. |
| 3 | Partially automated | The system takes over lateral and longitudinal control (for a certain amount of time and/or in specific situation)   * The driver must permanently monitor the system. * The driver must at any time be prepared to take over complete control of vehicle. |
| 4 | Highly automated | The system takes over lateral and longitudinal for a certain amount for a certain amount of time in specific situations   * The driver need not to permanently monitor the system as long as it is active. * If necessary, the driver is requested to take over control by the system with a certain time buffer. * All system limits are detected by the system. The system is not capable of re-establishing the minimal risk condition from every initial state. |
| 5 | Fully automated | The system takes over lateral and longitudinal control completely within the individual specification of the application.   * The driver need not to monitor the system * Before specified limits of the application are reached, the system requests the driver to take over with sufficient time buffer. * In absence of a takeover, the system will return to the minimal risk condition by itself. * All system limits are detected by the system, the system is capable to return to the minimum risk condition in all situations. |

Table 1: Levels of automation (Gasser & Westhoff, 2012)

Current driving automation systems, such as Tesla’s Autopilot, require that drivers are in control of the car at any time and regardless of the current conditions. Hence, they need to be considered Partially automated that only provide level 3 driving automation according to the BASt definitions. However, the term “self-driving” is commonly associated with these cars. To emphasize when we specifically refer to level 5 automation, it is called “fully automated” by Gasser and Westhoff (2012).

The major drawback of current driving automation systems is that the driver must be able to take control of driving at any time (e.g., Yadron and Tynan 2016). Drivers are misusing those systems for example by leaving the driver’s seat while driving on public roads using a level 3 driving automation system (Krok 2015). Considering how difficult it is for the driver to get back in the loop and properly react to certain traffic situations (Gold et al. 2013; Körber et al. 2016), such reports are troubling. They show that exaggerated benefit perceptions can have negative implications for driving safety and, thus, public acceptance.

A survey of public opinion about self-driving cars in the U.S., the U.K. and Australia with 1,533 respondents indicates that 56% of people have positive opinions towards autonomous vehicles while 13.8% express negative concerns and 29.4% are neutral towards the topic (Schoettle and Sivak 2014). The Consumer Technology Association (CTA) stated that 70% of drivers in the U.S. expressed interest in testing a self-driving car, and more than 60% of drivers showed a willingness in replacing their cars or trucks with a completely autonomous vehicle (Markwalter 2015). A study among 421 French drivers showed that 68.1% would be willing to use self- driving cars (Payre et al. 2014). Supporters argue that since 93% of car accidents are due to driver errors (Treat et al. 1977), the use of autonomous vehicles could reduce car accidents by that exact amount (Markwalter 2015; Fagnant and Kockelman 2015). However, opponents of this view state that self-driving cars might introduce new and currently unknown risks such as system failures or offsetting behaviors. Schoettle and Sivak (2014) concluded that autonomous vehicles may be no safer than an average driver and that they may increase the number of total vehicle accidents if self- and human-driven vehicles use the same roads.

In general, surveys show that people are accepting autonomous vehicles (e.g., Fraedrich et al. 2016) although they know only little about them. Previous research indicates that benefit perception positively influences technology acceptance (Hohenberger et al. 2017). However, focusing only on the benefits of self-driving cars might not be a sustainable approach to increase their initial acceptance. If autonomous vehicles become widely available, people may begin to recognize potential safety issues and risks when they use them as in the case of active cruise control. When active cruise control was introduced in production vehicles, people began to recognize their loss of control, resulting in a lack of acceptance (Eckoldt et al. 2012). Therefore, car manufacturers need to communicate risks and limitations of autonomous vehicles. Mis- conceptions about both risks and benefits need to be avoided or even counteracted.

## 2.3 Summary

Currently, developers and manufacturers of full autonomous vehicles are racing to be the first ones on the market. They see the enormous potential of this emerging technology and the technological challenges, but they undermine about the acceptance of customers (Rogers 2003). The prevalent method to measure acceptance is administering questionnaires, which might not be suitable for emerging technologies such as autonomous vehicles. Respondents to an acceptance questionnaire probably neither have detailed knowledge nor experience regarding autonomous vehicles leading to biased results (Fraedrich and Lenz 2014). Rather than using standardized questionnaires, exploratory and qualitative research should be conducted in this field at an early stage (König and Neumayr 2017).

The voice of future customers provides interesting research opportunities for emerging technologies (Griffin and Hauser 1993). The risk and benefit perceptions of future customers are likely to play a central role in the acceptance of autonomous vehicles (Ward et al. 2017). Even before public availability, risk and benefit perceptions should be closely monitored to identify any issues with an emerging technology or its public perception. Previous research has conducted qualitative exploratory analyses of textual data about risk and benefit perceptions of self-driving cars and has shown that this is a promising approach (Fraedrich and Lenz 2014; Bazilinskyy et al. 2015; Kohl et. al, 2018). Recent studies put considerable effort in the manual coding of all data but struggled with this somewhat lengthy and time- demanding approach (Bazilinskyy et al. 2015, p. 2450), which still could have biasness (Bazilinskyy et al. 2015, p. 2450). Furthermore, they suggest studying perceptions over time as they are likely to change as people become more familiar with this technology (Kauer et al. 2012; Haboucha et al. 2017; König and Neumayr 2017). In this context, it would be particularly interesting to study the effect of critical incidents with autonomous vehicles on public perceptions (Woisetschläger 2016). To address these findings and suggestions of previous research, we address the following propositions to answer our research questions:

Proposition 1: Machine learning approach could be implemented to analyze the publics’ risk and benefit perceptions regarding autonomous vehicles over social media.

P2a: Social media trends associated with benefits of self-driving cars (e.g., increased safety, reduced mobility costs) increases benefit perception of self-driving cars on Twitter.

P2b: News concerning the risks of self-driving cars (e.g., accidents, hacker attacks) increases risk perception of self-driving cars on Twitter.

