Task-oriented Dialogue Systems: performance vs. quality-optima, a review

Ryan Fellows*a, Hisham Ishaish*a, Steve Battle*a, Ciaran Haines*a, Peter Mayhew*a,b, J. Ignacio Deza*a,c

*a Computer Science Research Centre (CSRC), University of the West of England (UWE), Bristol, United Kingdom
b GE Aviation, Cheltenham, United Kingdom
c Universidad Atlántida Argentina, Mar del Plata, Argentina

Abstract

Task-oriented dialogue systems (TODS) are continuing to rise in popularity as various industries find ways to effectively harness their capabilities, saving both time and money. However, even state-of-the-art TODS are not yet reaching their full potential. TODS typically have a primary design focus on completing the task at hand, so the metric of task-resolution should take priority. Other conversational quality attributes that may point to the success, or otherwise, of the dialogue, may be ignored. This can cause interactions between human and dialogue system that leave the user dissatisfied or frustrated. This paper explores the literature on evaluative frameworks of dialogue systems and the role of conversational quality attributes in dialogue systems, looking at if, how, and where they are utilised, and examining their correlation with the performance of the dialogue system.

Keywords: Dialogue Systems, Chatbot, Conversational Agents, AI, Natural Language Processing, Quality Attributes

1. Introduction

The field of dialogue systems can be split into two categories [1]: the sub-field of chat-oriented dialogue systems, which have the objective of relaying contextually appropriate and stimulating responses [2], and task-oriented dialogue systems (TODS), which are designed to assist a user in completing their goals. Examples include finding transport times, booking tickets or finding products [3]. There has been significant uptake in the adoption of TODS over recent years as companies are recognising their potential in alleviating the resource requirements inherent in human-based dialogue services. A prediction by market research firm Grand View Research estimates that the global chatbot market will reach $1.23 billion by 2025 [4, 5].

Comparing the performance of dialogue systems is a non-trivial task, furthermore. This is due to the wide
range of domains in which the systems are deployed, and the criteria they are evaluated against. Interactions are also subjective. What might be an optimal response for one individual, could be completely unsuitable for another, with performance being gauged on that specific individual’s communicative preferences.

This paper explores quality attributes that describe different qualities of conversational interactions between a system and the user, besides task outcome. We analyse conversational quality attributes in TODS and explore how they are utilised, and to what effect. To accomplish this, a literature survey is undertaken to examine current considerations to conversational quality attributes used in conjunction with dialogue systems, as well as frameworks to evaluate their performance as a multivariate function of multiple conversational quality attributes.

The rest of the paper is organised as follows: Section 2 explores TODS conversational quality attributes, and surveys their application to study and evaluate dialogue systems. Section 3 explores existing evaluation framework theory and application. Further discussion and conclusions are provided Section 4.

2. Conversational Quality Attributes

In a real world, human-to-human, task-oriented interaction, a conversation would likely not be deemed successful if only the task was resolved. If the advisor, in this situation, was friendly, personable and efficient in their manner, the advisee would be significantly more likely to have a positive experience and return in the future. However, if the advisor was rude or did not convey information competently, the advisee would most likely be left frustrated or even angry, leaving with a bad impression. Of course interactions with a human do not translate perfectly to interactions with machines, yet findings from real world communication can be extrapolated and applied to virtual communication.

In most circumstances, a TODS should elicit a positive user experience while seeking to resolve tasks in the most effective way possible. Accordingly, the evaluation of TODS performance generally seeks to optimise two main qualities: task-resolution and dialogue efficiency.

This section surveys the state-of-the-art developments on conversational quality attributes in the context of TODS, and highlights some of the most prominent attributes addressed in the literature around TODS performance.

2.1. Task Resolution

Task-resolution, or goal completion, is one of the most accessible metrics — and arguably can be the easiest to derive given a well-defined user goal as well as a predefined function to quantify a resolved, unresolved or somewhere between, task — to evaluate the success of a TODS. The main purpose of a TODS is to assist a user with a specific task in an automated fashion. Therefore, the success of a dialogue system in fulfilling information requirements established by user goals is an indicator of dialogue system’s performance.

Practically, task-resolution (or success) is used to test dialogue systems success in providing not only the correct information, but also all user requested information — addressing such the components for a given user-task: a set of constraints (target information, or information scope) and a set of requests (all required information) [13]. This in fact is consistent with the established understanding in Psychology around the notion of ‘conversation’, that is, it is understood that when individuals engage in conversation, there is a mutual understanding of the goals, roles and behaviours that can be expected from the interaction [14][15][16][17]. Therefore, the ‘performance’ of the dialogue has to be evaluated on the basis of their mutual understanding and expectations.

In its simplest form, however, this metric can be quantified as a Boolean — binary task success (BTS) — value indicating whether a task or set of tasks has been resolved or not. Using this metric, organisations can capture useful statistics over a number of interactions to derive how effective their dialogue system is at solving tasks, in comparison to interactions with human assistance or even other dialogue systems.

One of the more inherent challenges of task-resolution, as a performance metric, is knowing whether the task in question has been resolved. Especially so as the different users may have different goals, or intrinsically multiple goals, and these may even change in response to system behaviour throughout the course of interaction. On top of this, different users may have varying definitions of success, for example, a domain-specific expert user may deem a task resolved with less detailed information acquired compared to a novice user.

Typically an interaction with a dialogue system will end when a user terminates the conversation, however this doesn’t necessarily imply that their goals have been met. Some dialogue systems opt to explicitly elicit “task completion” in some form: has your request been resolved? or is there anything else I can help you with?,...
others attempt to use some form of classifier to infer when a task has been resolved through a machine learning and NLP model (e.g. [15][19]). This requires a structured definition of goals and a mechanism to measure success relative to that goal. In this fashion, much of the work on automating the evaluation of task success has largely focused on the domain-specific TODS. This is usually an easier task as such systems can be highly scripted, and task success can be specifically defined — especially so in traditional dialogue systems, such as the Cambridge Restaurant System [20] and the ELVIS email assistant [10] — where the relevant ontology defines intents, slots and values for each slot of the domain.

However, a structured definition of goals will usually bind dialogue systems to a specific class of goals, constraining their ability to adapt to the diversity and dynamics of goals pertinent in human-human dialogue [21]. To address the shortcomings in adaptability and transferability encountered in single-domain systems, research into domain-aware, or multi-domain, dialogue systems has attracted noticeable attention in recent years [22][23][24]. This saw the invention of the concept of domain state tracker (DST), which accumulates the input of the turn along with the dialogue history to extract a belief state; user goals/intentions expressed during the course of conversation. User intentions are then encoded as a discrete set of dialogue states, i.e., a set of slots and their corresponding values, e.g., [25][26][27]. As a result, the multiple user intentions are subsequently evaluated, whether objectively met or otherwise — reader is advised to refer to Figure 1 in [24] for detailed characterisation of DSTs.

Reinforcement learning systems aim to find the optimal action that an automated agent can take in any given circumstance, by either maximizing a reward function or minimizing a cost function. With a dialogue system as the agent, the given circumstance is the belief state held by the DST, the reward function is linked to task-resolution, and the actions are the system’s output slots and values. Dialogue systems will inevitably encounter problems; examples include incorrectly identifying a word, or a user changing their goal. A system could assign confidence levels to the belief states, track multiple belief states, and include a plan to recover the conversational thread after the errors are noticed.

