

# Beneath the Tip of the Iceberg: Current Challenges and New Directions in Sentiment Analysis Research

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WE DEDICATE THIS PAPER TO THE MEMORY OF **PROF. JANYCE WIEBE**,  
WHO HAD ALWAYS BELIEVED IN THE FUTURE OF THE FIELD OF SENTIMENT ANALYSIS.

**Abstract**—Sentiment analysis as a field has come a long way since it was first introduced as a task nearly 20 years ago. It has widespread commercial applications in various domains like marketing, risk management, market research, and politics, to name a few. Given its saturation in specific subtasks — such as sentiment polarity classification — and datasets, there is an underlying perception that this field has reached its maturity. In this article, we discuss this perception by pointing out the shortcomings and under-explored, yet key aspects of this field that are necessary to attain *true* sentiment understanding. We analyze the significant leaps responsible for its current relevance. Further, we attempt to chart a possible course for this field that covers many overlooked and unanswered questions.

**Index Terms**—Natural Language Processing, Sentiment Analysis, Emotion Recognition, Aspect Based Sentiment Analysis.



## 1 INTRODUCTION

SENTIMENT analysis, also known as opinion mining, is a research field that aims at understanding the underlying sentiment of unstructured content. Since its early beginnings (Pang et al., 2002; Turney, 2002), sentiment analysis has established itself as an influential field of research with widespread applications in industry. The ever increasing popularity and demand stem from the interest of individuals, businesses, and governments in understanding people’s views about products, political agendas, or marketing campaigns. Public opinion also stimulates market trends, which makes it relevant for financial predictions. Furthermore, education and healthcare sectors make use of sentiment analysis for behavioral analysis of students and patients.

Over the years, the scope for innovation and commercial demand have jointly driven research in sentiment analysis. However, over the past few years, there has been an emerging perception that the problem of sentiment analysis is merely a text/content categorization task – one that requires content to be classified into two or three categories of sentiments: positive, negative, and/or neutral. This has led to a belief among researchers that sentiment analysis has reached its saturation. Through this work, we set forth to address this misconception.

Figure 1 shows that many benchmark datasets on the polarity detection subtask of sentiment analysis, like IMDB

or SST-2, have reached saturation points, as reflected by the near perfect scores achieved by many modern data-driven methods. However, this does not imply that sentiment analysis is solved. Rather, we believe that this perception of saturation has manifested from excessive research publications focusing only on shallow sentiment understanding, such as, k-way text classification whilst ignoring other key un- and under-explored problems relevant to this field of research.

Liu (2015) presents sentiment analysis as *mini-NLP*, given its reliance on topics covering almost the entirety of NLP. Similarly, Cambria et al. (2017) characterize sentiment analysis as a big suitcase of subtasks and subproblems, involving open syntactic, semantic, and pragmatic problems. As such, there remains a number of open research directions to be extensively studied, such as understanding motive and cause of sentiment; sentiment dialogue generation; sentiment reasoning; and so on. At its core, effective inference of sentiment requires understanding of multiple fundamental problems in NLP. These include assigning polarities to aspects, negation handling, resolving co-references, and identifying syntactic dependencies to exploit sentiment flow. Sentiment analysis is also influenced by the figurative nature of language which is often exploited using linguistic devices, such as, sarcasm and irony. This complex composition of multiple tasks makes sentiment analysis a challenging yet interesting research space.

Figure 1 also demonstrates that the methods with a contextual language model as their backbone, much like in other areas of NLP, have dominated these benchmark datasets. Equipped with millions of parameters, transformer-based networks such as BERT (Devlin et al.,

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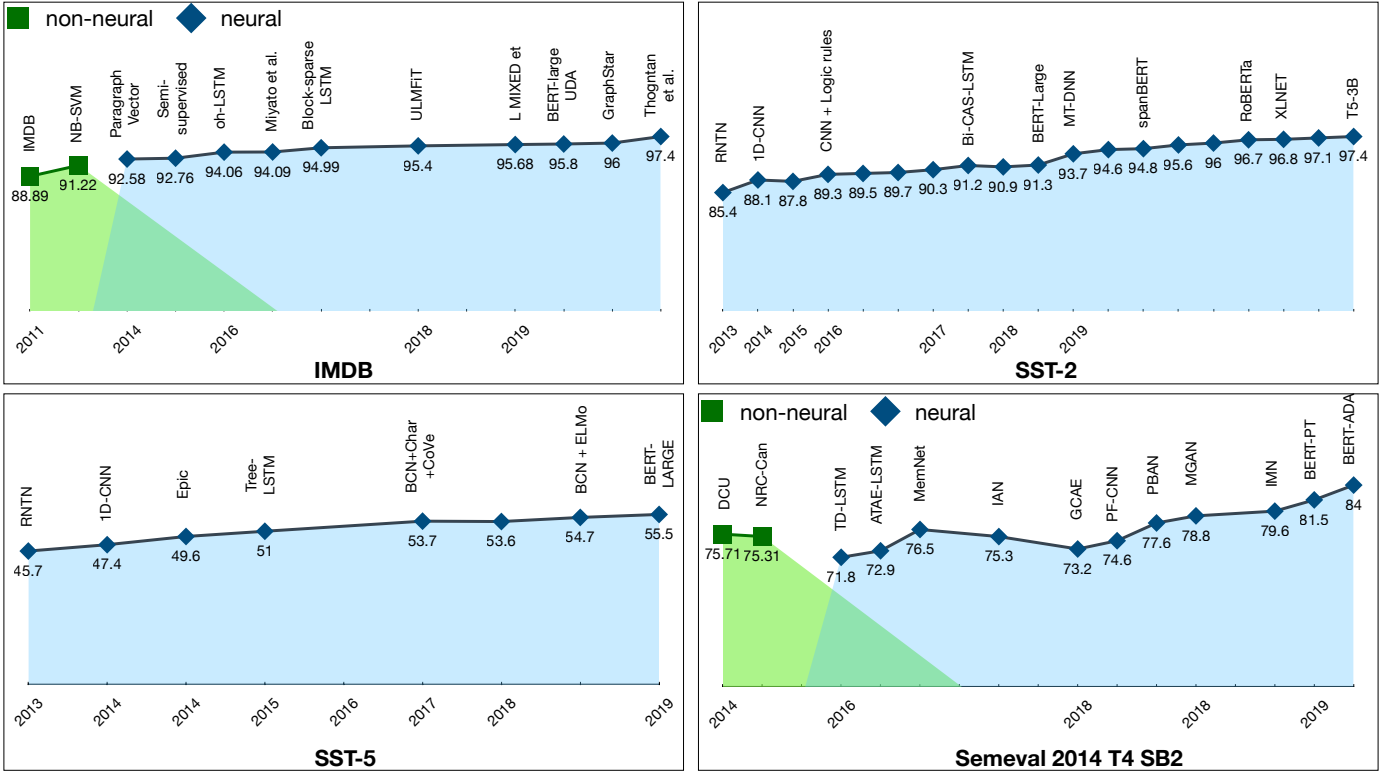


Fig. 1: Performance trends of recent models on IMDB (Maas et al., 2011), SST-2, SST-5 (Socher et al., 2013) and Semeval (Pontiki et al., 2014) datasets. The tasks involve sentiment classification in either aspect or sentence level. Note: Data obtained from <https://paperswithcode.com/task/sentiment-analysis>.

2019), RoBERTa (Liu et al., 2019), and their variants have pushed the state-of-the-art to new heights. Despite this performance boost, these models are opaque and their inner-workings are not fully understood. Thus, the question that remains is how far have we progressed since the beginning of sentiment analysis (Pang et al., 2002)?

The importance of lexical, syntactical, and contextual features have been acknowledged numerous times in the past. Recently, due to the advent of the powerful contextualized word embeddings and networks like BERT, we can compute much better representation of such features. Does this entail *true* sentiment understanding? Not likely, as we are far from any significant achievement in *multi-faceted sentiment research*, such as the underlying motivations behind an expressed sentiment, sentiment reasoning, and so on. We believe that, as members of this research community, we should strive to move past simple classification as the benchmark of progress, and instead direct our efforts towards learning tangible *sentiment understanding*. Taking a step in this direction would include analyzing, customizing, and training modern architectures in the context of sentiment, with an emphasis on fine-grained analysis and exploration of parallel new directions, such as multimodal learning, sentiment reasoning, sentiment-aware natural language generation, and figurative language.

The primary goal of this paper is to motivate new researchers approaching this area. We begin by summarizing the key milestones reached (Figure 3) in the last two decades of sentiment analysis research, followed by opening the discussion on new and understudied research areas of

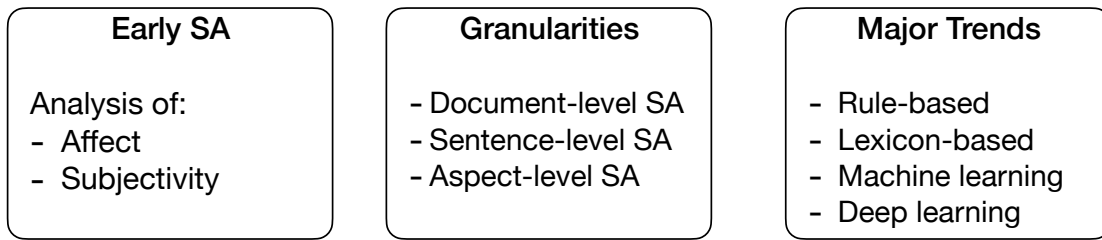
sentiment analysis. We also identify some of the critical shortcomings in several sub-fields of sentiment analysis and describe potential research directions. This paper is not intended as a survey of the field – we mainly cover a small number of key contributions that have either had a seminal impact on this field or have the potential to open new avenues. Our intention, thus, is to draw attention to key research topics within the broad field of sentiment analysis and identify critical directions left to be explored. We also uncover promising new frameworks and applications that may drive sentiment analysis research in the near future.

The rest of the paper is organized as follows: Section 2 briefly describes the key developments and achievements in the sentiment analysis research; we discuss the future directions of sentiment analysis research in Section 3; and finally, Section 4 concludes the paper. We illustrate the overall organization of the paper in Figure 2. We curate all the articles, that cover the past and future of sentiment analysis (see Figure 2), on this repository: <https://github.com/declare-lab/awesome-sentiment-analysis>.

## 2 NOSTALGIC PAST: DEVELOPMENTS AND ACHIEVEMENTS IN SENTIMENT ANALYSIS

The fields of **sentiment analysis** and **opinion mining** — often used as synonyms — aim at determining the sentiment polarity of unstructured content in the form of text, audio streams, or multimedia-videos.