# **3)- Method**

We use a novel approach to identify risks and benefits as Kohl et. al (2018) suggested. We get interesting results by analyzing the vast amount of existing data about autonomous vehicle on Social media forum called “Twitter” encoded in small text message named as “tweets”. This approach is theoretically founded in the quantitative content analysis (Neuendorf 2016), which allows conducting quantitative data analyses based on qualitative data and extends previous qualitative approaches (Fraedrich and Lenz 2014; Bazilinskyy et al. 2015). While content analysis has been used to analyze mainly unstructured social media data before (e.g., McCorkindale 2010), we automate most of the coding process using machine learning. This method is similar to sentiment analysis in marketing research (Okazaki et al. 2014) and has the advantage that only a small portion of the data needs manual coding when using supervised text classification method. By using this method, we avoid certain issues with questionnaires and studying technology acceptance, for example, common method variance (Sharma et al. 2009).

We follow the analysis process suggested by Okazaki et al. (2014) for sentiment analysis. It consists of data extraction, data preparation, model generation, model validation, and model application. Our approach to risk and benefit perception analysis is similar to sentiment analysis, which allows us to follow a common sentiment analysis process. Variations in the sentiment analysis process, for example, combining the steps of model generation and validation into one step (Feldman 2013) usually do not differ much.

We implemented the process of Okazaki et al. (2014) as follows: First, we obtain tweets using the Twitter Search API (data extraction). Second, we preprocess the text data in tweets to improve data quality, decrease data noise, reduce dimensionality, and avoid misclassification (data preparation). Third, we train the machine learning algorithm (model generation) and evaluate it using cross‐validation (model validation). Fourth, we apply the machine learning algorithm to classify the tweets (model application). We then analyze the classified tweets qualitatively and quantitatively to address our research propositions.

## 3.1 Twitter mining

Twitter has often proven to be a valuable source of data for prediction and monitoring of diverse phenomena ranging from disease outbreaks (St Louis and Zorlu 2012) to political elections (Tumasjan et al. 2010). Users of Twitter face a limit of 140 characters per message, referred to as “tweet,” to include all relevant information. Despite their limitation to words, tweets contain valuable information encoded in natural language (Pak and Paroubek 2010). It is an ongoing challenge to extract this information from the vast amount of noise present on Twitter. We build on previous findings from sentiment analysis (Pak and Paroubek 2010) and machine learning classification to extract information from tweets. We need to extend previous approaches, as sentiment analysis is not directly applicable to the extraction of risk and benefit perceptions. It traditionally only assigns a polarity, i.e., positive or negative sentiment, to a given statement (Medhat et al. 2014).

New developments on Twitter include Twitter bots that are difficult to discern from real persons (Boshmaf et al. 2011; Haustein et al. 2016) and Internet of Things (IoT) devices that communicate over Twitter (Kranz et al. 2010). Therefore, results of Twitter analyses require careful consideration. The Twitter bots have especially become increasingly good at emulating human communication and writing style. Researchers are concerned about the large-scale infiltration of so-called “social-bots” that are hardly discernable from humans (Boshmaf et al. 2011). Social- bots make a quantitative analysis, for example analyzing tweet counts, not only from Twitter but also other social platforms such as Facebook, challenging (Haustein et al. 2016). However, we will compare the results of our analysis with previous studies to detect manipulations of the Twitter data.

A further issue with tweets is that they are not directly accessible from the authors. We only retrieve tweets in this study that are returned by the Twitter Search API, which are determined by proprietary algorithms and are not a representative sample of the overall tweets (Ruths and Pfeffer 2014). Furthermore, Twitter users are not a representative sample of the population (Ruths and Pfeffer 2014). However, Twitter has a broad audience from different social and interest groups and, thus, is a valuable source to assess people’s perceptions (Pak and Paroubek 2010). We expect Twitter users to be more open to new technology, which could lead to slightly more positive results compared to previous surveys based on representative samples of the population.

Despite the limitations of Twitter mining, our approach allows accessing the voice of customers in millions of active Twitter users (Twitter 2017), which results in considerably more statements concerning the acceptance of autonomous vehicles than in previous research. To cope with the huge amounts of data from Twitter, we use machine learning to automate the classification of tweets. Thereby, we avoid the laborious manual coding of qualitative content, thus, making this research feasible.

## 3.2 Data extraction

Our dataset comprises tweets written in English concerning autonomous vehicles that were obtained using the Twitter Search API (Twitter 2016a). We used beautiful soup API to scrap tweets not older than 1 week (Twitter 2016b). A meaningful longitudinal analysis, however, requires being able to collect tweets for longer intervals by collecting the tweets daily and storing them in a database. Free version of tweeter accounts allows fetching tweets for last seven days and hence, we collected tweets on weekly basis. A comma-separated values(csv) data file was used to store the complete tweets returned by the Twitter Scarping API. This dataset includes unique tweet Identifier, time stamp of given tweets, quarter details of those time periods, date of creation of tweets, user ID i.e the tweet creator, username, their screen name, and the message body including text. The tweets have then been transferred to an in-memory data- base to process them efficiently. We used IPython Jupyer N otebook environment that allow us to process data using python key modules such as request and pandas to read twitter-based csv dataset. We started the data collection for this analysis on June 6, 2016, with the last tweets being collected on January 18, 2019. We used the following set of search queries (SQ) in our Twitter Search API requests:

* SQ1: self-driving OR driverless OR autonomous
* SQ2: tesla OR google OR apple OR icar OR ford OR opel OR gm OR general motors
* SQ3: volkswagen OR vw OR daimler OR mercedes OR benz OR bmw OR audi OR porsche.

The search queries were fixed before the data collection. They consist of a combination of topic-related keywords (SQ1), names of US-based companies actively working on self-driving cars and U.S. car manufacturers (SQ2), as well as active German car manufactures (SQ2 and SQ3). For our case, SQ2 and SQ3 resulted in many tweets that were not concerned with self-driving cars. In next phase, we used regular expressions

*(driver.?less|self.?driving|autonomous.?driving|automated.?driving|autonomous.?car|automated.?car)*

This implementation of regular expression library ensures that only tweets containing one of the following terms are included in the data analysis: driverless, self-driving, autonomous driving, automated driving, autonomous car, and automated car. The regular expression also ensures that slight variations of the terms are included, such as “driver less” or “driver-less.” This filtering method reduced the number of relevant tweets to 455,728.