Casting the conversation as a partially observable Markov decision process (POMDP) allows for these uncertainties to be encoded [28][29]. A POMDP is defined as a tuple $\{S, A, \tau, R, O, Z, \lambda, b_0\}$ where $S$ is a set of states describing the environment; $A$ is a set of actions that may be taken by the agent; $\tau$ is the transition probability $P(\cdot | s, a)$; $R$ defines the expected reward $r(s, a)$; $O$ is a set of verifiable observations the agent can receive about the world; $Z$ defines an observation probability, $P(o' | s, r, a)$; $\lambda$ is a geometric discount factor $0 \leq \lambda \leq 1$; and $b_0$ is an initial belief state $b_0(s)$. A POMDP dialogue system tracks multiple parallel belief states, selecting actions based on the belief state that is most likely. When misunderstandings occur, the current belief state can be made less likely, allowing the system to move to a new belief state. Because the belief states’ probabilities are tracked alongside the expected action rewards and the chance that an action will transition as expected, a POMDP is able to effectively plan how to manage a dialogue. This framework allows a TODS to track multiple possible user goals, to plan error checking of user utterances, and to use context to potentially identify when the dialogue system has misunderstood the user intention. However, converting this potential benefit into practice is not trivial. Such systems are known to require a significant amount of training, as the state-action space can be very large even for single domains, and uncertainty in the task resolution may weaken the agent’s learning [30].

In general, task-resolution is commonly quantified as the result of a performance metric in which user satisfaction is maximised. In PARADISE framework [6] — reported later in Section 3.2.1, which is frequently used as a baseline for task success evaluation throughout literature, this is usually solved for user satisfaction as a weighted linear combination of task success measures side by side with dialogue costs (reported in Sec. 2.2.2). These measures can be objective, which entail features such as word error rate [31], automatic speech recognition (ASR), word-level confidence score [22], number of errors made by the speech recognizer [33] and time to fire, task completion rate, and accuracy metrics as used in [34], or subjective such as intelligibility of synthesized speech [33] and perception tests [22].

2.2. Usability and Dialogue Efficiency

Usability attributes, such as user satisfaction, learnability, efficiency, etc, are the foundation of the design of “successful” dialogue systems, as these are ultimately created for the user, and for the user to achieve their intended, and occasionally variable, goal(s). While such attributes should ultimately be the criteria to evaluate a dialogue system, they are well-known to be subjective, and subsequently hard to measure. This is why much literature on evaluating dialogue systems tends to deal with quantifiable performance metrics, like task-resolution rate or elapsed-time —or turns— on task.
It has been proposed, however, that an agent’s competence in objectively measurable dialogue-quality attributes does not necessarily induce a better user experience, and subsequently a better system’s overall usability [33]. In fact the different metrics may even prompt contentious interpretations, or simply contradict each other [36].

Although usability ratings are notoriously hard to interpret, especially if the system is not equipped to infer and keep track of user goals, the successful encapsulation of such values can provide insight that explicit metrics stumble to capture. From the study of Malchanau et al, usability experts rated examined questions from a 110 item questionnaire and derived an evaluation of their agreement of usability concepts. This led to a collection of 8 attributes they saw as key factors: task completion and quality, robustness, learnability, flexibility, likeability, ease of use and usefulness (value) of an application [37]. This questionnaire was used to evaluate a dialogue system designed for training purposes, in which the overall system usability was determined by the quality of agreements reached, by the robustness and flexibility of the interaction, and by the quality of system responses.

Additionally, these different metrics may in fact have an inconsistent statistical interpretation to different designers. In the same way human evaluation will provide different outcomes based on the subjective criteria, the same can be said for metrics of usability which are difficult to consistently quantify [38].

2.2.1. User Sentiment

Because of the insights sentiment analysis reveals about the more concise bodies of text on social media, the field of sentiment analysis has seen a take-up of use over recent times [39]. These can be performed on large quantities of tweets and posts from different platforms to assess general opinion about a specific product or topic.

Different applications use a range of machine learning classification algorithms to categorise sentiment scores [40] [41], some use just two classes: positive and negative, while others use an n-point scale, e.g., very good, good, satisfactory, bad, very bad [42]. A review and a comparative study of existing techniques for opinion mining like machine learning and lexicon-based approaches is provided in [43].

Early studies on sentiment analysis in the context of dialogue systems explored the inclusion of user sentiment in rule-based systems, towards adaptive spoken dialogue systems, eg., [44] [45]. Most of these studies investigated modular-based dialogue systems (conventionally referred to as pipeline models), with predefined rules for systems to adapt to variability in user sentiment. In recent studies, however, much focus has been placed onto sentiment-adaptive end-to-end dialogue systems, particularly due to their adaptability in comparison with modular-based ones [46], which are known to be harder to train, and adapt to new contexts [47].

Studies exploring the conjunction of dialogue systems with sentiment analysis are often motivated by the notion of system adaptability, assuming a correlation between adaptability of the systems to user sentiment and their satisfaction. Some recent work emphasises the importance for conversational agents to adapt to different user (personality) types [48] [49]. Attention is paid to studying user sentiment as a variable to guide the design of sentiment-adaptive dialogue systems [50] [51]. A comprehensive list of development milestones on sentiment analysis application to the analysis and evaluation of dialogue systems, as well as on sentiment-adaptive systems is provided in Table 1.

It should be noted, nonetheless, that sentiment analysis methods have not been been extensively applied to conversational agents and dialogue systems. One reason for this is the fact sentiment analysis performs more effectively when pre-trained on a domain specific dataset, and would not often generalise to open domains of discourse inherent in many dialogue systems. One example is the well-known shortcomings when generalising sentiment classification of models trained on the IMDB movie database to classify sentiment about movies [64] [65] [66].

However, as data becomes more accessible and the sentiment analysis techniques become more mature, the performance and scalability of many sentiment analysis tools are constantly improving. This in fact can allow for further advances in the development of sentiment-aware dialogue systems, such that dialogue systems can adapt to the dynamics of user sentiment throughout the course of interaction. Depending on the objective function to optimise, there can be multiple approaches to extract and use the variability in user-sentiment, which can be categorised into two groups:

- **Individual user utterance**: looking at the sentiment score of individual user utterance, which can offer insight into the specific semantics and vectors of that single interaction such as that found in [67] [68]. This compartmentalised approach allows a deeper inspection of the content of that one message, whether this be a product, experience or other entity.
Table 1: Main user sentiment studies in dialogue systems reviewed in the literature.

| Domain     | Author                  | Year  | Proposal / findings                                                                 |
|------------|-------------------------|-------|-------------------------------------------------------------------------------------|
| SDS        | Schuller [52], Nwe [53] | 2003  | Emotion recognition in spoken dialogue using phonic features.                       |
| SDS and TOSS | Devillers [54], Liscombe [55] | 2003/05 | Automatic and ‘robust’ cues for emotion detection using extra linguistic features, lexical and discourse context. |
| DS         | TH Bui [56]             | 2006  | ‘Affective’ dialogue model: inferring user’s emotional state for an adaptive system’s response. Earlier work applied to spoken dialogue systems in [57]. |
| SDS        | Acosta [44, 58]         | 2010/11 | Gracie: inference of emotional state from utterance-by-utterance, and adaptive ‘emotional coloring’ system response. |
| TODS and SDS | Ferreira [59], Ultes [60] | 2013/17 | Proposed an expert-based reward shaping approach in dialogue management, and a live user satisfaction estimation model based on ‘Interaction Quality’, a ‘less subjective variant of user satisfaction’. |
| DS         | Shi [50]                | 2018  | Detecting user sentiment from multimodal channels (acoustic, dialogic and textual) and incorporating the detected sentiment as feedback into adaptive end-to-end DS. |
| DS         | Jaques [61]             | 2019  | Deep reinforcement learning model (off-policy batch RL algorithm).                   |
| DS         | Shin [62]               | 2019  | Happybot: on-policy learning in conjunction with a user-sentiment approximator to improve a seq2seq dialogue model. |
| DS         | Sasha [63]              | 2020  | Applying Reinforced Learning to manage multi-intent conversations with sentiment based immediate rewards. |

DS: Dialogue Systems, SDS: Spoken Dialogue Systems, TODS: Task-oriented Spoken Systems, TOSS: Task-oriented Spoken Systems.