## Nostalgic Past:



## Optimistic Future:

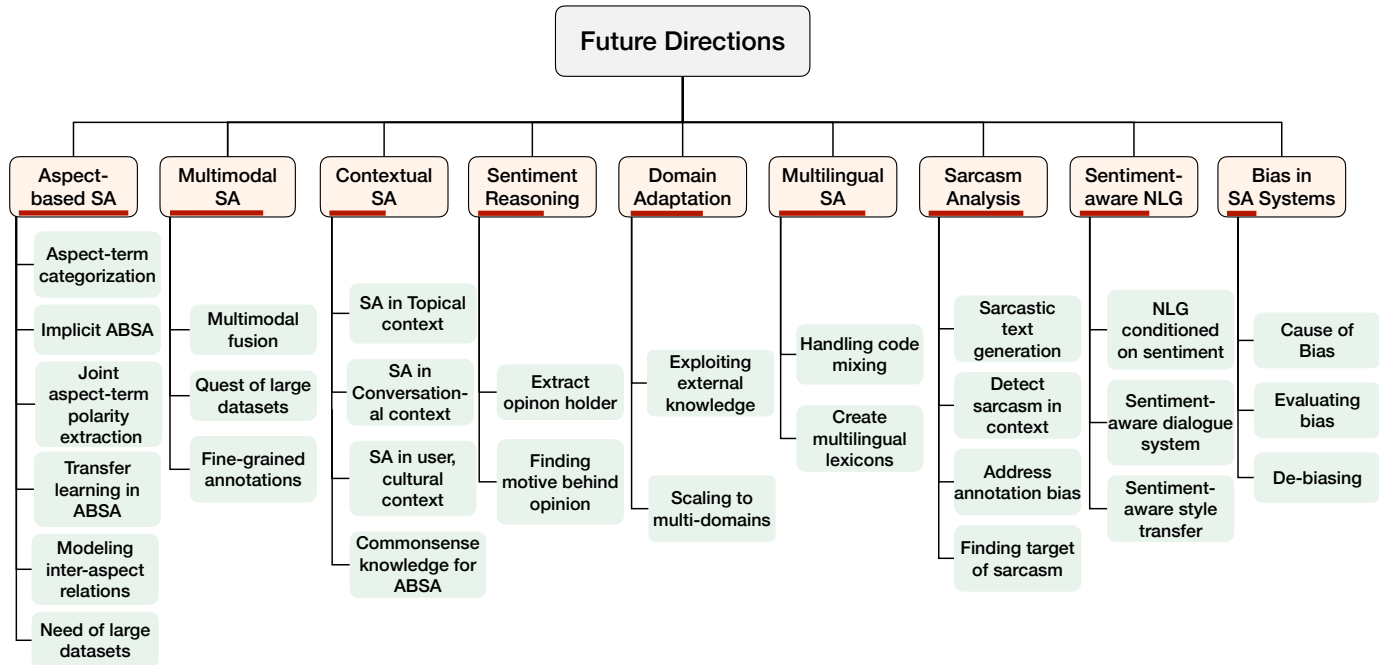


Fig. 2: The paper is logically divided into two sections. First, we analyze the past trends and where we stand today in the sentiment analysis Literature. Next, we present an *Optimistic* peek into the future of sentiment analysis, where we discuss several applications and possible new directions. The red bars in the figure estimates the present popularity of each application. The lengths of these bars are proportional to the logarithm of the publication counts on the corresponding topics in Google Scholar since 2000. Note: SA and ABSA are the acronyms for Sentiment Analysis and Aspect-Based Sentiment Analysis.

### 2.1 Early Sentiment Analysis

The task of sentiment analysis originated from the analysis of subjectivity in sentences (Wiebe et al., 1999; Wiebe, 2000; Hatzivassiloglou & Wiebe, 2000; Yu & Hatzivassiloglou, 2003; Wilson et al., 2005). Wiebe (1994) associated subjective sentences with *private states* of the speaker, that are not open for observation or verification, taking various forms such as opinions or beliefs. Research in sentiment analysis, however, became an active area only since 2000 primarily due to the availability of opinionated online resources (Tong, 2001; Morinaga et al., 2002; Nasukawa & Yi, 2003). One of the seminal works in sentiment analysis involves categorizing reviews based on their orientation (sentiment) (Turney, 2002). This work generalized phrase-level orientation mining by enlisting several syntactic rules (Hatzivassiloglou & McKeown, 1997) and also introduced the bag-of-words

concept for sentiment labeling. It stands as one of the early milestones in developing this field of research.

Although preceded by related tasks, such as identifying affect, the onset of the 21<sup>st</sup> century marked the surge of modern-day sentiment analysis.

### 2.2 Granularities

Traditionally, sentiment analysis research has mainly focused on three levels of granularity: document-level, sentence-level, and aspect-level sentiment analysis.

In *document-level sentiment analysis*, the goal is to infer the overall opinion of a document, which is assumed to convey a unique opinion towards an entity, e.g., a product (Pang & Lee, 2004; Glorot et al., 2011; Moraes et al., 2013b). Pang et al. (2002) conducted one of the initial works on document-level sentiment analysis, where they assigned positive/negative

polarity to review documents. They used a variety of features including unigrams (bag of words) and trained simple classifiers, such as Naive Bayes classifiers and SVMs. Although primarily framed as a classification/regression task, alternate forms of document-level sentiment analysis research include other tasks such as generating opinion summaries (Ku et al., 2006; Lloret et al., 2009).

*Sentence-level sentiment analysis* restricts the analysis to individual sentences (Yu & Hatzivassiloglou, 2003; Kim & Hovy, 2004). These sentences could belong to documents, conversations, or standalone micro-texts found in resources such as microblogs (Kouloumpis et al., 2011).

While both document- and sentence-level sentiment analysis provide an overall sentiment orientation, in many cases, they do not indicate the target of the sentiment. They have an implicit assumption that the text span (document or sentence) conveys a single sentiment towards an entity, which generally represents a strong assumption.

To overcome this challenge, the analysis is directed towards a finer level of scrutiny, i.e., *aspect-level sentiment analysis*, where sentiment is identified for each entity (Hu & Liu, 2004b) (along with its aspects). Aspect-level analysis allows a better understanding of the sentiment distribution. We discuss the challenges of aspect-level sentiment analysis in Section 3.1.

## 2.3 Trends in Sentiment Analysis Applications

**Rule-Based Sentiment Analysis:** A major section of the history of sentiment analysis research has focused on utilizing sentiment-bearing words and utilizing their compositions to analyze phrasal units for polarity. Early work identified that the simple counting of valence words, i.e., a bag-of-words approach, can provide incorrect results (Polanyi & Zaenen, 2006). This led to the emergence of *valence shifters* that incorporated changes in valence and polarity of terms based on contextual usage (Polanyi & Zaenen, 2006; Moilanen & Pulman, 2007). However, only valence shifters were not enough to detect sentiment – it also required understanding sentiment flows across syntactic units. Thus, researchers introduced the concept of modeling sentiment composition, learned via heuristics and rules (Choi & Cardie, 2008), hybrid systems (Rentoumi et al., 2010), syntactic dependencies (Nakagawa et al., 2010; Poria et al., 2014; Hutto & Gilbert, 2014), amongst others.

**Sentiment Lexicons** are at the heart of rule-based sentiment analysis methods. Defined simplistically, these lexicons are dictionaries that contain sentiment annotations for their constituent words, phrases, or synsets (Joshi et al., 2017a).

SentiWordNet (Esuli & Sebastiani, 2006) is one such popular sentiment lexicon that builds on top of Wordnet (Miller, 1995). In this lexicon, each synset is assigned with positive, negative, and objective scores, which indicate their subjectivity orientation. As the labeling is associated with synsets, the subjectivity score is tied to word senses. This trait is desirable as subjectivity and word-senses have strong semantic dependence, as highlighted in Wiebe & Mihalcea (2006).

Other popular lexicons include SO-CAL (Taboada et al., 2011), SCL-OPP (Kiritchenko & Mohammad, 2016a), SCL-NMA (Kiritchenko & Mohammad, 2016b), and so on. These

are lexicons that not just store word-polarity associations but also try to include phrases or rules that reflect complex sentiment compositions, e.g., negations, intensifiers.

Though lexicons provide valuable resources for archiving sentiment polarity of words or phrases, utilizing them to infer sentence-level polarities have been quite challenging. Moreover, no one lexicon can handle all the nuances observed from semantic compositionality or account for contextual polarity. Lexicons also have many challenges in their creation, such as combating subjectivity in annotations (Mohammad, 2017). Statistical solutions, instead, provide better opportunities to handle these factors.

**Machine Learning-Based Sentiment Analysis:** Statistical approaches that employ machine learning have been appealing to this area, particularly due to their independence over hand-engineered rules. Despite best efforts, the rules could never be enumerated exhaustively, which always kept the generalization capability limited. With machine learning, the opportunity to learn generic representations emerged. Throughout the development of sentiment analysis, ML-based approaches—both supervised and unsupervised—have employed myriad of algorithms that include SVMs (Moraes et al., 2013a), Naive Bayes Classifiers (Tan et al., 2009), nearest neighbour (Moghaddam & Ester, 2010), combined with features that range from bag-of-words (including weighted variants) (Martineau & Finin, 2009), lexicons (Gavilanes et al., 2016) to syntactic features such as parts of speech (Mejova & Srinivasan, 2011). A detailed review for most of these works has been provided in (Liu, 2010, 2012).

**Deep Learning Era:** The advent of deep learning saw the use of distributional embeddings and techniques for representation learning for various tasks of sentiment analysis. One of the initial models was the *Recursive Neural Tensor Network (RNTN)* Socher et al. (2013), which determined the sentiment of a sentence by modeling the compositional effects of sentiment in its phrases. This work also proposed the *Stanford Sentiment Treebank* corpus comprising of parse trees fully labeled with sentiment labels. The unique usage of recursive neural networks adapted to model the compositional structure in syntactic trees was highly innovative and influencing (Tai et al., 2015).