We select a subset of tweets for training a machine learning text classifier model. For this purpose, we used a dataset of 15,000 tweets labelled as beneficial, risky, and neutral. Top tweets are popular tweets trends that many other Twitter users have engaged with and thought were useful (Twitter 2016c). Analyzing such popular tweets relating to autonomous vehicles, we got an overview of the discussion of this topic on Twitter, which helped to acquire knowledge of latest trends related to our case study.However, we refrain from analyzing these tweets since they only represent a small fraction of the actual tweets published from June 2016 to January 2019 and are probably highly biased through the proprietary selection algorithms implemented and used by Twitter. Instead we only use them as training data for machine learning classification. In 43.12% of the tweets in the training dataset, no information about risk and benefit perceptions was present and were, thus, categorized as “Neutral.”

Table 2 shows the descriptive statistics of the training dataset.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Risk related Tweets | Benefit related tweets | Neutral tweets |
| Total Number(15000) | 795 | 1903 | 4245 |
| In percentage | 16.28% | 40.59% | 43.12% |

Table 2: Descriptive statistics of the training dataset

This process of labeling text data is significant in order to build an accurate training dataset for machine learning text classifier. It is important to note that applying a machine learning algorithm is an iterative process. It is common to review and adjust labels until label accuracy approaches a satisfactory level. In practice, researchers build custom annotation systems to review and update data labels as accurate labelled data is crucial for model quality. If there are issues with the labels, text classifier can’t effectively learn the ground truth which might lead to inaccurate predictions. One approach that researchers have used to improve the accuracy of their label data is through audit workflows. Audit workflows enable a group of reviewers to verify the accuracy of label and adjust them if required.

For text annotation, we used built-in audit workflow using Amazon SageMaker Ground Truth tool. It performs both label verification and label adjustment for semantic segmentation. This approach makes sure that labelling instruction and rules are consistent among all reviewers. This method is also useful in reviewing jobs made by other reviewers involved in labelling process.A screenshot of a cell phone

Description automatically generated

Fig2: An example of labelling job using SageMaker Gorund Truth

Figure 1: Data Labelling using Amazon SageMaker Ground Truth

# **4 Natural Language Processing Pipeline**

Input

(raw text)

Sentiment prediction

ML algorithm

Word Embedding

Feature extraction

Text cleaning

Figure 2: NLP data pipeline implemented for sentiment prediction

## 4.1. Text data cleaning

We performed data cleaning on the tweets to remove noise, to create consistent input for our model, and to reduce dimensionality in order to avoid misclassification .This is a common practice in text classification (Okazaki et al. 2014).Since text is most unstructured form of all available data, various types of noise are present in it and the data is not readily analyzable without pre-processing practices. The process of data preprocessing consists of two steps i.e data cleaning and vectorization. Cleaning procedure is about noise removal, lexicon normalization and object standardization whereas vectorization is to map words or phrases from vocabulary to a corresponding vector of real numbers which are then fed to machine learning algorithm for training.

Text data cleaning is comprised of three steps;

a)-Noise Removal: Any piece of text which is not relevant to the context of the data and the end-output can be specified as the noise. Noise removal is about removing characters digits and pieces of text that can interfere with given text analysis (Li et. al., 2018).

b)-Text Normalization: Another type of textual noise is about the multiple representations exhibited by single word. For example – “play”, “player”, “played”, “plays” and “playing” are the different variations of the word – “play”. For normalization, we have used a technique called “lemmatization” (Zhang et. Al, 2019). The main advantage of lemmatization is that it takes into consideration the context of the word to determine which is the intended meaning the user is looking for. This process allows to decrease noise and speed up computing.

c)-Text Standardization: Text data often contains words or phrases which are not present in any standard lexical dictionaries such as acronyms, hashtags with attached words, and colloquial slangs (Gupta & Joshi, 2017). This process involves transformation of text into a canonical (standard) form. For example, word “2moro”, “tomrw” and “2,rrw” can be transformed as just “tomorrow”.

Raw text

Clean text

Standardization

Noise removal

Normalization

Figure 3: Data cleaning pipeline

## 4.2. Feature Extraction

We implemented this natural language text cleaning methods for our tweet dataset. We obtained significant results for reducing data noise. We have made a comparative analysis for original raw data versus cleaned text data. We extracted additional features check the difference and quality of our cleaning procedure. Results of last five samples from dataset are shown below;

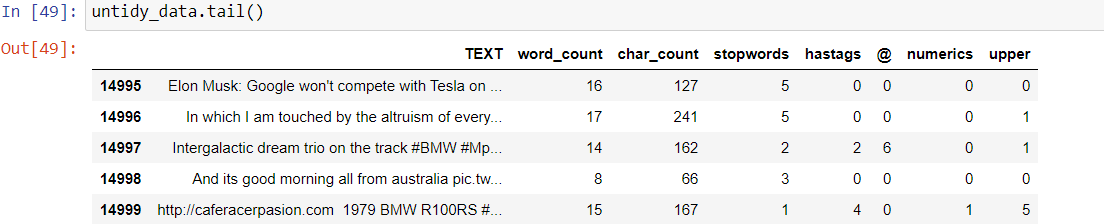


Figure 3: Data before applying NLP cleaning pipeline

In Figure 3, text data is shown per tweet with total number of words in each tweet, total characters in given tweet, number of stop-words, number of hashtag symbols (shows trends in tweets), number of @ symbols (shows any mentioned entity), numeric digits, and upper-case letters. All of these features measure data cleaning activity.

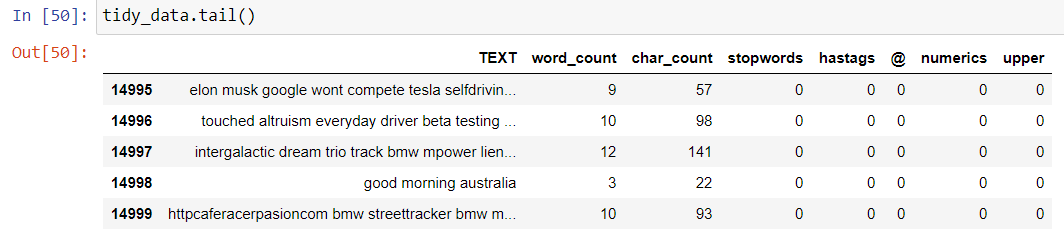


Figure 4: Data after applying NLP cleaning pipeline

Figure 4 shows last five samples of cleaned text in our dataset. It highlights that size of total number count of each tweet has reduced. We removed punctuation, digits, and hyperlinks. Punctuation is not required to determine the classification of the tweets as we will not perform a grammatical analysis. Next, we removed English stop words as provided by the nltk library. Stop words are terms that do not contain relevant information for the text classification (e.g., “a,” “by,” and “was”), so they are not needed in the further analysis. In addition to removing the English language stop words, we removed the Twitter-specific stop words such as “via” and “rt”.