- **Contextual user utterance**: the thread as a whole can be inspected from a temporal perspective, evaluating the evolution of the thread, rather than just individual messages [69, 70]. This can give insight as to why the sentiment of the user is going up or down and allows inspection as to why this is happening. When compared with other threads, trends can be found as to what is causing the fluctuation of sentiment. The difference of sentiment score between the first and last message, which can be referred to as the ‘sentiment swing’, can also be very useful, as this is an example of how the situation has progressed from the perspective of the user.

An example to illustrate user-sentiment swing during dialogue is provided in Table 2, which shows two "resolved" task-oriented interactions of 6 turns each. The sentiment score corresponding to user utterance at each turn is recorded. For simplicity, the variability in user-sentiment at each turn is smoothed in Fig[1]. Despite the similarity of their destinations, the two interactions exhibit diverging user-sentiment paths. While the first conversation has a positive swing of 0.7 over 6 turns, eliciting a noticeable improvement over the entire interaction, the second stays nearly constant which could also be deemed positive, nonetheless. A substantially negative sentiment swing might be cause for examination to assess when considering designs for sentiment-adaptive dialogue.

Figure 1: Sentiment score of conversation one and two over the course of an interaction.

Despite the scores fluctuating throughout the interaction, both threads end with a positive conclusion, indicating that the user was satisfied with the outcome. Whilst this is insightful in itself, the highs and lows provide a chance to understand why these values were exhibited at that point, which could allow for the examination of the objective attributes or semantics used, or that the values could just simply be the result of a contextual issue, such as, in this case, a restaurant being fully booked.

However, regardless of the domain in which sentiment analysis is utilised, a cautious apprehension should be taken in interpreting the obtained scores.
Modern sentiment analysis tools are advancing, but they are still not mature enough to accurately recognise sarcasm, jokes and nuances of language. There is also the limitation of a lack of distinctive sentiment annotations amongst an already limited amount of datasets readily available, as observed in [73], which subsequently makes it harder to perform accurate analysis on dialogues of a more extensive lexicon.

What’s more, sentiment analysis is sensitive to social conventions which are prevalent in human communication. Many interactions through email, for example, will exhibit some form of generic greeting such as ‘Good Morning’ as well as a sign off (sometimes inserted automatically through a template) such as ‘Best Wishes’. These terms are often used by individuals, regardless of the context of their email, which can therefore skew the sentiment score to be higher than the actual substance of their email might elicit.

Therefore it could be argued that the current state of sentiment analysis makes it a useful tool to gain analytical insight from a corpus of text, but to utilise them as the sole driver for action could potentially lead to erroneous decision making. The context of its usage is important.

2.2.2. Dialogue Cost

The term ‘dialogue cost’ appears frequently throughout dialogue system literature [74] and typically refers to multiple aspects of resource retrieval and utilisation ranging from the data itself, to the computational power required by the model being utilised. Some literature even refers to the explicit monetary cost of the dialogue system based on the manual labour required to label the data, often using the method of crowdsourcing [76] [77].

Relevant and feature rich data is the foundation for a high performing dialogue system, and no matter how good a model is, it cannot compensate for a small or poor quality dataset. Therefore such resources can be expensive to acquire, whether in terms of time or money [78]. In more domain specific dialogue, the data native to these sometimes unfamiliar domains, plays an even
more important role as it highlights semantic and pragmatic phenomena that is unique to that domain.

Alongside task-resolution, dialogue cost is often considered to infer ‘dialogue strategies’ [79] [74], which specify at each stage what the next action to be taken by the system. A dialogue strategy can have the objective of converging towards the goal state in the most efficient way possible through a series of interactions with the user. ‘Efficiency’ can for example, mean access to external resources, the dialogue duration, internal computation time, or resource use. The goal is to reduce these ‘costs’ to allow the system to achieve higher performance.

However, the ambiguity of the term ‘dialogue cost’ can make it a difficult area to assess. The PARADISE framework (see Sec. 3.2.1) describes efficiency measures such as the number of turns or elapsed time to complete a task [80] [81] [6], as well as qualitative measures such as inappropriate or repair utterances [82] [83] as potential dialogue costs. Whereas, some researchers explore the term from a reinforcement learning perspective, in which the dialogue cost is a penalisation assigned for taking the wrong action predicated on a predefined function. Therefore, it can be a difficult to quantify cost in relation to a dialogue. Even when considering what is typically agreed on, regardless of the context, that dialogue ‘cost’ should be minimised, i.e., to maximise system efficiency, there isn’t such established foundation to suggest that, for instance, a shorter—hence more ‘efficient’—dialogue is directly correlated to a better user experience. In fact it can simply be the opposite.

2.2.3. Retention Rate

The retention rate of a TODS is often referred to as a measure of the number users that return to use the system within a given time frame. This is another important, yet accessible metric for quantifying dialogue systems’ performance. If a company’s chatbot aims to replace other communication channels (e.g., lowering call volume), the goal is to obtain significantly higher retention, which can be indicative of higher consumer satisfaction [84]. However, there are plenty of other automated options that allow users to manage accounts easily without speaking to a human. Thus, if a chatbot is focused on customer support, a high retention rate does not necessarily have to be the measure of success [85].

The context and domain in which the TODS is deployed is an important factor to consider when looking at the retention rate of a given dialogue system. If the dialogue system in question is a health-based chatbot for a one-off issue, then the user is unlikely to have to reuse the chatbot, and therefore the metric is less valuable. However, if the chatbot is being deployed as a customer service replacement, then a high retention rate can be interpreted as a positive performance indicator, as it shows the user has enough confidence in the system to reuse it.

Related metrics are those of dropout rate and bounce rate. The dropout rate refers to the number of users who quit the session with the dialogue system before an outcome had been reached. A high dropout rate for a dialogue system can be a substantial indication of poor performance. The bounce rate is the volume of users that do not utilise the dialogue system for its intended use. A high retention rate with low dropout and bounce rates would suggest a high level of performance.

However, only so much can be derived from the metric of retention rate without some form of user feedback, as the metric is sensitive to anomalies. A dialogue system could perform perfectly, yet a user might not return for other, unknown reasons. This should not be indicative of the performance of the system, yet the metric might suggest this to be the case. Therefore, the larger the set of interactions retention is analysed on, the more insightful the findings will potentially be. Because of this, it could be argued that the rate of retention offers a good overview perspective of system performance, but such considerations should prevent retention rate from being a primary form of performance insight.

2.2.4. Response Time

The literature exploring dialogue response time is typically concerned with reducing the time it takes a conversational agent to respond to the user. The consensus is that a user wants responses as quickly as possible, and for the interaction to be as efficient as possible in terms of session time. The focus is often on the mechanics of the model in question, rather than the effect that response time could have on user satisfaction [86] [87]. Alternative studies on response time shift the focus from the desire for instant responses to adding more human-like delays. In their study of using dynamic response delays for machine generated messages, Gnewuch et al [88] prioritise the ‘feel’ of the conversation over speed of response, opting to “calculate a timing mechanism based on the complexity of the response and complexity of the previous message as a technique to increase the naturalness of the interaction”. As a result of these dynamic delays, they showed an increase in both the perception of humanness and social presence, as well as a greater satisfaction with the overall dialogue interaction; a faster response time is not necessarily better. However, as with the majority of the quality at-
tributes, the context and domain are very important to consider. ‘Replika’ [89] is an anthropomorphised chatbot designed as a companion to help battle loneliness. It utilises a slight delay to make the interaction feel more genuine and human-like, as instant replies would make the interaction feel too machine-like and break the social illusion. Conversely, ‘911bot’ [90] is a chatbot that allows a user to describe an emergency situation, and because of this context, any artificial delays would not be appropriate. This highlights the importance of context when considering such conversational attributes to evaluate TODS performance.