CNNs and RNNs were also used for feature extraction. The popularity of these networks, especially that of CNNs, can be traced back to Kim (2014). Although CNNs had been used in NLP systems earlier (Collobert et al., 2011), the investigatory work by Kim (2014) presented a CNN architecture which was simple (single-layered) and also delved into the notion of non-static embeddings. It was a popular network, that became the de-facto sentential feature extractor for many of the sentiment analysis tasks. Similar to CNNs, RNNs also enjoyed high popularity. Not just in polarity prediction, but these architectures showed dominance over traditional graphical models in structured prediction tasks such as aspect and opinion-term extraction (Poria et al., 2016; Irsoy & Cardie, 2014). Aspect-level sentiment analysis, in particular, saw an increase in complex neural architectures that involve attention mechanisms (Wang et al., 2016), memory networks (Tang et al., 2016b) and adversarial learning (Karimi et al., 2020; Chen et al., 2018). For a comprehensive review of modern deep learning architectures,

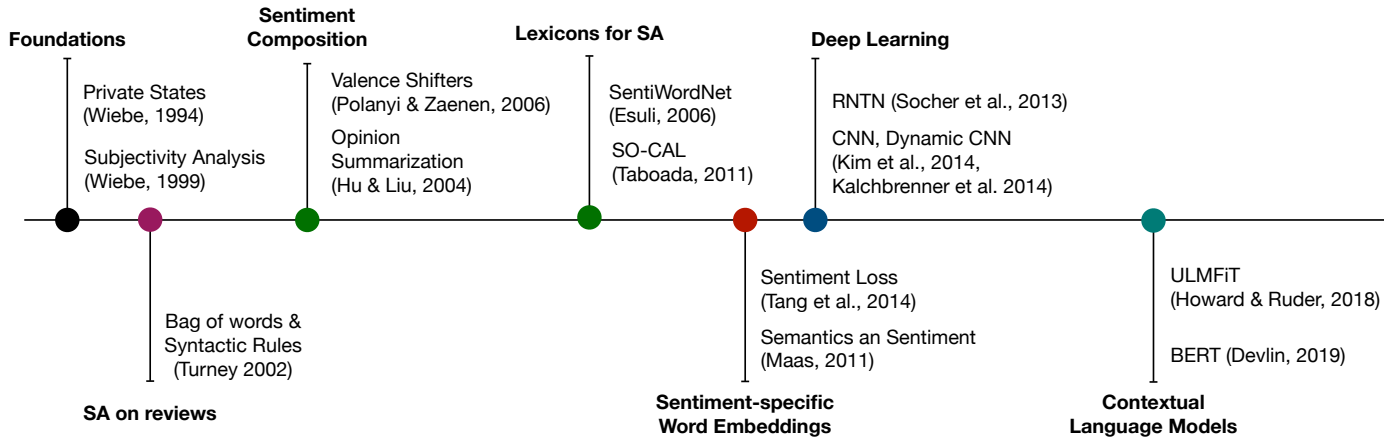


Fig. 3: A non-exhaustive illustration of some of the milestones of sentiment analysis research.

please refer to (Zhang et al., 2018a).

Although the majority of the works employing deep networks rely on automated feature learning, their heavy reliance on annotated data is often limiting. As a result, providing inductive biases via syntactic information, or external knowledge in the form of lexicons as additional input has seen a resurgence (Tay et al., 2018b).

As seen in Figure 1, the recent works based on neural architectures (Le & Mikolov, 2014; Dai & Le, 2015; Johnson & Zhang, 2016; Miyato et al., 2017; McCann et al., 2017; Howard & Ruder, 2018; Xie et al., 2019; Thongtan & Phientrakul, 2019) have dominated over traditional machine learning models (Maas et al., 2011; Wang & Manning, 2012). Similar trends can be observed in other benchmark datasets such as Yelp, SST (Socher et al., 2013), and Amazon Reviews (Zhang et al., 2015). Within neural methods, much like other fields of NLP, present trends are dominated by the contextual encoders, which are pre-trained as language models using the Transformer architecture (Vaswani et al., 2017). Models like BERT, XLNet, RoBERTa, and their adaptations have achieved the state-of-the-art performances on multiple sentiment analysis datasets and benchmarks (Hoang et al., 2019; Munikar et al., 2019; Raffel et al., 2019). Despite this progress, it is still not clear as to whether these new models learn the composition semantics associated to sentiment or simply learn surface patterns (Rogers et al., 2020).

**Sentiment-Aware Word Embeddings:** One of the critical building blocks of a deep-learning architecture is its word embeddings. It is known that word representations rely on the task it is being used for (Labutov & Lipson, 2013), however, most sentiment analysis-based models rely on generic word representations. Tang et al. (2014) proposed an important work in this direction that provided word representations tailored for sentiment analysis. While general embeddings mapped words with similar syntactic context into nearby representations, this work incorporated sentiment information into the learning loss to account for sentiment regularities. Although the community has proposed some approaches in this topic (Maas et al., 2011; Bessalov et al., 2011), promising traction has been limited (Tang et al., 2015). Further, with the popularity of contextual models such as BERT, it remains to be seen how can sentiment information

be incorporated into its embeddings.

**Sentiment Analysis in Micro-blogs:** Sentiment analysis in micro-blogs, such as Twitter, require different processing techniques compared to traditional text pieces. Being limited in length, one of the positives is that user’s tend to express their opinion in a straightforward manner. However, cases of sarcasm and irony often challenge these systems. Tweets are rife with internal slangs, abbreviations, and emoticons – which adds to the complexity for mining the opinions in them. Moreover, the limited length restricts the presence of contextual cues normally present in dialogues or documents (Kharde & Sonawane, 2016).

From a data point of view, opinionated data is found in abundance in these micro-blogs. Reflections of this has been observed in the recent benchmark shared tasks that has been mostly based on Twitter data. These include Semeval shared tasks for sentiment analysis, aspect based sentiment analysis and figurative language in Twitter <sup>1, 2, 3, 4</sup>.

A new trend amongst users in Twitter is the concept of daisy-chaining multiple tweets to compose a longer piece of text. Existing research, however, has not addressed this phenomena to acquire additional context.

### 3 OPTIMISTIC FUTURE: UPCOMING TRENDS IN SENTIMENT ANALYSIS

The previous section highlighted some of the milestones in sentiment analysis research, which helped developing the field into its present state. Despite the progress, we believe, the problems are far from solved along with the emergence of new problems and applications. In this section, we take an optimistic view on the road ahead in sentiment analysis research and highlight several applications rife with open problems and challenges.

Applications of sentiment analysis take form in many ways. Section 2.3 presents one such example where a user is chatting with a chit-chat style chatbot. In the conversation, to come up with an appropriate response, the bot needs an understanding of the user’s opinion. This involves

1. <http://alt.qcri.org/semeval2015/task10/>

2. <http://alt.qcri.org/semeval2015/task12/>

3. <http://alt.qcri.org/semeval2015/task11/>

4. <https://sites.google.com/view/figlang2020/>

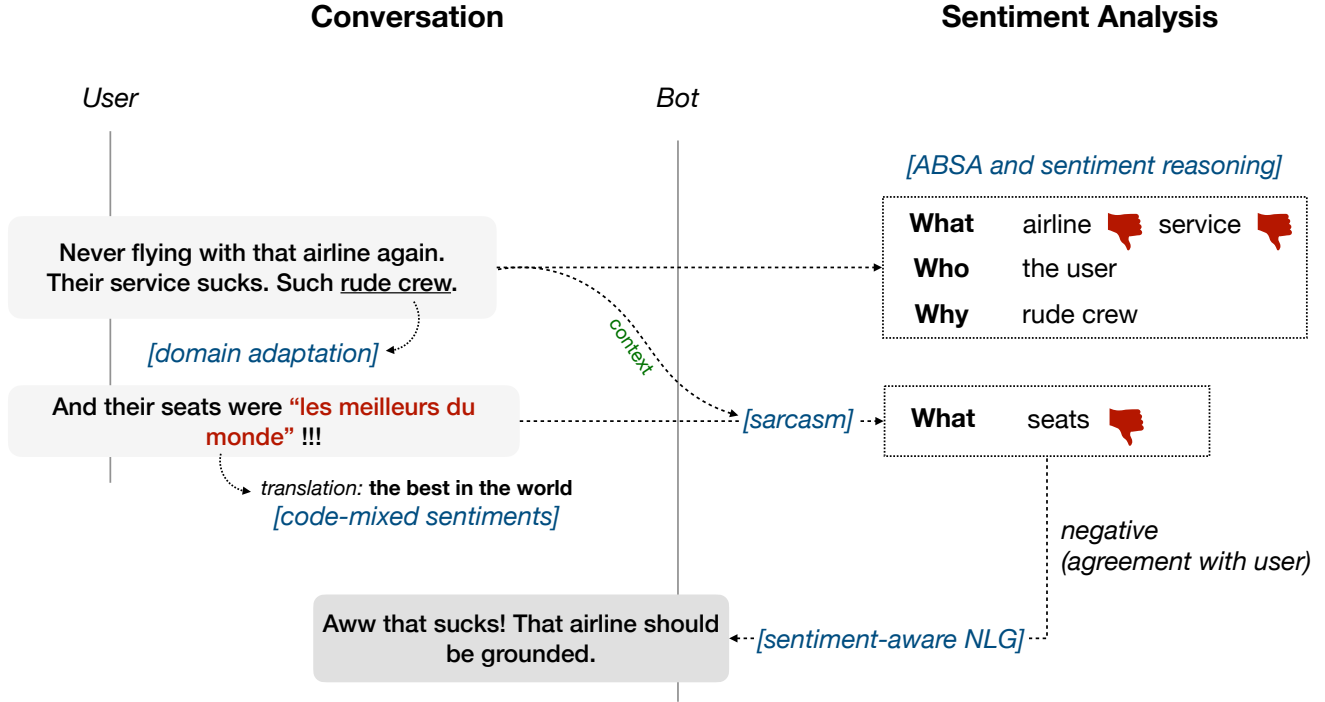


Fig. 4: The example illustrates the various challenges and applications that holistic sentiment analysis depends on.

multiple sub-tasks that include 1) extracting aspects like service, seats for the entity airline, 2) aspect-level sentiment analysis along with knowing 3) *who* holds the opinion and *why* (sentiment reasoning). Added challenges include analyzing code-mixed data (e.g. “les meilleurs du monde”), understanding domain-specific terms (e.g., rude crew), and handling sarcasm – which could be highly contextual and detectable only when preceding utterances are taken into consideration. Once the utterances are understood, the bot now has to determine appropriate response-styles and perform controlled-NLG based on the decided sentiment. The overall example demonstrates the dependence of sentiment analysis on these applications and sub-tasks, some of which are new and still at early stages of development. We discuss these applications next.

### 3.1 Aspect-Based Sentiment Analysis

Although sentiment analysis provides an overall indication of the author or speaker’s sentiments, it is often the case when a piece of text comprises of multiple aspects with varied sentiments associated to them. *Aspect-based Sentiment Analysis* (aspect-based sentiment analysis) takes a fine-grained view on this problem and aims to identify the sentiments towards each entity (and/or their aspects) (Liu, 2015; Liu & Zhang, 2012). The problem involves two major sub-tasks, 1) *Aspect-extraction*, which identifies the aspects<sup>5</sup> mentioned within a given sentence or paragraph. 2) *Aspect-level Sentiment Analysis* (aspect-level sentiment analysis), which determines the sentiment orientation associated with the corresponding aspects (or opinion targets) (Hu & Liu, 2004a). Proposed approaches for aspect extraction include

5. In the context of aspect-based sentiment analysis, *aspect* is the generic term utilized for topics, entities, or their attributes/features. They are also known as opinion targets.

rule-based strategies (Qiu et al., 2011; Liu et al., 2015), topic models (Mei et al., 2007; He et al., 2011), and more recently, sequential models such as CRFs (Shu et al., 2017). For aspect-level sentiment analysis, the algorithms primarily aim to model the relationship between the opinion targets and their context. To achieve this, models based on CNNs (Li & Lu, 2017), memory networks (Tay et al., 2017), and so on have been explored. Primarily, the associations have been learnt through attention mechanism (Wang et al., 2016).

Despite the advances in this field, there remain many factors which are open for research and hold the potential to improve performances further. We discuss them below.