A reduced noise pattern can be found in character count, number of stop-words, number of hashtag symbols, number of @ symbols, digits, and upper-case letters. Hence, we managed to reduce data noise and extra token considerably. Through this text cleaning procedure, the machine learning algorithm can compute more efficiently.

ADD Word Cloud

## 4.3. Word Embedding

Our processed tweets now contain words that are in reduced form for text classification model. However, machine learning models cannot process words so, we need to convert it into number of matrices. Traditionally, bag of words (BOW) approached is used which assigns a unique integer to a unique word and then keeps a count of how many that specific word has occurred in our corpus (Zhao & Mao, 2017). These are also called sparse matrix representations as there are lot of zeros in the vector representation of words. This approach of representation has couple of drawbacks. First of all, there is no relation captured between words. For our analysis, we need a mathematical structure of word representation to hold meaning rather than simple integers representing words. Secondly, the sparse representation of words need big vector space as our vocabulary size grows so it is not efficient (Li et. al, 2017).

Above mentioned problems are deal through word embedding process (Ren et. al, 2016). In this word representation method, words are represented as a set of matrices in a coordinate system where related words, based on a corpus of relationships, are placed closer together in form of vector space. This approach provides us matrix with context and also this approach is not computational costing because dense representation of matrix is applied to capture the word similarity using closeness between two vectors (Ren et. al, 2016; Li et. al, 2017).

## 4.4 Model building

The basic idea of text classification with supervised machine learning is to assign number of target classes to documents automatically using a much smaller set of training data compared to the overall number of documents to classify. Our training data contains automated labeling of target classes i.e risk related tweets, benefit related tweets or neutral tweets. Based on these classifications against their relevant text document, the machine learning algorithm creates a model that determines how to classify new documents. Many different machine learning algorithms could be used for this task such as Naïve Bayes, Maximum Entropy Classification, or Support Vector Machines (SVM) (Pang et al. 2002). These models are easy to implement however; these algorithms lack capability of remembering previous inputs. As our tweet documents are sequence of words that we converted into tokens for our analysis. Therefore, this sequential data must retain information of previous token. For this reason, we use Recurrent Neural Networks (RNN).

RNNs is essentially a fully connected neural network that contains a refactoring of some of its layers into a loop. That loop is typically an iteration over the addition or concatenation of two inputs, a matrix multiplication and a non-linear function forming recurrent layers. This lets training model to maintain information in 'memory' over time. But our dataset contains tweets which have variable length varying from few characters to maximum of 280-character limit therefore, it can be difficult to train standard RNNs. This is because the gradient of the loss function decays exponentially with time (called the vanishing gradient problem) (Chung et al, 2014).

To solve vanishing gradient problem, our training model require learning long-term temporal dependencies. LSTMs (Long Short Term Memory)( Hochreiter and Schmidhuber, 1997; Gers et al., 2000) deal with these problems by introducing new gates, such as input and forget gates, which allow for a better control over the gradient flow and enable better preservation of “long-range dependencies.(See appendix for details).

For our case, we would follow a text classification model architecture generally consists of the following component connected in sequence.

Output

Output layer(softmax)

LSTM network

Text(input)

Fully connected (Dense)

Fig 3: Model Architecture

For model validation, we used train-test split method using scikit learn library. We divided our train set as 5207 values and test set as 1736 samples. As an input, the LSTM gets fed with a sequence of vectors representing the word embeddings. The word embeddings of our dataset can be learned while training a neural network on the classification problem. Additionally, we add padding to make all the vectors of same length. As for model, we employ a one hidden-layer LSTM, trained on three-class prediction i.e neutral, risk related, and benefit related class.

A step by step procedure is following;

* Vectorize tweet, by turning each text into either a sequence of integers or into a vector.
* Set the max number of words in each complaint at 280(max size limit for twitter is 280 ).
* Truncate and pad the input sequences so that they are all in the same length for modeling

LSTM (Long Short Term Memory) model structure is given below;

* The first layer is the embedded layer that uses 100 length vectors to represent each word.
* SpatialDropout1D performs variational dropout in NLP models.
* The next layer is the LSTM layer with 100 memory units.
* The output layer must create 3 output values, one for each class.
* Activation function is softmax for multi-class classification.
* Adam as optimization algorithm to take care of weights and learning rate of our neural network so that loss would not begin to diverge after decrease to a point.
* Because it is a multi-class classification problem, categorical\_crossentropy is used as the loss function.

## 3.5)- Model results

On three-class sentiment prediction (risk, neutral, benefit) of full sentences, the model achieves 79.3 % accuracy. We also compute accuracy of each class based on confusion matrix with actual predicted results and percentage of predicted results (Table 3).

A screenshot of a cell phone

Description automatically generated

A screenshot of a cell phone

Description automatically generated

We can see that accuracy does not seem to very good. We encoded neutral class as 1, benefit related class as 0 and risk related class 2. We have got best results from neutral class i.e 82% and risk class does not look very accurate i.e 29%. However, accuracy is not a good metric for predictive models (Valverde-Albacete,2013). This is because our data contains imbalanced class neutral being 61.1% of our dataset whereas benefit related class is 27% almost half neutral class. Risk related class is even lower than half of what we have for benefit class i.e 11.4%.So, prior probabilities for these classes need to be accounted for in error analysis. We can see that we predicted in 103 times that given tweets are neutral but, those tweets were actually risk related. In other words, our model has enough neutral tweet related samples that it could not learn about risk related samples.

Precision and recall might be alternative measures to be considered in our case. Table 4 shows different evaluation metrics.

Table 4.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Classes** | **precision** | **recall** | **f1-score** | **support** |
| Benefit related tweets | 55% | 55% | 55% | 444 |
| Risk related tweets | 44% | 26% | 32% | 215 |
| Neutral tweets | 75% | 82% | 78% | 1077 |

we could identify issues of the classifier resulting from the imbalanced training set. For example, sensitivity for the classes “Risk” and “Benefit” and specificity for the class “Neutral” is relatively low, indicating that the classification is biased to assign the neutral class. However, for our analyses, we consider this result as a good compromise between sensitivity and specificity for all three classes.