Computationally, response time has become much less of a pressing issue in recent times, as abundant computational resources, and innovation in machine learning NLP approaches, make instantaneous responses entirely feasible, and as a result, expected. Therefore, it could be argued that whilst a dialogue system might not get praised on its performance for optimal response times, whether instant or timed, it will be negatively graded for sub-optimal response times.

2.2.5. Conversation Length

The literature exploring the explicit length of conversation is limited. This is due to the fact that the developers predominantly focus on the substance of a message first, with the subsequent message length being as long or short as it needs to be. However, the length of an agent’s responses can significantly alter the dynamic of an interaction, as it determines how much information can be conveyed in a single turn. Depending on the topic at hand, if the messages are too short, there is a risk the user will grow frustrated with the lack of detail in the answer, but if the messages are too long, the user’s attention may wander.

In their guide to developing “better” chatbots for mental health, Dosovitsky et al [91] argue that “developers should strive to find a module length that enhances intervention fidelity without compromising engagement” and “should focus on creating a few engaging and effective modules at the beginning rather than developing a large variety of untested modules”. Simply put, system utterance length should be dynamic, changing relative to the stage of the conversation.

Other work examined the effect of message length relative to the dialogue domain, e.g., [85], emphasising that one of the most important chatbot performance metrics is conversation length and structure. Industry trends suggest aiming for shorter conversations with simple structure, in line with the notion of efficient service. For example, banking chatbots are assumed to provide quick solutions such as sending and receiving money, or checking a balance. When the social aspect of the conversation is more important, fast and concise responses may turn counterproductive.

However, just looking at conversation length from an objective perspective can be misleading. If an analysis is performed in which it is deemed shorter messages are preferred for a given domain, and are subsequently rewarded, then this may undermine the very relevant factor of context. Dialogue systems often have the objective of being as efficient as possible, which would encourage the idea of concise discourse, which may not be a problem. However, some issues and topics simply do not lend themselves to this approach and require further development in the conversation. Therefore, it would be detrimental to the system to simply penalise longer message without any thought to the semantics and context involved. This is not to say conversation length is not a useful quality attribute, as the literature suggests, it is, yet the optimisation of this parameter needs more than just the configuration of a value for utterance length or number of turns.

3. Evaluation

TODS are difficult to evaluate on a consistent basis. Comparing dialogue systems using human judgement can be problematic as this often varies from one person to another, an issue that is pointed up by the fact that there is no current standard to measure against. Evaluating dialogue system performance relative to statistical criteria, such as task outcome or rate of retention, does allow for a consistent, though blunt, assessment. Besides, these methods often lack contextual information, which is a necessary component for in-depth evaluation of dialogue.

3.1. Evaluation Methods

The methods to evaluate dialogue system typically fall into three categories; human evaluation, user behaviour modelling and automatic evaluation.

3.1.1. Human Evaluation

A comprehensive evaluation of a machine-produced dialogue interacting with humans eventually requires their judgment. Conventionally this has been carried out through benchmarking dialogue relative to human-generated supervised feedback, see [6] and [7]. In recent times, the process of dialogue system evaluation by humans has become increasingly commonplace [92]. Evaluators are often recruited via crowdsourcing to rate system generated responses relative to criteria such as
appropriateness’, ‘empathy’ and ‘helpfulness’ as used in [93] or ‘grammar’, ‘context relevance’ and ‘correctness’ as used in [94]. Previous research which employs crowdsourced judgments has used metrics such ease of answering, information flow and coherence [95], ‘naturalness’ [96] and ‘interestingness’ [96, 97].

Such process however is time consuming, and expensive. Arguably a more pressing issue is the lack of a standard for humans to use as a baseline, which can cause issues of consistency when evaluating dialogues [98].

To overcome the challenges arising from the subjective rating of humans, further approaches to the evaluation of dialogue systems’ performance have been adopted, namely methods for user-modelling, and automatic evaluation.

3.1.2. User-modelling

User-modelling, or simulation, aims at simulating users’ interaction behaviour with the agent, which is used as a training environment for a dialogue system. The approach assumes that there is a small collection of annotated in-domain dialogues available [13], or out-of-domain dialogues that have a matching dialogue format [99]. In instances where there is no such data available, manually crafted values can be attributed to the simulation model arguments, given that the model is simple enough [100].

To achieve a seemingly realistic interaction through simulation, a significant amount of work needs to be done. For a high level virtual patient to be created, Campillos-Llanos et al [101] demonstrated the need for the formalisation of ontological concepts for natural language understanding (NLU). NLU in fact could additionally rely on text requiring representations for resolving recurring paraphrasing concerns [102], e.g., a collection of texts for questions and replies overseen by experts [103] and canned questions and answers [104].

3.1.3. Automatic Evaluation

The process of the automatic evaluation of dialogue systems does not require a direct human interference once the evaluation script has been written [92]. The aim is to provide an objective measurement of the system performance by quantifying various attributes of dialogue into mathematical formulations [92]. By utilising automatic evaluation, the process of recruiting human evaluators, which can cost significant time and money, can be avoided.

BLEU [105] for example, is a metric that evaluates a generated sentence to a reference sentence, giving a score of 1.0 for a perfect answer and 0.0 for a completely inappropriate answer. It is typically used to evaluate machine translation performance but has since been applied in the field of dialogue systems [106, 107]. Another widely utilised evaluation metric is ROUGE, a method of text summarisation which uses measures to automatically determine the quality of a summary by comparing it to an ideal one created by a human [108]. Automated evaluation methods provide the most efficient and undemanding approach to assess dialogue systems [92]. However, they have also drawn criticism in the field. Liu et al [95] argue that automated metrics are generally perceived as sub-standard indicators of true dialogue quality. Other studies suggest that automated metrics can have a poor correlation with the judgements made by humans, e.g., [109], indicating poor utility of such metrics.

3.2. Evaluation Frameworks

3.2.1. PARADISE Framework

The Paradigm for dialogue system evaluation, or PARADISE, is one of the earliest frameworks developed for the purpose of evaluating spoken dialogue agents and is still widely used as a baseline to evaluate dialogue systems’ performance. The strengths of the framework include separation of task requirements from an agent’s dialogue behaviours, the ability to compare competing dialogue strategies, as well as supporting the calculation of a metric of performance spanning both sub-dialogues and whole dialogues [6]. Because of the explicit metrics that can be generated from these methods, the framework can measure the capabilities of multiple agents performing different tasks, whilst allowing normalisation over task complexity [110].

Researchers had previously used evaluation techniques, such as having a reference answer to compare against [111], or using various metrics to compare different dialogue strategies, for example, inappropriate turn correction ratio, concept accuracy, utterance ratio and implicit recovery [112, 81, 113]. However, these proved insubstantial for the rapidly improving dialogue systems of the time. The PARADISE framework sought to overcome the limitations of these approaches and addressed the following three research goals [6]:

• “To support the comparison of multiple systems or multiple versions of the same system doing the same domain tasks”.

• “To provide a method for developing predictive models of the usability of a system as a function of a range of system properties”. 
• “To provide a technique for making generalizations across systems about which properties of a system impact usability, i.e. to figure out what really matters to users”.

The framework gives designers the opportunity to predict user satisfaction, derived from a linear combination of objective metrics such as mean recognition score and task completion [10-13]. It elicits a performance function that can be quantified with user satisfaction as the dependant variable, with task success, dialogue quality, and dialogue efficiency measures as independent variables [115].