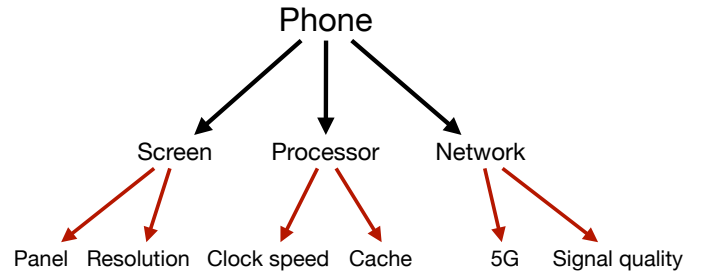


Fig. 5: An example of the aspect term auto-categorization.

#### 3.1.1 Aspect-Term Auto-Categorization

Aspect-terms extraction is the first step towards aspect-level sentiment analysis. This task has been studied rigorously in the literature (Poria et al., 2016). Thanks to the advent of deep sequential learning, the performance of this task on the benchmark datasets (Hu & Liu, 2004b; Pontiki et al., 2016) has reached a new level. Aspect terms are needed to be categorized into aspect groups to present a coherent view



of the expressed opinions. We illustrate this categorization in Fig. 5. Approaches to aspect-term auto-categorization are mostly supervised and unsupervised topic classification based and lexicon driven. All these three types of approaches succumb to scalability issues when subjected to new domains with novel aspect categories. We believe that entity linking-based approaches, coupled with semantic graphs like Probase (Wu et al., 2012), should be able to perform reasonably while overcoming scalability issues. For example, the sentence “*With this phone, I always have hard time getting signal indoors.*” contains one aspect term *signal*, that can be passed to an entity linker — on a graph containing a tree shown in Fig. 5 — with the surrounding words as context to obtain aspect category *phone:signal-quality*.

### 3.1.2 Implicit Aspect-Level Sentiment Analysis

Sentiment can be expressed implicitly on aspects. Although under-studied, the importance of detecting implicit aspect level sentiment can not be ignored as they represent a unique nature of the natural language. For example, in the sentence “*Oh no! Crazy Republicans voted against this bill*”, the speaker expresses her/his negative sentiment on the *republicans* explicitly. By doing so, we can infer that the speaker’s sentiment towards the *bill* is positive. In the work by Deng et al. (2014), it is called as *opinion-oriented implicatures*. Approaches (Deng et al., 2014; Deng & Wiebe, 2014) to this problem primarily focus on linear programming, logic rules, and belief propagation in the graph network. Major attention from the neural network community to address this research problem is yet to be witnessed.

### 3.1.3 Aspect Term-Polarity Co-Extraction

Most existing algorithms in this area consider aspect extraction and aspect-level sentiment analysis as sequential (pipelined) or independent tasks. In both these cases, the relationship between the tasks is ignored. Efforts towards joint learning of these tasks have gained traction in recent trends. These include hierarchical neural networks (Lakkaraju et al., 2014), multi-task CNNs (Wu et al., 2016), and CRF-based approaches by framing both the sub-tasks as sequence labeling problems (Li et al., 2019a; Luo et al., 2019). The notion of joint learning opens up several avenues for exploring the relationships between both the sub-tasks and also, possible dependencies from other tasks. This strategy is adopted by transfer learning approaches, which we discuss next.

### 3.1.4 Transfer Learning in Aspect-Based Sentiment Analysis (ABSA)

Much like the recent trends in the overall field of NLP, transfer learning approaches such as BERT have shown potential in aspect-based sentiment analysis too (Huang & Carley, 2019). Simple baselines utilizing BERT has demonstrated competitive performances against sophisticated state-of-the-art methods (Li et al., 2019b) and also in out-of-domain settings (Hoang et al., 2019). These trends indicate the role of semantic understanding for the task of aspect-based sentiment analysis. What remains to be seen is the future role of BERT-based networks working in conjunction with the task-dependent designs existing as the present state of the arts in this area (Sun et al., 2019).

Knowledge can also be transferred from one sentiment task to another. E.g., aspect extraction can be utilized as a scaffolding for aspect-based sentiment analysis as these two tasks are correlated. It would also be interesting to transfer knowledge from textual to multimodal ABSA system.

### 3.1.5 Exploiting Inter-Aspect Relations for Aspect-Level Sentiment Analysis

The primary focus of algorithms proposed for aspect-level sentiment analysis has been to model the dependencies between opinion targets and their corresponding opinionated words in the context (Tang et al., 2016a). Besides, modeling the relationships between aspects also holds potential in this task (Hazarika et al., 2018c). For example, in the sentence “*my favs here are the tacos pastor and the tostada de tinga*”, the aspects “*tacos pastor*” and “*tostada de tinga*” are connected using conjunction “*and*” and both rely on the sentiment bearing word “*favs*”. Understanding such inter-aspect dependency can significantly aid the aspect-level sentiment analysis performance and remains to be researched extensively.

### 3.1.6 Quest for Richer and Larger Datasets

The two widely used publicly available datasets for aspect-based sentiment analysis are Amazon product review (Hu & Liu, 2004b) and Semeval 2017 (Pontiki et al., 2016) datasets. Both these datasets are quite small in size that hinders any statistically significant improvement in performance when comparing the methods that utilize these datasets.

## 3.2 Multimodal Sentiment Analysis

The majority of research works on sentiment analysis have been conducted using only textual modality. However, with the increasing number of user-generated videos available on online platforms such as YouTube, Facebook, Vimeo, and others, multimodal sentiment analysis has emerged at the forefront of sentiment analysis research. The commercial interests fuel this rise as the enterprises tend to make business decisions on their products by analyzing user sentiments in these videos. Figure 6 presents examples where the presence of multimodal signals in addition to the text itself is necessary in order to make correct predictions of their emotions and sentiments. Multimodal fusion is at the heart of multimodal sentiment analysis with an increasing number of works proposing new fusion techniques. These include Multiple Kernel Learning, tensor-based non-linear fusion (Zadeh et al., 2017), memory networks (Zadeh et al., 2018a), amongst others. The granularity at which such fusion methods are applied also varies – from word-level to utterance-level.

Below, we identify three key directions that can aid future research:

### 3.2.1 Complex Fusion Methods vs Simple Concatenation

Multimodal information fusion is a core component of multimodal sentiment analysis. Although several fusion techniques (Zadeh et al., 2018c,a, 2017) have been recently proposed, in our experience, a simple concatenation-based fusion method performs at par with most of these methods. We believe these methods are unable to provide significant

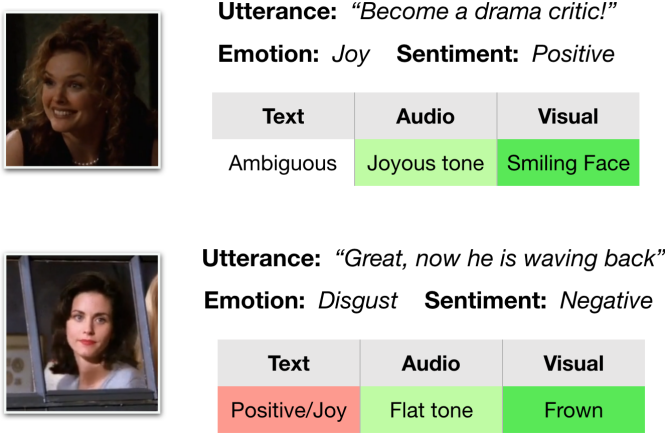


Fig. 6: Importance of multimodal cues. Green shows primary modalities responsible for sentiment and emotion.

improvements in the fusion due to their inability to model correlations among different modalities and handle noise. Reliable fusion remains as a major future work.

### 3.2.2 Lack of Large Datasets

The field of multimodal sentiment analysis also suffers from the lack of larger datasets. The available datasets, such as MOSI (Zadeh et al., 2016), MOSEI (Zadeh et al., 2018b), MELD (Poria et al., 2018) are not large enough and carry suboptimal inter-annotator agreement that impedes the performance of complex deep learning frameworks.

### 3.2.3 Fine-Grained Annotation

The primary goal of multimodal fusion is to accumulate the contribution from each modality. However, measuring that contribution is not trivial as there is no available dataset that annotates the individual role of each modality. We show one such example in Figure 6, where each modality is labeled with the sentiment it carries. Having such rich fine-grained annotations should better guide multimodal fusion methods and make them more interpretable. This fine-grained annotation can also open the door to the new types of multimodal fusion approaches.

## 3.3 Contextual Sentiment Analysis

### 3.3.1 Influence of Topics

The usage of sentiment words varies from one topic to another. Words that sound neutral on the surface can bear sentiment when conjugated with other words or phrases. For example, the word *big* in *big house* can carry positive sentiment when someone intends to purchase a *big house* for leisure. The same word, however, could evoke negative sentiments when used in the context – *A big house is hard to clean*. Unfortunately, research in sentiment analysis has not focused much on this aspect. The sentiment of some words can be vague and specified only when seen in context, e.g., the word *massive* in the context of *massive earthquake* and *massive villa*. In the future, a dataset composed of such contextual sentiment bearing phrases would be a great contribution to the research community.

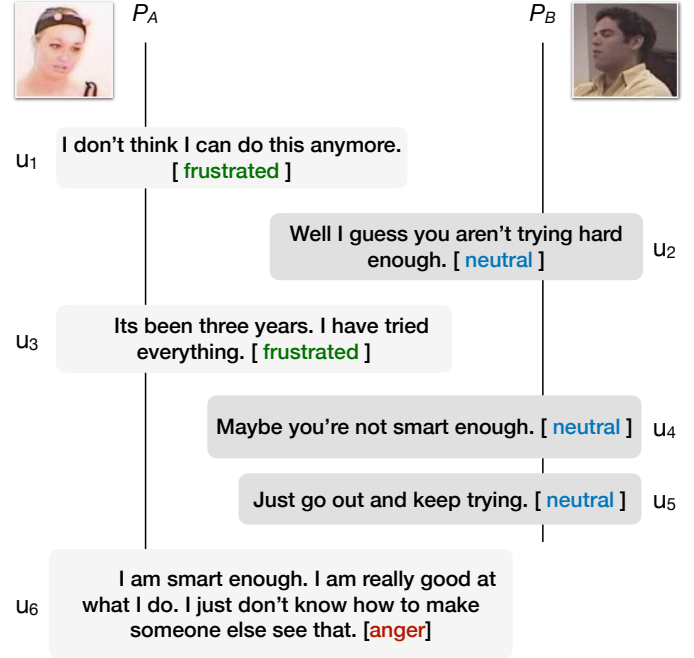


Fig. 7: An abridged dialogue from the IEMOCAP dataset (Busso et al., 2008).

This research problem is also related to word sense disambiguation. Below we present an example, borrowed from the work by Choi et al. (2017):

- The Federal Government *carried* the province for many years.
- The troops *carried* the town after a brief fight.

In the first sentence, the sense of *carry* has a positive polarity. However, in the second sentence, the same word has negative connotations. Hence, depending on the context, sense of words and their polarities can change. In (Choi et al., 2017), the authors adopted topic models to associate word senses with sentiment. As this particular research problem widens its scope to the task of word sense disambiguation, it would be useful to employ contextual language models to decipher word senses in contexts and assign the corresponding polarity.