It is clear that accuracy only gives a glimpse of our prediction results. We can see that most reliable prediction results are for neutral tweet class. We want to see how our model would perform on risk related tweets versus benefit related tweets. For this reason, we build a binary classification model to train our dataset. We removed all tweets that are referring to neutral tweets. After removal of neutral tweets, we have 1903(70.5%) benefit related tweets and 795(29.5%) risk related tweets. We still can find imbalance among classes but, this is not as significant as was in our multi-classifier case.

We get accuracy of 73% which is an improvement however; we need to see in depth if we could better risk vs benefit analysis of tweets. Results of confusion matrix are given below;

A screenshot of a cell phone

Description automatically generated

A screenshot of a cell phone

Description automatically generated

In above figure, benefit tweet class is represented as 0 and risk related tweet class is represented as 1. There are 98 instances where our model predicts risk related tweets but, these tweets are actually benefit related tweets. Such instances are called False Negative. Then we have 85 False Positive cases where our model predicted benefit related tweets but, these tweets are risky.

Other evaluation metrics are shown in table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Classes** | **Precision** | **Recall** | **F1score** | **Support** |
| Risk related tweets | 0.55 | 0.51 | 0.53 | 202 |
| Benefit related tweets | 0.80 | 0.82 | 0.81 | 473 |

# **References**

Alessandrini A, Holguin C, Parent M (2011) Advanced transport systems showcased in La Rochelle. In: Proceedings IEEE conference on intelligent transportation systems, ITSC. pp 896–900

Alhakami AS, Slovic P (1994) A psychological study of the inverse relationship between perceived risk and perceived benefit. Risk Anal 14:1085–1096. https://doi.org/10.1111/j.1539-6924.1994.tb000 80.x

Bansal P, Kockelman KM, Singh A (2016) Assessing public opinions of and interest in new vehi- cle technologies: an Austin perspective. Transp Res Part C Emerg Technol 67:1–14. https://doi. org/10.1016/j.trc.2016.01.019

Bazilinskyy P, Kyriakidis M, de Winter J (2015) An international crowdsourcing study into people’s statements on fully automated driving. Proc Manuf. https://doi.org/10.1016/j.promfg.2015.07.540

Benbasat I, Barki H (2007) Quo vadis TAM? J Assoc Inf Syst 8:211–218. http://aisel.aisnet.org/jais/vol8/ iss4/7/

Blake ER (1995) Understanding outrage: how scientists can help bridge the risk perception gap. Environ Health Perspect 103:123–125. https://doi.org/10.2307/3432360

Bongaerts R, Kwiatkowski M, König T (2016) Disruption technology in mobility: customer acceptance and examples. In: Phantom Ex machina: digital disruption’s role in business model transformation. Springer International Publishing, Switzerland, pp 119–135

Boshmaf Y, Muslukhov I, Beznosov K, Ripeanu M (2011) The socialbot network. In: Proceedings of the 27th annual computer security applications conference on—ACSAC’11. ACM Press, New York, USA, p 93

Brown B (2017) The social life of autonomous cars. Computer (Long Beach Calif) 50:92–96. https://doi. org/10.1109/MC.2017.59

Burns LD (2013) Sustainable mobility: a vision of our transport future. Nature 497:181–182. https://doi. org/10.1038/497181a

Butakov V, Ioannou P (2015) Driving autopilot with personalization feature for improved safety and com- fort. In: 2015 IEEE 18th international conference on intelligent transportation systems. IEEE, Las Palmas, Spain, pp 387–393

Chang C, Lin C (2011) LIBSVM: a library for support vector machines. ACM Trans Intell Syst Technol 2:1–39.https://doi.org/10.1145/1961189.1961199

[Chung et al. (2014)](http://arxiv.org/abs/1412.3555). Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling.

Choi JK, Ji YG (2015) Investigating the importance of trust on adopting an autonomous vehicle. Int J Hum Comput Interact. https://doi.org/10.1080/10447318.2015.1070549

Christie D, Koymans A, Chanard T et al (2016) Pioneering driverless electric vehicles in Europe: the city automated transport system (CATS). Transp Res Proc 13:30–39. https://doi.org/10.1016/j.trpro .2016.05.004

Conover GD (1994) The eleven commandments for IVHS. In: Vehicle navigation and information sys- tems conference proceedings. Yokohama, Japan, pp 503–506

Cosh K, Wordingham S, Ramingwong S (2017) Investigating public opinion regarding autonomous vehi- cles: a perspective from Chiang Mai, Thailand. Lect Notes Electr Eng 450:3–10

Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information tech- nology. MIS Q 13:319–340

Davis FD, Bagozzi RP, Warshaw PR (1989) User acceptance of computer technology: a comparison of two theoretical models. Manage Sci 35:982–1003. https://doi.org/10.1287/mnsc.35.8.982

Debortoli S, Müller O, Junglas I, Vom Brocke J (2016) Text mining for information systems researchers: an annotated topic modeling tutorial. Commun Assoc Inf Syst 39:110–135

Duncan, R. B. (1976). The ambidextrous organization: Designing dual structures for innovation. The management of organization, 1(1), 167-188.

Earle TC, Cvetkovich G (1995) Social trust: toward a cosmopolitan society. Praeger Publishers, Westport Eckoldt K, Knobel M, Hassenzahl M, Schumann J (2012) An experiential perspective on advanced driver

assistance systems. Inf Technol 54:165–171. https://doi.org/10.1524/itit.2012.0678  
Fagnant DJ, Kockelman K (2015) Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp Res Part A Policy Pract 77:167–181. https://doi.org/10.1016/jtra.2015.04.003

Feinerer I, Hornik K, Meyer D (2008) Text mining infrastructure in R. J Stat Softw 25:1–54  
Feldman R (2013) Techniques and applications for sentiment analysis. Commun ACM 56:82. https://doi. org/10.1145/2436256.2436274

Fishbein M, Ajzen I (1975) Belief, attitude, intention and behavior: an introduction to theory and research. Addison-Wesley, Reading

Fraedrich E, Lenz B (2014) Automated driving: individual and societal aspects. Transp Res Rec 2416:64–72