Practically, a task and a set of scenarios need to be initially defined. Table 3, used for illustration in [6], summarises the task information requirements of a train timetable service, through the representation of an attribute value matrix (AVM). Each attribute is coupled with a value which is obtained through the interaction between user and system. The information flow indicates who the information is being acquired by in that turn (agent or user), although this information is purely informative and not further used for evaluation.

| Attribute               | Possible Values          | Information Flow |
|-------------------------|--------------------------|------------------|
| depart-city             | Milano, Roma, Tornio, Trento | to agent         |
| arrival-city            | Milano, Roma, Tornio, Trento | to agent         |
| depart-range            | morning, evening         | to agent         |
| depart-time             | 6am, 8am, 6pm, 8pm       | to user          |

Table 3: An AVM of a simplified train timetable [6].

Task success accordingly can be quantified as to how well the process of achieving the task requirements have gone by the end of the interaction. A confusion matrix is utilised to represent the information requirements of a task for a set of dialogues, instantiating a set of scenarios [6]. This then is summarised by the Kappa coefficient $\kappa$ [116], also referred to as Kappa statistic [10], a quantity that is used to measure agreement after having corrected for chance,

$$\kappa = \frac{P(A) - P(E)}{1 - P(E)}$$

$\kappa$ is derived from the confusion matrix values, as an objective measure to calculate a metric of agreement for the correct responses for each task scenario, where $P(A)$ is the ratio of agreements between the actual set of dialogue and AVMs, and $P(E)$ is the ratio of instances that the AVMs are expected to agree on. The measure is thought to be an appropriate form of dialogue system measurement, because it takes into account the inherent ambiguity of human – computer interaction by this correction for chance expected agreement [6].

PARADISE was an innovative framework of its time, and whilst its evaluative strengths are comprehensive, it has its limitations. The utilisation of incorporating a user satisfaction score as a performance measurement can be powerful and harness a metric that is often overlooked in other dialogue evaluation techniques. However, Evanini et al [117] raise the question of reliability with user satisfaction surveys, stating that individuals tend to have different interpretations of the question, which can cause issues of consistency when incorporated into the model. Ultes et al [118] believed the act of users having to rate live dialogue is also an impractical one in a real-world environment.

The framework is far less utilised for TODS evaluation in modern times, and is instead frequently used as a baseline reference point for newer evaluation techniques. The rigours and necessary characteristics of more sophisticated ‘chatbots’, arguably incorporate too many complexities for the PARADISE framework to effectively assess and therefore, practically, it is now used much less.

### 3.2.2. Analytic Hierarchy Process

Developed between 1971 and 1975, L Saaty designed and established the Analytic Hierarchy Process (AHP) as a general theory of measurement, which ‘can be utilised to derive ratio scales from both discrete and continuous paired comparisons’ [119]. Since its inception in the 1970’s, the framework has been the basis for further studies and developments, with variants such as the fuzzy AHP [120] and the Analytic Network Process (ANP) taking inspiration from the original concept. AHP’s have been adapted for a wide spectrum of domains ranging from agriculture [121] to the military [122], supplemented by the vast literature on the applications of AHP, with more than 1300 papers and 100 doctoral dissertations studying the topic [123].

As explored in this section, the AHP can be utilised effectively to evaluate dialogue systems providing an interaction attributes are effectively represented.

For an AHP to be effectively utilised, the problem in question needs to be modelled as a hierarchy. This hierarchy is made up of a goal at the top level, such as ‘choose a dialogue system’, with a number of relevant factors that link the potential candidates to the top level goal/question. The factors for the choice of dialogue system might be: efficiency of the system, ease of use of the system, standard of the systems user interface, and cost of the system, which in this case will refer to the monetary cost of implementation. Each of these factors...
will link to the three possible dialogue systems which will be the possible options/candidates, as shown in figure 2.

Nodes are represented in a AHP by a box. A node can be the goal, a criterion or a candidate. From the perspective of a given node, any nodes above that node are parent nodes, and any below are children nodes or sub-nodes. Initially, the criteria need to be manually populated with the appropriate nodes, from which a series of pairwise comparisons can be made between attributes to determine their relative importance. If attribute A is substantially more important than attribute B when evaluating the pair against each other, then if A is rated at a 9, B should be rated at 1/9. A scale of 1-9 is typically used for AHP’s. This is known as the Saaty rating scale, as demonstrated in Table 4 which compares the conversational agents ease of use and gives a caption to justify these scores—an optional addition. Comparison matrices are derived and the first principal eigenvector is computed to assess relative and global priorities. The value of the child has twice as much chance of reaching the goal in comparison to a node with a value of 0.15. The value of the goal node is always 1, with the corresponding alternatives summing to 1. The weights of the children nodes will always sum to the priority value of the parent node.

For the ‘choose a dialogue system’ example, a coefficient of priority needs to be assigned to each criterion on the process of choosing the correct dialogue system candidate. An equally important process is to determine the weight to be assigned to each candidate relative to each of the criteria, dependent on how important the people involved perceive it to be. The AHP is particularly useful in this respect because it allows the designers to input an explicit value to each of the criteria.

The priority coefficients, or weights of the nodes in any group are assigned priority values, which are absolute values between 0 and 1. If a node has a value of 0.3, it has twice as much chance of reaching the goal in comparison to a node with a value of 0.15. The value of the goal node is always 1, with the corresponding alternatives summing to 1. The weights of the children nodes will always sum to the priority value of the parent node. As represented in Table 5, the designers have to assign the criteria to the necessary values in respect of the goal, which is again done with pairwise comparisons.

Table 7 shows the steps required to synthesise the final priorities. The value for each criterion is multiplied by the priority vector for that attribute, which is done for each option. These values are collated in Table 8 for illustration, with Conversation Agent 2 (CA2) having the highest goal score of 0.658, making it the best dialogue system using this criteria.

AHP’s are generally agreed to be easy to use in which the user(s) can plug in their nodes and values following simple instruction. Just by doing this, a systematic outcome can be achieved which allows for consistency in decision making which is backed by a logical process. It also simplifies what can be a daunting decision-making process, into smaller, easy to digest steps. However, AHP’s still require human judgement to be quantified into numerical values, which can be subjective and hard to agree on amongst parties.
| Criterion | P vs G | Alt. | A   | B   | C   |
|-----------|-------|------|-----|-----|-----|
| EoU       | 0.726 | CA1  | 0.217 | 0.157 | |
|           |       | CA2  | 0.717 | x 0.726 | 0.52 |
|           |       | CA3  | 0.066 | 1.000 | 0.042 |
| Cost      | 0.179 | CA1  | 0.265 | 0.01  | |
|           |       | CA2  | 0.672 | x 0.179 | 0.12 |
|           |       | CA3  | 0.082 | 1.000 | 0.011 |
| Efficiency| 0.097 | CA1  | 0.743 | 0.072 | |
|           |       | CA2  | 0.194 | x 0.097 | 0.018 |
|           |       | CA3  | 0.063 | 1.000 | 0.006 |

Table 7: Table of all calculations for conversational agents results for each attribute. P vs G: Priority vs Goal; Alt.: Alternative CA.

| Candidate | EoU | Cost | Efficiency | UI | Goal |
|-----------|-----|------|-----------|----|------|
| CA1       | 0.119 | 0.024 | 0.201 | 0.015 | 0.359 |
| CA2       | 0.392 | 0.01  | 0.052 | 0.038 | 0.492 |
| CA3       | 0.036 | 0.093 | 0.017 | 0.004 | 0.15  |
| Total     | 0.547 | 0.127 | 0.27  | 0.057 | 1     |

Table 8: Final results of each conversational agents score for each attribute, with totals.