### 3.3.2 Sentiment Analysis in Monologues and Conversational Context

Context is at the core of NLP research. According to several recent studies (Peters et al., 2018; Devlin et al., 2019), contextual sentence and word-embeddings can improve the performance of the state-of-the-art NLP systems by a significant margin.

The notion of context can vary from problem to problem. For example, while calculating word representations, the surrounding words carry contextual information. Likewise, to classify a sentence in a document, other neighboring sentences are considered as its context. Poria et al. (2017) utilize surrounding utterances in a video as context and experimentally show that contextual evidence indeed aids in classification.

There have been very few works on inferring implicit sentiment (Deng & Wiebe, 2014) from context. This is crucial



for achieving true sentiment understanding. Let us consider this sentence “*Oh no. The bill has been passed*”. As there are no explicit sentiment markers present in the sentence – “*The bill has been passed*”, it would sound like a neutral sentence. Consequently, the sentiment behind ‘bill’ is not expressed by any particular word. However, considering the sentence in the context – “*Oh no*”, which exhibits negative sentiment, it can be inferred that the opinion expressed on the ‘bill’ is negative. The inferential logic that one requires to arrive at such conclusions is the understanding of sentiment flow in the context. In this particular example, the contextual sentiment of the sentence – “*Oh no*” flows to the next sentence and thus making it a negative opinionated sentence. Tackling such tricky and fine-grained cases require bespoke modeling and datasets containing an ample quantity of such non-trivial samples. Further, commonsense knowledge can also aid in making such inferences. In the literature (Poria et al., 2017), the use of LSTMs to model such sequential sentiment flow has been ineffectual. We think it would be fruitful to utilize logic rules, finite-state transducers, belief, and information propagation mechanisms to address this problem. We also note that contextual sentences may not always help. Hence, one can ponder the use of a gate or switch to learn and further infer when to count on contextual information.

In conversational sentiment-analysis, to determine the emotions and sentiments of an utterance at time  $t$ , the preceding utterances at time  $< t$  can be considered as its context. However, computing this context representation can often be difficult due to complex sentiment dynamics.

Sentiments in conversations are deeply tied with emotional dynamics consisting of two important aspects: *self* and *inter-personal dependencies* (Morris & Keltner, 2000). Self-dependency, also known as *emotional inertia*, deals with the aspect of influence that speakers have on themselves during conversations (Kuppens et al., 2010). On the other hand, inter-personal dependencies relate to the sentiment-aware influences that the counterparts induce into a speaker. Conversely, during the course of a dialogue, speakers also tend to mirror their counterparts to build rapport (Navarretta et al., 2016). This phenomenon is illustrated in Figure 7. Here,  $P_a$  is frustrated over her long term unemployment and seeks encouragement ( $u_1, u_3$ ).  $P_b$ , however, is pre-occupied and replies sarcastically ( $u_4$ ). This enrages  $P_a$  to appropriate an angry response ( $u_6$ ). In this dialogue, self-dependencies are evident in  $P_b$ , who does not deviate from his nonchalant behavior.  $P_a$ , however, gets sentimentally influenced by  $P_b$ . Modeling self and inter-personal relationships and dependencies may also depend on the topic of the conversation as well as various other factors like argument structure, interlocutors personality, intents, viewpoints on the conversation, attitude towards each other, and so on. Hence, analyzing all these factors is key for a true self and inter-personal dependency modeling that can lead to enriched context understanding.

The contextual information can come from both local and distant conversational history. As opposed to the local context, distant context often plays a lesser important role in sentiment analysis of conversations. Distant contextual information is useful mostly in the scenarios when a speaker refers to earlier utterances spoken by any of the speakers in

the conversational history.

The usefulness of context is more prevalent in classifying short utterances, like *yeah, okay, no*, that can express different sentiment depending on the context and discourse of the dialogue. The examples in Figure 8 explain this phenomenon. The sentiment expressed by the same utterance “*Yeah*” in both these examples differ from each other and can only be inferred from the context.

Leveraging such contextual clues is a difficult task. Memory networks, RNNs, and attention mechanisms have been used in previous works, e.g., HRLCE (Huang et al., 2019a) or DialogueRNN (Majumder et al., 2019), to grasp information from the context. However, these models fail to explain the situations where contextual information is needed. Hence, finding contextualized conversational utterance representations is an active area of research.

### 3.3.3 User, Cultural, and Situational Context

Sentiment also depends on the user, cultural, and situational context.

Individuals have subtle ways of expressing emotions and sentiments. For instance, some individuals are more sarcastic than others. For such cases, the usage of certain words would vary depending on if they are being sarcastic. Let’s consider this example,  $P_a$  : *The order has been cancelled.*,  $P_b$  : *This is great!*. If  $P_b$  is a sarcastic person, then his response would express negative emotion to the order being canceled through the word *great*. On the other hand,  $P_b$ ’s response, *great*, could be taken literally if the canceled order is beneficial to  $P_b$  (perhaps  $P_b$  cannot afford the product he ordered). As necessary background information is often missing from the conversations, speaker profiling based on preceding utterances often yields improved results.

The underlying emotion of the same word can vary from one person to another. E.g., the word *okay* can bear different sentiment intensity and polarity depending on the speaker’s character. This incites the need to do user profiling for fine-grained sentiment analysis, which is a necessary task for e-commerce product review understanding.

Understanding sentiment also requires cultural and situational awareness. A *hot* and *sunny* weather can be treated as a good weather in USA but certainly not in Singapore. Eating *ham* could be accepted in one religion and prohibited by another.

A basic sentiment analysis system that only relies on distributed word representations and deep learning frameworks are susceptible to these examples if they do not encompass rudimentary contextual information.

### 3.3.4 Role of Commonsense Knowledge in Sentiment Analysis

In layman’s term, commonsense knowledge consists of facts that all human beings are expected to know. Due to this characteristic, humans tend to ignore expressing commonsense knowledge explicitly. As a result, word embeddings trained on the human-written text do not encode such trivial yet important knowledge that can potentially improve language understanding. The distillation of commonsense knowledge, thus, has become a new trend in modern NLP research. We show one such example in the Fig. 9 which illustrates the latent commonsense concepts that humans

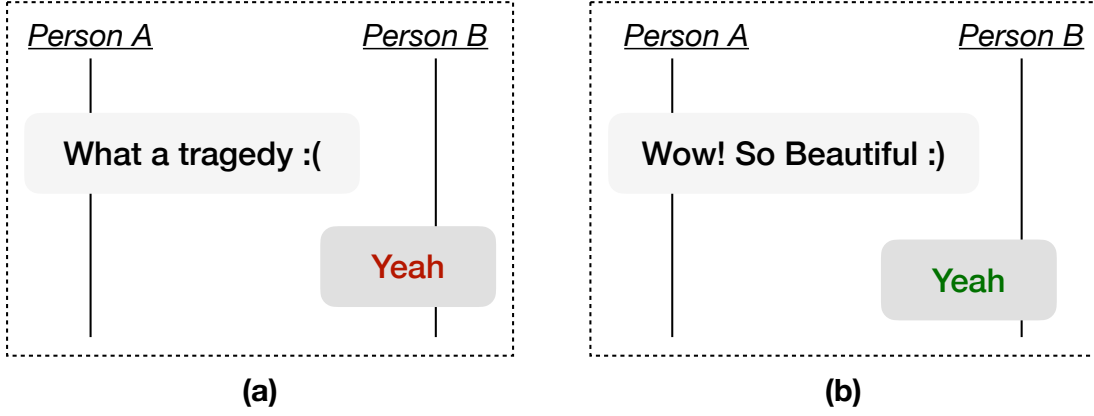


Fig. 8: Role of context in sentiment analysis in conversation.

easily infer or discover given a situation. In particular, the present scenario informs that David is a good cook and will be making pasta for some people. Based on this information, commonsense can be employed to infer related events such as, dough for the pasta would be available, people would eat food (pasta), the pasta is expected to be good (David is good cook), etc. These inferences would enhance the text representation with many more concepts that can be utilized by neural systems in diverse downstream tasks.

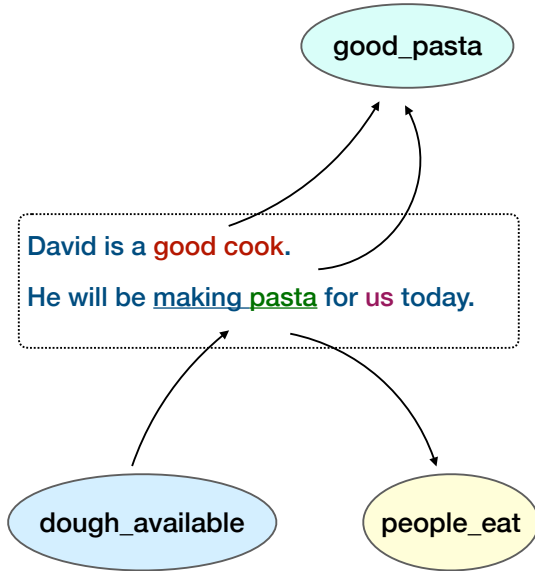


Fig. 9: An illustration of commonsense reasoning and inference.

In the context of sentiment analysis, utilizing commonsense for associating aspects with their sentiments can be highly beneficial for this task. Commonsense knowledge graphs connect the aspects to various sentiment-bearing concepts via semantic links (Ma et al., 2018). Additionally, semantic links between words can be utilized to mine associations between the opinion target and the opinion-bearing word. What is the best way to grasp commonsense knowledge is still an open research question.

Commonsense knowledge is also required to understand *implicit* sentiment of the sentences that do not accommodate

any explicit sentiment marker. E.g., the sentiment of the speaker in this sentence, “*We have not seen the sun since last week*” is negative as not catching the sight of the sun for a long time is generally treated as a negative event in our society. A system not adhering to this commonsense knowledge would fail to detect the underlying sentiment of such sentences correctly.

With the advent of commonsense modeling algorithms such as Comet (Bosselut et al., 2019), we think, there will be a new wave of research focusing on the role of commonsense knowledge in sentiment analysis in the near future.

### 3.4 Sentiment Reasoning

Apart from exploring the *what*, we should also explore the *who* and *why*. Here, the *who* detects the entity whose sentiment is being determined, whereas *why* reveals the stimulus/reason for the sentiment.

#### 3.4.1 Who? The Opinion Holder

While analyzing opinionated text, it is often important to know the opinion holder. In most of the cases, the opinion holder is the person who spoke/wrote the sentence. Yet, there can be situations where the opinion holder is an entity (or entities) mentioned in the text (Mohammad, 2017). Consider the following two lines of opinionated text:

- The movie was too slow and boring.*
- Stella found the movie to be slow and boring.*

In both the sentences above, the sentiment attached to the movie is negative. However, the opinion holder for the first sentence is the speaker while in the second sentence it is Stella. The task could be further complex with the need to map varied usage of the same entity term (e.g. Jonathan, John) or the use of pronouns (he, she, they) (Liu, 2012).