Fraedrich E, Cyganski R, Wolf I, Lenz B (2016) User perspectives on autonomous driving. In: Arbeits- berichte 187. Geographisches Institut, Humboldt-Universität, Berlin

Gasser TM, Westhoff D (2012) BASt-study: definitions of automation and legal issues in Germany. In: Proceedings of the 2012 road vehicle automation workshop

Gogoll J, Müller JF (2017) Autonomous cars. in favor of a mandatory ethics setting. Sci Eng Ethics 23:681–700. https://doi.org/10.1007/s11948-016-9806-x

Gold C, Dambock D, Lorenz L, Bengler K (2013) “Take over!” How long does it take to get the driver back into the loop? In: Proceedings of the human factors and ergonomics society annual meeting. pp 1938–1942

Griffin A, Hauser JR (1993) The voice of the customer. Mark Sci 12:1–27. https://doi.org/10.1287/ mksc.12.1.1

Gupta N, Fischer ARH, Frewer LJ (2012) Socio-psychological determinants of public acceptance of tech- nologies: a review. Public Underst Sci 21:782–795. https://doi.org/10.1177/0963662510392485

Gupta N, Fischer ARH, Frewer LJ (2015) Ethics, risk and benefits associated with different applications of nanotechnology: a comparison of expert and consumer perceptions of drivers of societal accept- ance. Nanoethics 9:93–108. https://doi.org/10.1007/s11569-015-0222-5

Gupta, I., & Joshi, N. (2017, December). Tweet normalization: A knowledge based approach. In *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions)(ICTUS*) (pp. 157-162). IEEE.

Haboucha CJ, Ishaq R, Shiftan Y (2017) User preferences regarding autonomous vehicles. Transp Res Part C Emerg Technol. https://doi.org/10.1016/j.trc.2017.01.010

Haustein S, Bowman TD, Holmberg K et al (2016) Tweets as impact indicators: examining the implica- tions of automated “bot” accounts on Twitter. J Assoc Inf Sci Technol 67:232–238. https://doi. org/10.1002/asi.23456

Hohenberger C, Spörrle M, Welpe IM (2016) How and why do men and women differ in their willing- ness to use automated cars? The influence of emotions across different age groups. Transp Res Part A Policy Pract 94:374–385. https://doi.org/10.1016/j.tra.2016.09.022

Hohenberger C, Spörrle M, Welpe IM (2017) Not fearless, but self-enhanced: the effects of anxiety on the willingness to use autonomous cars depend on individual levels of self-enhancement. Technol Forecast Soc Change 116:40–52. https://doi.org/10.1016/j.techfore.2016.11.011

Hopkins DJ, King G (2010) A method of automated nonparametric content analysis for social science. Am J Pol Sci 54:229–247. https://doi.org/10.1111/j.1540-5907.2009.00428.x

Hsu C-W, Chang C-C, Lin C-J (2016) A practical guide to support vector classification. In: Natl. Taiwan Univ. http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf. Accessed 25 Oct 2016

Joachims T (1998) Text categorization with support vector machines: learning with many relevant features. In: Nédellec C, Rouveirol C (eds) Machine learning: ECML-98. Springer, Berlin, pp 137–142

Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47:263. https://doi.org/10.2307/1914185

Kasperson RE, Kasperson JX (1996) The social amplification and attenuation of risk. Ann Am Acad Pol Soc Sci 545:95–105. https://doi.org/10.1177/0002716296545001010

Kasperson RE, Renn O, Slovic P et al (1988) The social amplification of risk: a conceptual framework. Risk Anal 8:177–187. https://doi.org/10.1111/j.1539-6924.1988.tb01168.x

Kauer M, Franz B, Schreiber M et al (2012) User acceptance of cooperative maneuverbased driving—a summary of three studies. Work 41:4258–4264. https://doi.org/10.3233/WOR-2012-0720-4258

Kleijnen M, Lee N, Wetzels M (2009) An exploration of consumer resistance to innovation and its ante- cedents. J Econ Psychol 30:344–357. https://doi.org/10.1016/j.joep.2009.02.004

Kohavi R (1995) A study of cross-validation and bootstrap for accuracy estimation and model selection. Int Jt Conf Artif Intell 14:1137–1143. https://doi.org/10.1067/mod.2000.109031

König M, Neumayr L (2017) Users’ resistance towards radical innovations: the case of the self-driving car. Transp Res Part F Traffic Psychol Behav 44:42–52. https://doi.org/10.1016/j.trf.2016.10.013

Körber M, Gold C, Lechner D, Bengler K (2016) The influence of age on the take-over of vehicle control in highly automated driving. Transp Res Part F Traffic Psychol Behav. https://doi.org/10.1016/j. trf.2016.03.002

Kranz M, Roalter L, Michahelles F (2010) Things that twitter: social networks and the internet of things. In: What can the internet of things do for the citizen (CIoT) workshop at the eighth international conference on pervasive computing (Pervasive 2010)

Kraus S, Althoff M, Heißing B, Buss M (2009) Cognition and emotion in autonomous cars. In: IEEE Intelligent vehicles symposium, proceedings. pp 635–640

Krok A (2015) This is the stupidest misuse of Tesla’s autopilot yet. http://www.cnet.com/news/this-is-the- stupidest-misuse-of-teslas-autopilot-yet/. Accessed 25 Nov 2015

Kuderer M, Gulati S, Burgard W (2015) Learning driving styles for autonomous vehicles from demon- stration. In: 2015 IEEE International conference on robotics and automation (ICRA). IEEE, Seat- tle, pp 2641–2646

Kuhn M (2008) Building predictive models in R using the caret package. J Stat Softw 28:1–26. https:// doi.org/10.1053/j.sodo.2009.03.002

Kyriakidis M, Happee R, de Winter JCF (2015) Public opinion on automated driving: results of an inter- national questionnaire among 5000 respondents. Transp Res Part F Traffic Psychol Behav 32:127– 140. https://doi.org/10.1016/j.trf.2015.04.014

Lancelot Miltgen C, Popovič A, Oliveira T (2013) Determinants of end-user acceptance of biometrics: integrating the “Big 3” of technology acceptance with privacy context. Decis Support Syst 56:103– 114. https://doi.org/10.1016/j.dss.2013.05.010

Langdon P, Politis I, Bradley M, et al (2018) Obtaining design requirements from the public understand- ing of driverless technology. In: Advances in intelligent systems and computing. pp 749–759

Lee E-K, Gerla M, Pau G et al (2016) Internet of vehicles: from intelligent grid to autonomous cars and vehicular fogs. Int J Distrib Sens Netw 12:241–246. https://doi.org/10.1177/1550147716665500 .