In these situations, it can be argued that the process is unnecessarily lengthened. The rigidity of the frameworks methodologies can make it hard to take into account uncertainty, a component often inherent in the domains they are often deployed in.

**ChatEval**

ChatEval is a unified framework that harnesses already existing tools and provides a platform on the web for researchers to collaborate with their dialogue systems [127]. The benefits of this tool are significant, as even though there is a pre-existing community in the NLP and dialogue system space, there is less opportunity for researchers and developers to compare their findings. This is one of the reasons the Loebner prize is almost held as a standard in itself [128], as it is a forum in which chatbots can be directly compared to others in the field.

The fields of dialogue systems and conversational agents suffer from the issue of reproducibility, as replicating the exact threads of conversation can prove difficult, subsequently making it a tough task to assess exactly how a model is performing [129]. This is an issue that is problematic for the field of NLP in general, and especially so in the research into dialogue systems in particular, because unlike other machine learning fields, there is a significant lack of automatic metrics to evaluate dialogue system outputs.

Unlike the previous frameworks examined, ChatEval is not a standalone framework in its own right. The evaluation toolkit of ChatEval utilises both an automatic evaluation component and human evaluation component. The automatic evaluation consists of various components such as a BLEU-2 score over the mean of the sentence [95], a metric of mean cosine-similarity [130], a lexical diversity metric [131] and response perplexity score [132]. The human evaluation segment involves a human choosing the better (or equal) response from a prompt and two possible responses.

Although the overall concept behind ChatEval is a simple one, it helps fill a void in the field, allowing for real progress to be made. In their machine learning problems, especially those of a classification nature, competitions can be held to see who can get the highest accuracy through benchmarking for a given dataset, which encourages substantial variation in terms of the models utilised. ChatEval essentially offers the same opportunity for dialogue systems.

Whilst the benchmarking capabilities of ChatEval can offer substantial utility, the rigidity of the framework makes it difficult to evaluate interactions on the go. This limits the ability to optimise the conversation as they happen, and instead offers a forum of delayed feedback to allow for future design tweaks. Therefore ChatEval can be of great use for dialogue system evaluation, but the context upon how it will be used holds significance.

4. Discussion and Conclusions

It is clear that there is no shortage of studies exploring the field of TODS and their performance. However, research into TODS in conjunction with conversational quality attributes, beyond that of task-resolution, are less abundant. One potential reason for this is because these attributes, such as conversation length, response time and user-sentiment are often referred to more as by-products of the dialogue systems performance in meeting user information requirements.

Although many studies on optimising TODS performance examined metrics for performance evaluation beyond that of task-resolution, thus far, however, the modelling of TODS performance as a multivariate function of multiple conversational quality attributes remains an open question.

Additionally, TODS are still difficult to evaluate. Although there are established methods and frameworks which are frequently referred to in literature, with PARADISE arguably the most applied, yet there is still no standard in place for a novel TODS to be measured against. This is undoubtedly a hindrance to the field,
as it gives a lack of consistency when designing a system and subsequently comparing it with others in the industry. Also, with the growing complexity of modern virtual assistants such as Siri, Bixby and Alexa to name a few, where each could be described as a sophisticated TODS, the task of objectively evaluating such systems is only going to become a more complex process.

Therefore, although significant progress has been made in the field of TODS over a relatively short time, there are still various challenges to be overcome. Arguably the most pressing issue is the lack of a standardised protocol for human evaluation, which makes it challenging to compare different approaches to one another [25]. On the other hand, automatic evaluation metrics have proven their utility with their efficiency and understanding approach to dialogue assessment, but are still considered less reliable in comparison to human judgement [133]. A shortage of task-oriented open-source datasets also acts as a bottleneck in the progression of the field, especially when approaching multiple domains. All of which is compounded by a growing expectation of the average user, as TODS are generally becoming more and more innovative on a global scale.

Acknowledgement

This work has been funded by IT Services at UWE-Bristol. Authors would like to acknowledge the assistance provided by Mark Davis and his team in the initial discussions leading to this study and for their collaboration on the project.

References

[1] P.-H. Su, M. Gasic, N. Mrksic, L. Rojas-Barahona, S. Ultes, D. Vandyke, T.-H. Wen, S. Young, On-line active reward learning for policy optimisation in spoken dialogue systems, arXiv preprint arXiv:1605.07669.
[2] O. Vinyals, Q. Le, A neural conversational model, arXiv preprint arXiv:1506.05869.
[3] M. Henderson, B. Thomson, J. D. Williams, The second dialogue state tracking challenge, in: Proceedings of the 15th annual meeting of the special interest group on discourse and dialogue (SIGDIAL), 2014, pp. 263–272.
[4] Chatbot market size to reach $1.25 billion by 2025 — cagr: 24.3%: Grand view research, inc. [shorturl.at/gjqr7] accessed: 2021-07-14.
[5] W. Wang, K. Siau, Trust in health chatbots, Thirty ninth International Conference on Information Systems, San Francisco 2018.
[6] M. A. Walker, D. J. Littman, C. A. Kamn, A. Abella, Paradise: A framework for evaluating spoken dialogue agents, arXiv preprint cmp-lg/9704004.
[7] S. Möller, R. Englert, K.-P. Engelbrecht, V. Hafner, A. Jameson, A. Oulasvirta, A. Raake, N. Reithinger, Memo: towards automatic usability evaluation of spoken dialogue services by user error simulations, Ninth International Conference on Spoken Language Processing.
[8] J. D. Williams, K. Asadi, G. Zweig, Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning, in: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Association for Computational Linguistics, Vancouver, Canada, 2017, pp. 665–677.
[9] C. Kann, User interfaces for voice applications, Proceedings of the National Academy of Sciences 92 (22) (1995) 10031–10037.
[10] M. Walker, J. C. Fromer, S. Narayanan, Learning optimal dialogue strategies: A case study of a spoken dialogue agent for email, in: COLING 1998 Volume 2: The 17th International Conference on Computational Linguistics, 1998.
[11] N. Fraser, D. Gibson, R. Moore, R. Winski, Assessment of interactive systems., Mouton de Gruyter, 1998, pp. 564–615.
[12] J. M. Deriu, A. Rodrigo, A. Otegi, G. Echegoeyn, S. Rosset, E. Agirre, M. Cieliebak, Survey on evaluation methods for dialogue systems, Artificial Intelligence Review 54 (1) (2020) 755–810.
[13] J. Schatzmann, B. Thomson, K. Weilhammer, H. Ye, S. Young, Agenda-based user simulation for bootstrapping a pomdp dialogue system, in: Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers, 2007, pp. 149–152.
[14] H. H. Clark, S. E. Brennan, Grounding in communication., Perspectives on socially shared cognition.
[15] H. H. Clark, Using language, Cambridge university press, 1996.
[16] H. H. Clark, E. F. Schaefer, Collaborating on contributions to conversations, Language and cognitive processes 2 (1) (1987) 19–41.
[17] H. H. Clark, E. F. Schaefer, Contributing to discourse, Cognitive science 13 (2) (1989) 259–294.
[18] D. Vandyke, P.-H. Su, M. Gasic, N. Mrksic, T.-H. Wen, S. Young, Multi-domain dialogue success classifiers for policy training, in: 2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU), 2015, pp. 763–770.
[19] P.-H. Su, D. Vandyke, M. Gasic, D. Kim, N. Mrksic, T. H. Wen, S. Young, Learning from real users: Rating dialogue success with neural networks for reinforcement learning in spoken dialogue systems, arXiv preprint arXiv:1508.03386.
[20] B. Thomson, S. Young, Bayesian update of dialogue state: A pomdp framework for spoken dialogue systems, Computer Speech and Language 24 (4) (2010) 562–588.
[21] M. Noseworthy, J. C. K. Cheung, J. Pineau, Predicting success in goal-driven human-human dialogues, in: Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, Association for Computational Linguistics, Saarbrücken, Germany, 2017, pp. 253–262.
[22] J. Planells, L. Hurtado Oliver, E. Segarra, E. Sanchis, A multi-domain dialog system to integrate heterogeneous spoken dialog systems, 2013, pp. 1891–1895.
[23] Y. Huang, J. Feng, M. Hu, X. Wu, X. Du, S. Ma, Meta-reinforced multi-domain state generator for dialogue systems, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics, Online, 2020, pp. 7109–7118.
[24] C.-S. Wu, A. Madotto, E. Hosseini-Asl, C. Xiong, R. Socher, P. Fung, Transferable multi-domain state generator for task-oriented dialogue systems, in: ACL, 2019.
[25] N. Mrksic, D. Ó Séaghdha, T.-H. Wen, B. Thomson, S. Young, Neural belief tracker: Data-driven dialogue state tracking, in:
Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, Vancouver, Canada, 2017, pp. 1777–1788.