Many works have studied the task of opinion-holder identification – a subtask of opinion extraction (opinion holder, opinion phrase, and opinion target identification). These works include approaches that use named-entity recognition (Kim & Hovy, 2004), parsing and ranking candidates (Kim & Hovy, 2006), semantic role labeling (Wiegand & Ruppenhofer, 2015), structured prediction using CRFs (Choi et al., 2006), multi-tasking (Yang & Cardie, 2013), amongst others. The MPQA corpus (Deng & Wiebe, 2015) provided supervised annotations for this task. However,

with respect to deep learning approaches, this topic has been understudied (Zhang et al., 2019; Quan et al., 2019).

### 3.4.2 Why? The Sentiment Stimulus

The majority of the sentiment analysis research works to date are about classifying contents into positive, negative and neutral. This oversimplification of the sentiment analysis task has resulted in the saturation of any major breakthrough. The future research in sentiment analysis should focus on what drives a person to express positive or negative sentiment on a topic or aspect.

To reason about a particular sentiment of an opinion-holder, it is important to understand the target of the sentiment (Deng & Wiebe, 2014), and whether there are implications of holding such sentiment. For instance, when stating “I am sorry that John Doe went to prison.”, understanding the target of the negative sentiment is “John Doe goes to prison”, and knowing that “go to prison” has negative implications on the actor John Doe, it implies positive sentiment toward John Doe.<sup>6</sup> Moreover, it is important to understand what caused the sentiment. Li & Hovy (2017) discuss two possible reasons that give rise to opinions. Firstly, an opinion-holder might have an emotional bias towards the entity/topic in question. Secondly, the sentiment could be borne out of mental (dis)satisfaction towards a goal achievement.

The ability to reason is necessary for any explainable AI system. In the context of sentiment analysis, it is often desired to understand the cause of an expressed sentiment by the speaker. E.g, in a review on a smartphone, the speaker might dislike it because the battery drains so fast. While it is important to detect the negative sentiment expressed on *battery*, digging into the detail that causes this sentiment is also of prime importance (Liu, 2012). Till date, there is not much work exploring this aspect of the sentiment analysis research.

Grasping the cause of sentiment is also very important in dialogue systems. As an example, we can refer to Figure 10, Joey expresses *anger* once he ascertains Chandler’s *deception* in the previous utterance.

It is hard to define a taxonomy or tagset for the reasoning of both emotions and sentiments. At present, there is no available dataset which contains such rich annotations. Building such dataset would enable future dialogue systems to frame meaningful argumentation logic and discourse structure, taking one step closer to human-like conversation.

## 3.5 Domain Adaptation

Most of the state-of-the-art sentiment analysis models enjoy the privilege of having in-domain training datasets. However, this is not a viable scenario as curating large amounts of training data for every domain is impractical. Domain adaptation in sentiment analysis solves this problem by learning the characteristics of the unseen domain. Sentiment classification, in fact, is known to be sensitive towards domains as mode of expressing opinions across domains vary. Also, valence of affective words may vary based on different domains (Liu, 2012).

6. Example provided by Jan Wiebe (2016), personal communication.

Diverse approaches have been proposed for cross-domain sentiment analysis. One line of work models domain-dependent word embeddings (Sarma et al., 2018; Shi et al., 2018; K Sarma et al., 2019) or domain-specific sentiment lexicons (Hamilton et al., 2016), while others attempt to learn representations based on either co-occurrences of domain-specific with domain-independent terms (pivots) (Blitzer et al., 2007; Pan et al., 2010; Ziser & Reichart, 2018; Sharma et al., 2018) or shared representations using deep networks (Glorot et al., 2011).

One of the major breakthroughs in domain adaption research employs adversarial learning that trains to fool a domain discriminator by learning domain-invariant representations (Ganin et al., 2016). In this work, the authors utilize bag of words as the input features to the network. Incorporating bag of words features limits the network to get access to any external knowledge about the unseen words of the target domain. Hence, the performance improvement can be completely attributed to the efficacy of the adversarial network. However, in recent works, researchers tend to utilize distributed word representations such as Glove, BERT. These representations, aka word embeddings, are usually trained on huge open-domain corpora and consequently contain domain invariant information. Future research should explain whether the gain in domain adaptation performance comes from these word embeddings or the core network architecture.

In summary, the works in domain adaptation lean towards outshining the state of the art on benchmark datasets. What remains to be seen is the interpretability of these methods. Although some of the works claim to learn the domain-dependent sentiment orientation of the words during domain invariant training, there is barely any well-defined analysis to validate such claims.

### 3.5.1 Use of External Knowledge

The key idea that most of the existing works encapsulate is to learn domain-invariant shared representations as a means to domain adaptation. While global or contextual word embeddings have shown their efficacy in modeling domain-invariant and specific representations, it might be a good idea to couple these embeddings with multi-relational external knowledge graphs for domain adaptation. Multi-relation knowledge graphs represent semantic relations between concepts. Hence, they can contain complementary information over the word embeddings, such as Glove, since these embeddings are not trained on explicit semantic relations. Semantic knowledge graphs can establish relationships between domain-specific concepts of several domains using domain-general concepts – providing vital information that can be exploited for domain adaptation. One such example is presented in Fig. 11. Researchers are encouraged to read these early works (Alam et al., 2018; Xiang et al., 2010) on exploiting external knowledge for domain adaptation.

### 3.5.2 Scaling Up to Many Domains

Most of the present works in this area use the setup of a *source* and *target* domain pair for training. Although appealing, this setup requires retraining as and when the target domain changes. The recent literature in domain adaptation

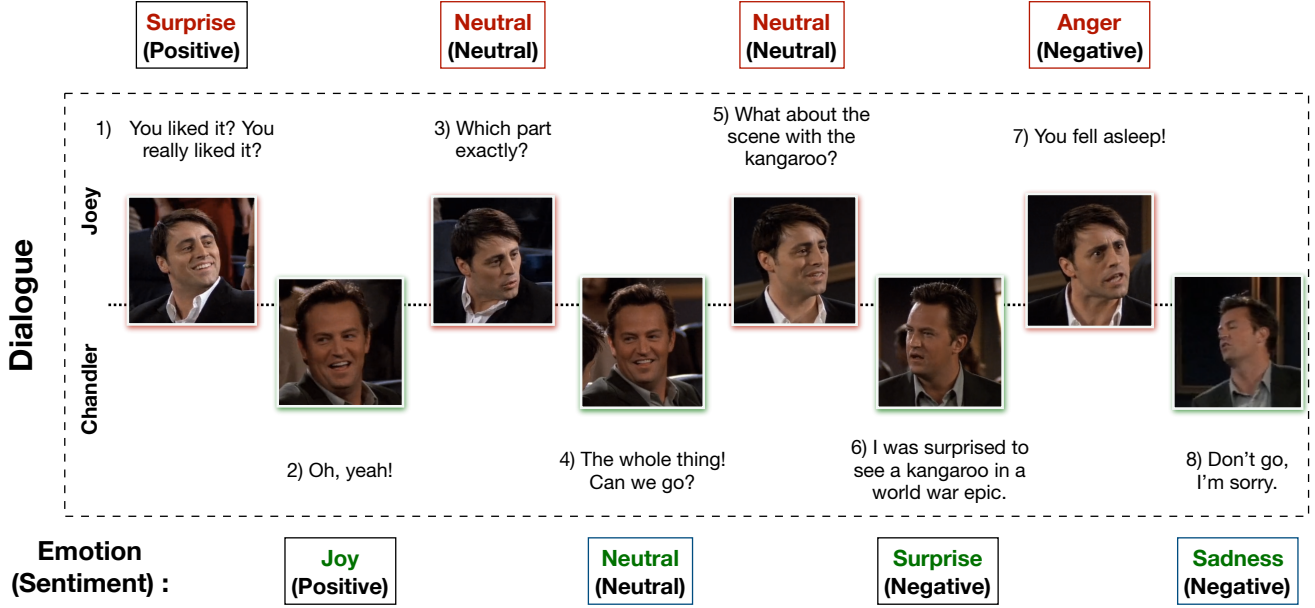
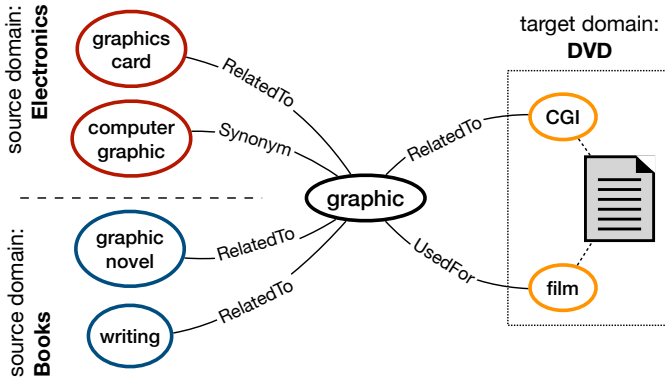


Fig. 10: Sentiment cause analysis.

Fig. 11: Domain-general term *graphic* bridges the semantic knowledge between domain specific terms in Electronics, Books and DVD.

goes beyond single-source-target (Zhao et al., 2018) to multi-source and multi-target (Gholami et al., 2020b,a) training. However, in sentiment analysis, these setups have not been fully explored and deserve more attention (Wu & Huang, 2016).

### 3.6 Multilingual Sentiment Analysis

Majority of the research work on sentiment analysis has been conducted using English datasets. However, the advent of social media platforms has made multilingual content available via platforms such as Facebook and Twitter. Consequently, there is a recent surge in works with diverse languages (Dashtipour et al., 2016). The NLP community, in general, is now also vocal to promote research on languages other than English.<sup>7</sup>

7. Because of a now widely known statement made by Professor Emily M. Bender on Twitter, we now use the term *#BenderRule* to require that the language addressed by research projects by explicitly stated, even when that language is English <https://bit.ly/3aIq50C>

In the context of sentiment analysis, despite the recent surge in multilingual sentiment analysis, several directions need more traction:

#### 3.6.1 Language Specific Lexicons

Today's rule-based sentiment analysis system, such as Vader, works great for the English language, thanks to the availability of resources like sentiment lexicons. For other languages such as Hindi, French, Arabic, not many well-curated lexicons are available.

#### 3.6.2 Sentiment Analysis of Code-Mixed Data

In many cultures, people on social media post content that are a mix of multiple languages (Lal et al., 2019; Guptha et al., 2020; Gambäck & Das, 2016). For example, "*Itna izzat diye aapne mujhe !!!* Tears of joy. :( :(", in this sentence, the bold text is in Hindi with roman orthography and the rest is in English. Code-mixing poses a significant challenge to the rule- and deep learning-based methods. A possible future work to combat this challenge would be to develop language models on code-mixed data. How and where to mix languages are a person's own choice, which is one of the main hardships. Another critical challenge associated with this task is to identify the deep compositional semantic that lies in the code mixed data. Unfortunately, only a little research has been carried out on this topic (Lal et al., 2019).