Li, X., Wang, Y., Zhang, A., Li, C., Chi, J., & Ouyang, J. (2018). Filtering out the noise in short text topic modeling. Information Sciences, 456, 83-96.

Li, Y., Pan, Q., Yang, T., Wang, S., Tang, J., & Cambria, E. (2017). Learning word representations for sentiment analysis. *Cognitive Computation*, *9*(6), 843-851.

Madigan R, Louw T, Wilbrink M et al (2017) What influences the decision to use automated public trans- port? Using UTAUT to understand public acceptance of automated road transport systems. TranspRes Part F Traffic Psychol Behav 50:55–64. https://doi.org/10.1016/j.trf.2017.07.007  
Markwalter B (2015) The path to driverless cars. IEEE Consum Electron Mag 6:125–126. https://doi. org/10.1109/MCE.2016.2640625

Martins C, Oliveira T, Popovič A (2014) Understanding the Internet banking adoption: a unified theory of acceptance and use of technology and perceived risk application. Int J Inf Manage 34:1–13. https://doi.org/10.1016/j.ijinfomgt.2013.06.002

McCorkindale T (2010) Can you see the writing on my wall? A content analysis of the Fortune 50’s Face- book social networking sites. Public Relat J 4:1–14. https://doi.org/10.1017/CBO978110741532 4.004

Medhat W, Hassan A, Korashy H (2014) Sentiment analysis algorithms and applications: a survey. Ain Shams Eng J 5:1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Nees MA (2016) Acceptance of self-driving cars: an examination of idealized versus realistic portray- als with a self-driving car acceptance scale. Proc Hum Factors Ergon Soc Annual Meet. https://doi. org/10.1177/1541931213601332

Neuendorf K (2016) The content analysis guidebook. SAGE Publications, London  
NHTSA (2013) National highway traffic safety administration preliminary statement of policy concerning automated vehicles.

Niculescu AI, Dix A, Yeo KH (2017) Are you ready for a drive? User perspectives on autonomous vehicles. In: Conference on human factors in computing systems—proceedings. pp 2810–2817

Okazaki S, Diaz-Martin AM, Rozano M, Menendez-Benito H (2014) How to mine brand tweets procedural guidelines and pretest. Int J Mark Res 56:467–489. https://doi.org/10.2501/IJMR-2014-008

Olson EL (2017) Will songs be written about autonomous cars? The implications of self-driving vehicle technology on consumer brand equity and relationships. Int J Technol Mark 12:23. https://doi.org/10.1504/IJTMKT.2017.081506

Pak A, Paroubek P (2010) Twitter as a corpus for sentiment analysis and opinion mining. In: Proceedings of the seventh conference on international language resources and evaluation. pp 1320–1326  
Pang B, Lee L (2008) Opinion mining and sentiment analysis. Found Trends Inf Retr 2:1–135. https://doi.org/10.1561/1500000001

Pang B, Lee L, Vaithyanathan S (2002) Thumbs up? Sentiment classification using machine learning techniques. In: Proceedings of the ACL-02 conference on empirical methods in natural language processing—EMNLP’02. pp 79–86

Payre W, Cestac J, Delhomme P (2014) Intention to use a fully automated car: attitudes and a priori acceptability. Transp Res Part F Traffic Psychol Behav 27:252–263. https://doi.org/10.1016/j. trf.2014.04.009

Pendleton S, Uthaicharoenpong T, Chong ZJ, et al (2015) Autonomous golf cars for public trial of mobil- ity-on-demand service. In: 2015 IEEE/RSJ international conference on intelligent robots and sys- tems (IROS). IEEE, pp 1164–1171

Pettersson I, Karlsson ICM (2015) Setting the stage for autonomous cars: a pilot study of future autonomous driving experiences. IET Intell Transp Syst 9:694–701. https://doi.org/10.1049/ iet-its.2014.0168

Piao J, McDonald M, Hounsell N, et al (2016) Public views towards implementation of automated vehi- cles in urban areas. In: Transportation research procedia

Portouli E, Karaseitanidis G, Lytrivis P, et al (2017) Public attitudes towards autonomous mini buses operating in real conditions in a Hellenic city. In: 2017 IEEE intelligent vehicles symposium (IV). IEEE, pp 571–576

Ramos J (2003) Using TF-IDF to determine word relevance in document queries. In: Proceedings of the first instructional conference on machine learning. pp 133–142

Rödel C, Stadler S, Meschtscherjakov A, Tscheligi M (2014) Towards autonomous cars: the effect of autonomy levels on acceptance and user experience. In: AutomotiveUI 2014—6th international conference on automotive user interfaces and interactive vehicular applications, in cooperation with ACM SIGCHI—Proceedings

Rogers EM (2003) Diffusion of innovations, 5th edn. Free Press, New York  
Rubinkam M (2015) Driverless truck meant to improve safety in work zones. In: Yahoo! news. https:// [www.yahoo.com/news/driverless-truck-meant-improve-safety-zones-202055180.html. Accessed Aug 2016](http://www.yahoo.com/news/driverless-truck-meant-improve-safety-zones-202055180.html.%20Accessed%20Aug%202016)

Ren, Y., Wang, R., & Ji, D. (2016). A topic-enhanced word embedding for Twitter sentiment classification. *Information Sciences*, *369*, 188-198.

Ruths D, Pfeffer J (2014) Social media for large studies of behavior. Science 346(80):1063–1064. https:// doi.org/10.1126/science.346.6213.1063

SAE International (2014) Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. In: On-Road Autom. Veh. Stand. Comi. http://standards.sae.org/j3016\_201401/. Accessed 24 Oct 2016

Salon. 2020. Google engineer triggered self-driving car accident that went unreported | Salon.com. [ONLINE] Available at: <https://www.salon.com/2018/10/16/googles-self-driving-cars-involved-in-unreported-crashes/>. [Accessed 12 February 2020].