[26] P. Xu, Q. Hu, An end-to-end approach for handling unknown slot values in dialogue state tracking, 2018, pp. 1448–1457.

[27] V. Zhong, C. Xiong, R. Socher, Global-locally self-attentive encoder for dialogue state tracking, in: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Association for Computational Linguistics, Melbourne, Australia, 2018, pp. 1458–1467.

[28] J. D. Williams, S. Young, Partially observable markov decision processes for spoken dialog systems, Computer Speech & Language 21 (2) (2007) 393–422.

[29] M. Gašić, S. Young, Gaussian processes for pomd-p-based dialogue manager optimization, IEEE/ACM Transactions on Audio, Speech, and Language Processing 22 (1) (2013) 28–40.

[30] Z. Zhang, R. Takanobu, Q. Zhu, M. Huang, X. Zhu, Recent advances and challenges in task-oriented dialog systems, Science China Technological Sciences (2020) 1–17.

[31] J. F. Allen, B. W. Miller, E. K. Ringger, T. Sikorski, Robust understanding in a dialogue system, in: Proceedings of the 34th Annual Meeting of the Association for Computational Linguistics, Vol. 62, 1996, p. 70.

[32] R. Meena, G. Skantze, J. Gustafson, Data-driven models for timing feedback responses in a map task dialogue system, Computer Speech & Language 28 (4) (2014) 903–922.

[33] Z. Callegas, R. López-Cózar, Relations between de-facto criteria in the evaluation of a spoken dialogue system, Speech Communication 50 (8-9) (2008) 646–665.

[34] S. M. Robinson, A. Roque, A. Vaswani, D. Traum, C. Hernandez, B. Milispaugh, Evaluation of a spoken dialogue system for virtual reality call for fire training, Tech. rep., University of Southern California Marina Del Rey Ca Inst for Creative Technologies (2007).

[35] L. Lamel, S. Rosset, J.-L. Guavain, Considerations in the design and evaluation of spoken language dialog systems.

[36] A. Kamm, M. Walker, D. Litman, Evaluating spoken language systems.

[37] A. Malchenau, V. Petukhova, H. Bunt, Multimodal dialogue system evaluation: a case study applying usability standards, in: 9th International Workshop on Spoken Dialogue System Technology, Springer, 2019, pp. 145–159.

[38] E. Raita, A. Olalasvirta, Too good to be bad: Favorable product perception and influence on subjective usability ratings, Interacting with Computers 23 (4) (2011) 363–371.

[39] V. M., J. Vala, P. Balani, A survey on sentiment analysis algorithms for opinion mining, International Journal of Computer Applications 133 (2016) 7–11.

[40] W. Medhat, A. Hassan, H. Korashy, Sentiment analysis algorithms and applications: A survey, Ain Shams Engineering Journal 5 (4) (2014) 1093–1113.

[41] H. Sinha, A. Kaur, A detailed survey and comparative study of sentiment analysis algorithms, in: 2016 2nd International Conference on Communication Control and Intelligent Systems (CCIS), 2016, pp. 94–98.

[42] R. Prabowo, M. Thelwall, Sentiment analysis: A combined approach, Journal of Informetrics 3 (2) (2009) 143–157.

[43] V. Kharde, S. Sonawane, Sentiment analysis of twitter data: A survey of techniques, International Journal of Computer Applications 139 (2016) 5–15.

[44] J. Acosta, Using emotion to gain rapport in a spoken dialogue system., in: Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, Companion Volume: Student Research Workshop and Doctoral Consortium, 2009, pp. 49–54.

[45] J. Pittermann, A. Pittermann, W. Minker, Emotion recognition and adaptation in spoken dialogue systems, International Journal of Speech Technology 13 (2010) 49–60.

[46] B. Liu, I. Lane, End-to-end learning of task-oriented dialogues, in: Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop, Association for Computational Linguistics, New Orleans, Louisiana, USA, 2018, pp. 67–73.

[47] N. Braunschweiler, A. Papangelis, Comparison of an End-to-end Trainable Dialogue System with a Modular Statistical Dialogue System, in: Proc. Interspeech 2018, 2018, pp. 576–580.

[48] Q. V. Liao, W. Geyer, M. Muller, Y. Khazaen, Conversational Interfaces for Information Search, Springer International Publishing, Cham, 2020, pp. 267–287.

[49] E. Ruane, S. Farrell, A. Ventresque, User perception of text-based chatbot personality, in: A. Fasel, T. Araujo, S. Papadopoulos, E. L.-C. Law, E. Lugé, M. Goodwin, P. B. Brandtzæg (Eds.), Chatbot Research and Design, Springer International Publishing, Cham, 2021, pp. 32–47.

[50] W. Shi, Z. Yu, Sentiment adaptive end-to-end dialogue systems, in: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 2018, pp. 1509–1519.

[51] T. Saha, S. Saha, P. Bhattacharyya, Towards sentiment aided dialogue policy learning for multi-intent conversations using hierarchical reinforcement learning, PLOS ONE 15 (2020) e0235367.

[52] B. Schuller, G. Rigoll, M. Lang, Hidden markov model-based speech emotion recognition, in: 2003 International Conference on Multimedia and Expo. ICME ’03. Proceedings (Cat. No.03TH8698), Vol. 1, 2003, pp. 1–401.

[53] T. L. Nwe, S. W. Foo, L. C. De Silva, Speech emotion recognition using hidden markov models, Speech Communication 41 (4) (2003) 603–623.

[54] L. Devillers, L. Lamel, I. Vasilescu, Emotion detection in task-oriented spoken dialogues, in: 2003 International Conference on Multimedia and Expo. ICME ’03. Proceedings (Cat. No.03TH8698), Vol. 3, 2003, pp. III–549.

[55] J. Lascombe, G. Riccardi, D. Hakkani-Tur, in: INTERSPEECH 2005 - Eurospeech, 9th European Conference on Speech Communication and Technology, 2005, pp. 1845–1848.

[56] T. Bui, J. Zwiers, M. Poel, A. Nijholt, Towards affective dialogue modeling using partially observable markov decision processes, in: 1st workshop on Emotion and Computing – Current Research and Future Impact, 2006, pp. 47–50.

[57] N. Roy, J. Pineau, S. Thrun, Spoken dialogue management using probabilistic reasoning, in: Proceedings of the 38th Annual Meeting on Association for Computational Linguistics, ACL ’00, USA, 2000, p. 93–100.

[58] J. C. Acosta, N. G. Ward, Achieving rapport with turn-by-turn, user-responsive emotional coloring, Speech Communication 53 (9) (2011) 1137–1148, sensing Emotion and Affect - Facing Realism in Speech Processing.