### 3.7 Sarcasm Analysis

The study of sarcasm analysis is highly integral to the development of sentiment analysis due to its prevalence in opinionated text (Maynard & Greenwood, 2014). Detecting sarcasm is highly challenging due to the figurative nature of text, which is accompanied by nuances and implicit meanings (Jorgensen et al., 1984). Over recent years, this field of research has established itself as an important problem in NLP with many works proposing different solutions to address this task (Joshi et al., 2017b). Broadly, the main

contributions have emerged from the speech and text community. In speech, existing works leverage different signals such as prosodic cues (Bryant, 2010; Woodland & Voyer, 2011), acoustic features including low-level descriptors and spectral features (Cheang & Pell, 2008). Whereas in textual systems, traditional approaches consider rule-based (Khattari et al., 2015) or statistical patterns (González-Ibáñez et al., 2011b), stylistic patterns (Tsur et al., 2010), incongruity (Joshi et al., 2015; Tay et al., 2018a), situational disparity (Riloff et al., 2013), and hashtags (Maynard & Greenwood, 2014). While stylistic patterns, incongruity, and valence shifters are some of the ways that humans use to express sarcasm, it is also highly contextual. In addition, sarcasm also depends on a person’s personality, intellect and the ability to reason over commonsense. In the literature, these aspects of sarcasm remain under-explored.

### 3.7.1 Leveraging Context in Sarcasm Detection

Although the research for sarcasm analysis has primarily dealt with analyzing the sentence at hand, recent trends have started to acquire contextual understanding by looking beyond the text.

**User Profiling and Conversational Context:** Two types of contextual information have been explored for providing additional cues to detect sarcasm: *authorial context* and *conversational context*. Leveraging authorial context delves with analyzing the author’s sarcastic tendencies (user profiling) by looking at their historical and meta data (Bamman & Smith, 2015). Similarly, the conversational context uses the additional information acquired from surrounding utterances to determine whether a sentence is sarcastic (Ghosh et al., 2018). It is often found that sarcasm is apparent only when put into context over what was mentioned earlier. For example, when tasked to identify whether the sentence *He sure played very well* is sarcastic, it is imperative to look at prior statements in the conversation to reveal facts (*The team lost yesterday*) or gather information about the speakers sincerity in making the current statement (*I never imagined he would be gone in the first minute*).

#### Utterance

##### 1) Chandler :

Oh my god! You almost gave me a heart attack!

- **Text** : suggests fear or anger.
- **Audio** : animated tone
- **Video** : smirk, no sign of anxiety



##### 2) Sheldon :

Its just a *privilege* to watch your mind at work.

- **Text** : suggests a compliment.
- **Audio** : neutral tone.
- **Video** : straight face.



Fig. 12: Incongruent modalities in sarcasm present in the MUSTARD dataset (Castro et al., 2019).

Given this contextual dependency, the question remains – *how can we model context efficiently?* The most popular approaches are based on sequential models e.g., LSTM (Poria et al., 2017) and doc2vec (Hazarikar et al., 2018a). However, the results reported in these papers show only a minor improvement under the contextual setting. The quest for better contextual modeling is thus open – one that can explicitly understand facts and incongruity across sentences. These models are also not interpretable; hence, they fail to explain when and how they rely on the context.

**Multimodal Context:** Apart from gathering essential cues from the author and conversational context, we also identify *multimodal signals* to be important for sarcasm detection. Sarcasm is often expressed without linguistic markers, and instead, by using verbal and non-verbal cues. Change of tone, overemphasis on words, straight face, are some such cues that indicate sarcasm. There have been very few works that adopt multimodal strategies to determine sarcasm (Schifanella et al., 2016). Castro et al. (2019) recently released a multimodal sarcasm detection dataset that takes conversational context into account. Other works that consider multimodality focus on sarcasm perceived by the reader/audience. These works utilize textual features along with cognitive features such as gaze-behavior of readers (Mishra et al., 2016), electro/magneto-encephalographic (EEG/MEG) signals (Filik et al., 2014; Thompson et al., 2016). Figure 12 presents two cases where sarcasm is expressed through the incongruity between modalities. In the first case, the language modality indicates fear or anger. In contrast, the facial modality lacks any visible sign of anxiety that would agree with the textual modality. In the second case, the text is indicative of a compliment, but the vocal tonality and facial expressions show indifference. In both cases, the incongruity between modalities acts as a strong indicator of sarcasm. The only publicly available multimodal sarcasm detection dataset, MUSTARD, contains only 500 odd instances, posing a significant challenge to training deep networks on this dataset.

### 3.7.2 Annotation Challenges: Intended vs. Perceived Sarcasm

Sarcasm is a highly subjective tool and poses significant challenges in curating annotations for supervised datasets. This difficulty is particularly evident in *perceived sarcasm*, where human annotators are employed to label text as sarcastic or not. Sarcasm recognition is known to be a difficult task for humans due to its reliance on pragmatic factors such as common ground (Clark, 1996). This difficulty is also observed through the low annotator agreements across the datasets curated for perceived sarcasm (González-Ibáñez et al., 2011a; Castro et al., 2019). To combat such perceptual subjectivity, recent approaches in emotion analysis utilize *perceptual uncertainty* in their modeling (Zhang et al., 2018b; Gui et al., 2017; Han et al., 2017).

In our experience of curating a multimodal sarcasm detection dataset (Castro et al., 2019), we observed poor annotation quality, which occurred mainly due to the hardships associated with this task. Hovy et al. (2013) noticed that people undertaking such tasks remotely online are often guilty of *spamming*, or providing careless or random responses.



One solution to this problem is to rely on self annotated data collection. While convenient, obtaining labeled data from hashtags has been found to introduce both noises (incorrectly-labeled examples) and bias (only certain forms of sarcasm are likely to be tagged (Davidov et al., 2010), and predominantly by certain types of Twitter users (Bamman & Smith, 2015)).

Recently, Oprea & Magdy (2019) proposed the iSarcasm dataset, which annotates labels by the original writers for the sarcastic posts. This kind of annotation is promising as it circumvents the issues mentioned above while capturing the intended sarcasm. To combat annotations for perceived sarcasm, Best-Worst Scaling (MaxDiff) (Kiritchenko & Mohammad, 2016c) could be employed to alleviate the effect of subjectivity in annotations.

### 3.7.3 Target Identification in Sarcastic Text

Identifying the target of ridicule within a sarcastic text – a new concept recently introduced by Joshi et al. (2018) – has important applications. It can aid chat-based systems better understand user frustration, and help aspect-based sentiment analysis tasks to assign the sarcastic intent with the correct target in general. Though similar, there are differences from the vanilla aspect extraction task (Section 3.1) as the text might contain multiple aspects/entities with only a subset being a sarcastic target (Patro et al., 2019). When expressing sarcasm, people tend not to use the target of ridicule explicitly, which makes this task immensely challenging to combat.

### 3.7.4 Style Transfer between Sarcastic and Literal Meaning

Translations between sarcastic and literal forms of text has many applications. We discuss about some of the promising directions in this topic below.

*Figurative to Literal Meaning Conversion:* Converting a sentence from its figurative meaning to its honest and literal form is an exciting application. It involves taking a sarcastic sentence such as “I loved sweating under the sun the whole day” to “I hated sweating under the sun the whole day”. It has the potential to aid opinion mining, sentiment analysis, and summarization systems. These systems are often trained to analyze the literal semantics, and such a conversation would allow for accurate processing. Present approaches include converting a full sentence using monolingual machine translation techniques (Peled & Reichart, 2017), and also word-level analysis, where target words are disambiguated into their sarcastic or literal meaning (Ghosh et al., 2015). This application could also help in 1) performing data augmentation and 2) generating adversarial examples as both the forms (sarcastic and literal) convey the same meaning but with different lexical forms.

*Generating Sarcasm from Literal Meaning:* The ability to generate sarcastic sentences is an important yardstick in the development of Natural Language Generation (NLG). The goal of building socially-relevant and engaging interactive systems demand such creativity. Sarcastic content generation can also be beneficial for content/media generation that find applications in fields like advertisements. Mishra et al. (2019b) recently proposed a modular approach to generate sarcastic text from negative sentiment-aware scenarios. End-to-end counterparts to this approach have not been well

studied yet. Also, most of the works here rely on a particular type of sarcasm – one which involves incongruities within the sentence. The generation of other flavors of sarcasm (as mentioned before) has not been yet studied. Detailed research on this topic with an emphasis on end-to-end learning is demanding yet lucrative.

## 3.8 Sentiment-Aware Natural Language Generation (NLG)

Language generation is considered one of the major components of the field of NLP. Historically, the focus of statistical language models has been to create syntactically coherent text using architectures such as n-grams models (Stolcke, 2002) or auto-regressive recurrent architectures (Bengio et al., 2003; Mikolov et al., 2010; Sundermeyer et al., 2012). These generative models have important applications in areas including representation learning, dialogue systems, amongst others. However, present-day models are not trained to produce affective content that can emulate human communication. Such abilities are desirable in many applications such as comment/review generation (Dong et al., 2017), and emotional chatbots (Zhou et al., 2018).

Early efforts in this direction included works that either focused on related topics such as personality-conditioned text generation (Mairesse & Walker, 2007) or pattern-based approaches for the generation of emotional sentences (Keshkar & Inkpen, 2011). These works were significantly pipe-lined with specific modules for sentence structure and content planning, followed by surface realization. Such sequential modules allowed constraints to be defined based on personality/emotional traits, which were mapped to sentential parameters that include sentence length, vocabulary usage, or part-of-speech (POS) dependencies. Needless to say, such efforts, though well-defined, are not scalable to general scenarios and cross-domain settings.

### 3.8.1 Conditional Generative Models

We, human beings, count on several variables such as emotion, sentiment, prior assumptions, intent, or personality to participate in dialogues and monologues. In other words, these variables control the language that we generate. Hence, it is an overstatement to claim that a vanilla seq2seq framework can generate *near perfect* natural language. In recent trends, conditional generative models have been developed to address this task. Conditioning on attributes such as sentiment can be approached in several ways. One way to achieve this is by learning *disentangled representations*, where the key idea is to separate the textual content from high-level attributes such as sentiment and tense in the hidden latent code. Present approaches utilize generative models such as VAEs (Hu et al., 2017), GANs (Wang & Wan, 2018) or Seq2Seq models (Radford et al., 2017). Learning disentangled representations is presently an open area of research. Enforcing independence of factors in the latent representation and presenting quantitative metrics to evaluate the factored hidden code are some of the challenges associated with these models.