Schoettle B, Sivak M (2014) A survey of public opinion about autonomous and self-driving vehicles in the U.S., the U.K., and Australia. https://deepblue.lib.umich.edu/handle/2027.42/108384

Sharma R, Yetton P, Crawford J (2009) Estimating the effect of common method variance: the method- method pair technique with an illustration from TAM research. MIS Q 33:473–490

Siegrist M (2000) The influence of trust and perceptions of risks and benefits on the acceptance of gene technology. Risk Anal 20:195–204. https://doi.org/10.1111/0272-4332.202020

Slovic P (1987) Perception of risk. Science 236(80):280–285. https://doi.org/10.1126/science.3563507

Socher R, Lin CC-Y, Ng AY, Manning CD (2011) Parsing natural scenes and natural language with recursive neural networks. In: ICML’11 Proceedings of the 28th international conference on international conference on machine learning. pp 129–136

Spinrad N (2014) Google car takes the test. Nature 514:528. <https://doi.org/10.1038/514528a>

Sriram B, Fuhry D, Demir E, et al (2010) Short text classification in twitter to improve information filter- ing. In: Proceedings of the 33rd international ACM SIGIR conference on research and development in information retrieval—SIGIR’10. pp 841–842  
St Louis C, Zorlu G (2012) Can twitter predict disease outbreaks? BMJ 344:e2353. https://doi. org/10.1136/bmj.e2353

Tan A-H (1999) Text mining: the state of the art and the challenges. In: Proceedings of the PAKDD 1999 workshop on knowledge disocovery from advanced databases. pp 65–70

Treat JR, Tumbas NS, McDonald ST, et al (1977) Tri-level study of the causes of traffic accidents: final report. https://trid.trb.org/view.aspx?id=144150. Accessed 1 Aug 2016

Tumasjan A, Sprenger TO, Sandner PG, Welpe IM (2010) Predicting elections with twitter: what 140 characters reveal about political sentiment. In: Proceedings of the fourth international AAAI con- ference on weblogs and social media. pp 178–185

Twitter (2016a) The search API. [https://dev.twitter.com/rest/public/search. Accessed 1 Aug 2016](https://dev.twitter.com/rest/public/search.%20Accessed%201%20Aug%202016)

Twitter (2016b) Public API: GET search/tweets. [https://dev.twitter.com/rest/reference/get/search/tweets. Accessed 1 Aug 2016](https://dev.twitter.com/rest/reference/get/search/tweets.%20Accessed%201%20Aug%202016)

Twitter (2016c) Help center: the basics. [https://support.twitter.com/articles/131209. Accessed 1 Aug 2016](https://support.twitter.com/articles/131209.%20Accessed%201%20Aug%202016)

Twitter (2017) Selected company metrics and financials. https://investor.twitterinc.com/. Accessed 29 Sep 2017.

Venkatesh V, Morris MG, Davis GB, Davis FD (2003) User acceptance of information technology: toward a unified view. MIS Q 27:425–478. <https://doi.org/10.2307/30036540>

Venkatesh V, Davis FD, Morris MG (2007) Dead or alive? The development, trajectory and future of tech- nology adoption research. J Assoc Inf Syst 8:267–286. <https://doi.org/10.1016/j.wneu.2011.04.002>.

Venkatesh V, Thong JYL, Xu X (2016) Unified theory of acceptance and use of technology: a synthesis and the road ahead. J Assoc Inf Syst 17:328–376

Valverde-Albacete; Carillo-de-Albornoz; Peláez-Moreno (2013), "A Proposal for New Evaluation Metrics and Result Vizualization Technique for Sentiment Analysis Tasks", Information Access Evaluation. Multilinguality, Multimodality, and Visualization, Springer, [ISBN](https://en.wikipedia.org/wiki/International_Standard_Book_Number) [9783642408021](https://en.wikipedia.org/wiki/Special:BookSources/9783642408021)

Ward C, Raue M, Lee C, et al (2017) Acceptance of automated driving across generations: The role of risk and benefit perception, knowledge, and trust. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) 10271:254–266

Woisetschläger DM (2016) Consumer perceptions of automated driving technologies: an examination of use cases and branding strategies. In: Autonomous driving: technical, legal and social aspects. pp 687–706

Yadron D, Tynan D (2016) Tesla driver dies in first fatal crash while using autopilot mode. In: Guard. https://www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk

Yap MD, Correia G, van Arem B (2016) Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transp Res Part A Policy Pract. https://doi. org/10.1016/j.tra.2016.09.003 .

Zhao, R., & Mao, K. (2017). Fuzzy bag-of-words model for document representation. *IEEE transactions on fuzzy systems*, *26*(2), 794-804.

Zhang, H., Sproat, R., Ng, A. H., Stahlberg, F., Peng, X., Gorman, K., & Roark, B. (2019). Neural models of text normalization for speech applications. Computational Linguistics, 45(2), 293-337.

Zmud JP, Sener IN (2017) Towards an understanding of the travel behavior impact of autonomous vehicles. Transp Res Proc 25:2500–2519. https://doi.org/10.1016/j.trpro.2017.05.281

Zmud JP, Sener IN, Wagner J (2016) Self-driving vehicles. Transp Res Rec J Transp Res Board 2565:57– 64. https://doi.org/10.3141/2565-07

# **Appendix**

### *Embedding Layer*

Word Embedding is a representation of text where words that have the same meaning have a similar representation. In other words it represents words in a coordinate system where related words, based on a corpus of relationships, are placed closer together. In the deep learning frameworks such as TensorFlow, Keras, this part is usually handled by an embedding layer which stores a lookup table to map the words represented by numeric indexes to their dense vector representations.

### *Deep Network*

Deep network takes the sequence of embedding vectors as input and converts them to a compressed representation. The compressed representation effectively captures all the information in the sequence of words in the text. The deep neywrok part is usually an RNN or some forms of it like LSTM/GRU. The dropout is added to overcome the tendency to overfit, a very common problem with RNN based networks.

### *Fully Connected Layer*

The **fully connected layer** takes the deep representation from the RNN/LSTM and transforms it into the final output classes or class scores. This component is comprised of fully connected layers along with batch normalization and optionally dropout layers for regularization.

### *Output Layer*

Based on the problem at hand, this layer can have **Softmax** for and multi classification output.