An alternate method is to pose the problem as an *attribute-to-text* translation task (Dong et al., 2017; Zang & Wan, 2017). In this setup, desired attributes are encoded



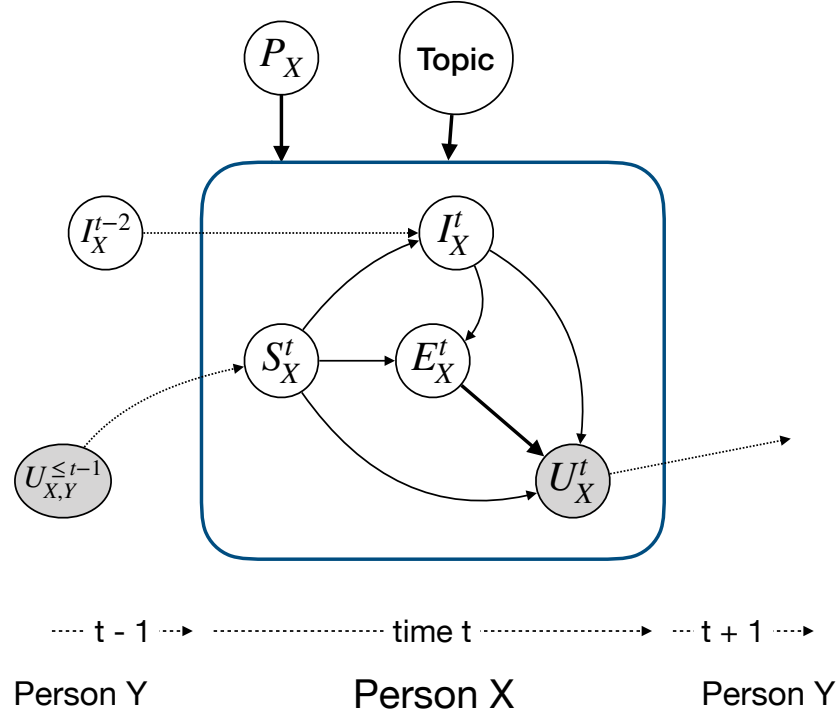


Fig. 13: Dyadic conversation—between person X and Y—are governed by interactions between several latent factors. Emotions are a crucial component in this generative process. In the illustration,  $P$  represents the personality of the speaker;  $S$  represents speaker-state;  $I$  denotes the intent of the speaker;  $E$  refers to the speaker’s emotional/sentiment-aware state, and  $U$  refers to the observed utterance. Speaker personality and the topic always condition upon the variables. At turn  $t$ , the speaker conceives several pragmatic concepts such as argumentation logic, viewpoint, and inter-personal relationship - which we collectively represent using the speaker-state  $S$  (Hovy, 1987). Next, the intent  $I$  of the speaker gets formulated based on the current speaker-state and previous intent of the same speaker (at  $t-2$ ). These two factors influence the emotional feeling of the speaker, which finally manifests as the spoken utterance.

into hidden states which condition upon a decoder tasked to generate the desired text. The attributes could include user’s preferences (including historical text), descriptive phrases (e.g. product description for reviews), and sentiment. Similar to general translation tasks, this approach demands parallel data and raises challenges in generalization, such as cross-domain generalization. Moreover, the attributes might not be available in desired formats. As mentioned, attributes might be embedded in conversational histories which would require sophisticated NLU capabilities similar to the ones used in task-oriented dialogue bots. They might also be in the form of structured data, such as Wikipedia tables or knowledge graphs, tasked to be translated into textual descriptions, i.e., data-to-text – an open area of research (Mishra et al., 2019a).

### 3.8.2 Sentiment-Aware Dialogue Generation

The area of controlled-text has also percolated into dialogue systems. The aim here is to equip emotional intelligence into these systems to improve user interest and engagement (Partala & Surakka, 2004; Prendinger & Ishizuka, 2005). Two key functionalities are important to achieve this goal (Hasegawa et al., 2013):

- 1) Given a user-query, anticipate the best emotional/sentiment response adhering to social rules of conversations.
- 2) Generate the response eliciting that emotion/sentiment.

Present works in this field either approach these two sub-problems independently (Ghosh et al., 2017) or in a joint manner (Gu et al., 2019). The proposed models range over various approaches, which include affective language models (Ghosh et al., 2017) or seq2seq models that are customized to generate emotionally-conditioned text (Zhou et al., 2018; Asghar et al., 2018). Kong et al. (2019) take an adversarial approach to generate sentiment-aware responses in the dialogue setup conditioned on sentiment labels. For a brief review of some of the recent works in this area, available corpora and evaluation metrics, please refer to Pamungkas (2019).

Despite the recent surge of interest in this application, there remains significant work to be done to achieve robust emotional dialogue models. Upon trying various emotional response generation models such as ECM (Zhou et al., 2018), we surmise, these models lack the ability of conversational emotion recognition and tend to generate generic, emotionally incoherent responses. Better emotion modeling is required to improve contextual emotional understanding (Hazari et al., 2018b), followed by emotional anticipation strategies for the response generation. These strategies could be optimized to steer the conversation towards a particular emotion (Lubis et al., 2018) or be flexible by proposing appropriate emotional categories. For the generation stage, the quest for better text with diversity and coherence and fine-grained control over emotional intensity

are still open problems. Also, automatic evaluation is a notorious problem that has plagued all applications of dialogue models.

To this end, following the work by Hovy (1987), we illustrate a sentiment and emotion-aware dialogue generation framework in Figure 13 that can be considered as the basis of future research. The model incorporates several cognitive variables i.e., intent, sentiment and interlocutor’s latent state for coherent dialogue generation.

### 3.8.3 Sentiment-Aware Style Transfer

Style transfer of sentiment is a new area of research. It focuses on flipping the sentiment of sentences by deleting or inserting new sentiment bearing words. E.g., to change the sentiment of “*The chicken was delicious*”, we need to find a replacement of the word *delicious* that carries negative sentiment.

Recent methods on sentiment-aware style transfer attempt to disentangle sentiment bearing contents from other non-sentiment bearing parts in the text by relying on rule-based (Li et al., 2018) and adversarial learning-based (John et al., 2019) techniques.

Adversarial learning-based methods to sentiment style transfer suffer from the lack of available parallel corpora which opens the door to a potential future work. Some initial works, such as (Shen et al., 2017), address non-parallel style transfer, albeit with strict model assumptions. We also think this research area should be studied together with the ALSA (aspect-level sentiment analysis) research to learn the association between topics/aspects and sentiment words. Considering the example above, learning better association between topics/aspects and opinionated words should aid a system to substitute *delicious* with *unpalatable* instead of another negative word *rude*.

## 3.9 Bias in Sentiment Analysis Systems

Exploring bias in machine learning has gained much traction recently. Studying bias in sentiment analysis is crucial, as the derived commercial systems are often shared by diverse demographics. Sentiment analysis systems are often used in such areas as healthcare, which deals with sensitive topics like counseling. Customer calls and marketing leads, from various backgrounds, are often screened for sentiment cues, and major decision-making is driven by the acquired analytics. Thus, understanding the presence of bias, especially for demographics, is critical. Unfortunately, the field is at its nascent stage and has received minimal attention. However, some developments have been observed in this area, which opens up numerous research directions. There can be different types of bias, such as gender, race, age, etc. For the sake of brevity, in the following discussions, we use examples of gender bias.

### 3.9.1 Identifying Causes of Bias in Sentiment Analysis Systems

Bias can be introduced into the sentiment analysis models through three main sources:

- 1) *Bias in word embeddings*: Word embeddings are often trained on publicly available sources of text, such as Wikipedia. However, a survey by Collier & Bear (2012)

found that less than 15% of contributions to Wikipedia come from women. Therefore, the resultant word embeddings would naturally under-represent women’s point of view.

- 2) *Bias in the model architecture*: Sentiment-analysis systems often use meta information, such as gender identifiers and indicators of demographics that include age, race, nationality, and geographical cues. Twitter sentiment analysis is one such application where conditioning on these variables is prevalent (Mitchell et al., 2013; Vosoughi et al., 2015; Volkova et al., 2013). Though helpful, such design choices can often lead to bias from these conditioned variables. A cogent solution to this issue could be to develop culture-specific sentiment analysis models rather than creating a generic one, albeit computationally inefficient.
- 3) *Bias in the training data*: There are different scenarios where a sentiment-analysis system can inherit bias from its training data. These include highly frequent co-occurrence of a sentiment phrase with a particular gender — for example, *woman* co-occurring with *nasty* —, over- or under-representation of a particular gender within the training samples, strong correlation between a particular demographic and sentiment label — for instance, samples from *female* subjects frequently belonging to *positive* sentiment category.

An author’s stylistic sense of writing can also be one of the many sources of bias in sentiment systems. E.g., one person uses strong sentiment words to express a positive opinion but prefers to use milder sentiment words in exhibiting negative opinions. A similar trend might prevail across races and genders, thereby making the task of identifying bias and de-biasing difficult.

### 3.9.2 Evaluating Bias

Recent works present corpora that curate examples, specifically to evaluate the existence of bias. The Equity Evaluation Corpus (EEC) (Kiritchenko & Mohammad, 2018) is one such example that focuses on finding *gender* and *racial* bias. The sentences in this corpus are generated using simple templates, such as <Person> made me feel <emotional state word>. While this is a good step, the work is limited to exploring bias that is related only to gender and race. Moreover, the templates utilized to create the examples might be too simplistic and identifying such biases and de-biasing them might be relatively easy. Future work should design more complex cases that cover a wider range of scenarios. Challenge appears when we have scenarios like *John told Monica that she lost her mental stability* vs. *John told Peter that he lost his mental stability*. If the sentiment polarity in either of these two sentences is classified significantly different from the other, that would indicate a likely gender bias issue.

### 3.9.3 De-biasing

The primary approach to de-biasing is to perturb a text with word substitution to generate counterfactual cases in the training data. These generated instances can then be used to regularize the learning of the model, either by constraining the embedding spaces to be invariant to the perturbations or

minimizing the difference in predictions between both the correct and perturbed instances. While recent approaches, such as (Huang et al., 2019b), have proposed these methods in language models, another direction could be to mask out bias contributing terms during training. However, such a method presents its own challenges since masking might cause semantic gaps.

In general, we observe that while many works demonstrate or discuss the existence of bias, and also propose bias detection techniques, there is a shortage of works that propose de-biasing approaches.

Apart from the traditional bias in models, bias can also exist at a higher level when making research choices. A simple example is the tendency of the community to resort to English-based corpora, primarily due to the notion of increased popularity and wider acceptance. Such trends diminish the research growth of marginalized topics and study of arguably more interesting languages – a gap which widens through time (Hovy & Spruit, 2016). As highlighted in Section 3.6, as a community, we should make conscious choices to help in the equality of under-represented communities within NLP and Sentiment Analysis.

## 4 CONCLUSION

Sentiment analysis is often regarded as a simple classification task to categorize contents into positive, negative, and neutral sentiments. In contrast, the task of sentiment analysis is highly complex and governed by multiple variables like human motives, intents, contextual nuances. Disappointingly, these aspects of sentiment analysis remain either un- or under-explored.

Through this paper, we strove to diverge from the idea that sentiment analysis, as a field of research, has saturated. We argued against this fallacy by highlighting several open problems spanning across subtasks under the umbrella of sentiment analysis, such as aspect level sentiment analysis, sarcasm analysis, multimodal sentiment analysis, sentiment-aware dialogue generation, and others. Our goal was to debunk, through examples, the common misconceptions associated with sentiment analysis and shed light on several future research directions. We hope this work would help reinvigorate researchers and students to fall in love with this immensely interesting and exciting field, again.

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## NOTE

This paper will be updated periodically to keep the community abreast of any latest developments that inaugurate new future directions in sentiment analysis.

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