[59] E. Ferreira, F. Lefèvre, Expert-based reward shaping and exploration scheme for boosting policy learning of dialogue management processes, in: 1st workshop on Emotion and Computing – Current Research and Future Impact, 2006, pp. 47–50.

[60] J. Acosta, A. Lapedriza, N. Jones, S. Gu, R. Picard, Way of policy batch deep reinforcement learning of human preferences in dialogue policy learning.

[61] N. Jaques, A. Chandhariouj, H. Shen, C. Ferguson, A. Lapedriza, N. Jones, S. Gu, R. Picard, Way off-policy batch deep reinforcement learning of human preferences in dialog (2020).
K. Sche, H. Saif, Y. He, H. Alani, Semantic sentiment analysis of twitter and social media text, 2015. arXiv:1506.08467

T. Saha, S. Saha, P. Bhattacharyya, Towards sentiment aided dialogue policy learning for multi-intent conversations using hierarchical reinforcement learning, PLOS ONE 15 (7) (2020) 1–28.

H. Kumar, B. Harish, H. Darshan, Sentiment analysis on imdb movie reviews using hybrid feature extraction method., International Journal of Interactive Multimedia & Artificial Intelligence 5 (5).

A. Yenter, A. Verma, Deep cnn- lstm with combined kernels from multiple branches for imdb review sentiment analysis, in: 2017 IEEE 9th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), IEEE, 2017, pp. 540–546.

Z. Shaukat, A. A. Zulfiqar, C. Xiao, M. Azeem, T. Mahmood, Sentiment analysis on imdb using lexicon and neural networks, SN Applied Sciences 2 (2) (2020) 1–10.

A. Agarwal, B. Xie, I. Vovsha, O. Rambow, R. J. Passonneau, Z. Shaukat, A. A. Zulfiqar, C. Xiao, M. Azeem, T. Mahmood, H. Kumar, B. Harish, H. Darshan, Sentiment analysis on imdb using lexicon and neural networks, SN Applied Sciences 2 (2) (2020) 1–10.

A. Saif, Y. He, H. Alani, Semantic sentiment analysis of twitter, in: International semantic web conference, Springer, 2012, pp. 30–38.

H. Saif, Y. He, H. Alani, Semantic sentiment analysis of twitter, in: International semantic web conference, Springer, 2012, pp. 508–524.

T. Fukuhara, H. Nakagawa, T. Nishida, Understanding sentiment of people from news articles: Temporal sentiment analysis of sentiment expressions, in: ICWSM, Citeseer, 2007.

P. G. Preethi, V. Uma, et al., Temporal sentiment analysis and causal rules extraction from tweets for event prediction, Procedia computer science 48 (2015) 84–89.

T.-H. Wen, D. Vandyke, N. Mrkic, M. Gasic, L. M. Rosas-Barahona, P.-H. Su, S. Ultes, S. Young, A network-based end-to-end trainable task-oriented dialogue system, arXiv preprint arXiv:1604.04562.

C. Hutto, E. Gilbert, Vader: A parsimonious rule-based model for sentiment analysis of social media text, 2015.

H. Saif, M. Fernández, Y. He, H. Alani, Evaluation datasets for twitter sentiment analysis: a survey and a new dataset, the sts-gold.

K. Scheffler, S. Young, Automatic learning of dialogue strategy using dialogue simulation and reinforcement learning, in: Proceedings of HLT, Vol. 2, 2002.

J. Relato-Gil, D. Tapia, M. C. Gancedo, M. Charfuelán, L. Hernández, Robust and flexible mixed-initiative dialogue for telephone services, in: Ninth Conference of the European Chapter of the Association for Computational Linguistics, 1999, pp. 287–290.

M. Mitchell, D. Bohus, E. Kamar, Crowdsourcing language generation templates for dialogue systems, in: Proceedings of the INLG and SIGDIAL 2014 Joint Session, 2014, pp. 172–180.

P. Shah, D. Hakkani-Tür, B. Liu, G. Tür, Bootstrapping a neural conversational agent with dialogue self-play, crowdsourcing and on-line reinforcement learning, in: Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers), 2018, pp. 41–51.

R. Manvininakurike, M. Paetzel, D. DeVault, Reducing the cost of dialogue system training and evaluation with online, crowdsourced dialogue data collection, Proceedings of SEMDIAL 2015 13–121.

E. Levin, R. Pieraccini, W. Eckert, Learning dialogue strategies within the markov decision process framework, in: 1997 IEEE Workshop on Automatic Speech Recognition and Understanding Proceedings, IEEE, 1997, pp. 72–79.

A. Abella, M. K. Brown, B. Buntschuh, Development principles for dialog-based interfaces, in: Workshop on Dialogue Processing in Spoken Language Systems, Springer, 1996, pp. 141–155.

L. Hirschman, C. Pao, The cost of errors in a spoken language system, in: Third European Conference on Speech Communication and Technology, 1993.

M. Danielei, E. Gerbino, Metrics for evaluating dialogue strategies in a spoken language system, in: Proceedings of the 1995 AAAI spring symposium on Empirical Methods in Discourse Interpretation and Generation, Vol. 16, 1995, pp. 34–39.

A. Simpson, N. M. Eraser, Black box and glass box evaluation of a spoken dialogue system, in: Third European Conference on Speech Communication and Technology, 1993.

M. Dhyani, R. Kumar, An intelligent chatbot using deep learning with bidirectional rnn and attention model, Materials Today: Proceedings 34 (2019) 817–824.

A. Przegalinska, L. Ciechanowski, A. Stroz, P. Gloor, G. Mazurek, In bot we trust: A new methodology of chatbot performance measures, Business Horizons 62 (6) (2019) 785–797.

A. Nursetyo, E. R. Subhiyakto, et al., Smart chatbot system for e-commerce assistance based on ai ml, in: 2018 International Seminar on Research of Information Technology and Intelligent Systems (ISRTIT), IEEE, 2018, pp. 641–645.

M. Kowsher, A. Tahubilder, M. Z. I. Sanjid, N. J. Prottasha, M. M. H. Sarker, Knowledge-base optimization to reduce the response time of bangla chatbot, 2020 Joint 9th International Conference on Informatics, Electronics and Vision and 2020 4th International Conference on Imaging, Vision and Pattern Recognition, ICIEV and icVIP 2020.

U. Gnewuch, S. Morana, M. T. Adam, A. Maedche, Faster is not always better: understanding the effect of dynamic response delays in human-chatbot interaction, in: 26th European Conference on Information Systems: Beyond Digitization: Facets of Socio-Technical Change, ECIS 2018, Portsmouth, UK, June 23–28, 2018, Ed.: U. Frank, 2018, p. 143975.

Replika.

https://github.com/surgeforward/Happybot

G. Dosovitsky, B. S. Pineda, N. C. Jacobson, C. Chang, M. Escorero, E. L. Bunge, Artificial intelligence chatbot for depression: Descriptive study of usage, JMIR Formative Research 4, 2016.

S. E. Finch, J. D. Choi, Towards unified dialogue system evaluation: A comprehensive analysis of current evaluation protocols, arXiv preprint arXiv:2006.06110.

A. Xu, Z. Liu, Y. Guo, V. Sinha, R. Akkiraju, A new chatbot for customer service on social media, in: Proceedings of the 2017 CHI conference on human factors in computing systems, 2017, pp. 3506–3510.

W. Zhu, K. Mo, Y. Zhang, Z. Zhu, X. Peng, Q. Yang, Flexible end-to-end dialogue system for knowledge grounded conversation, arXiv preprint arXiv:1709.04264.

C.-W. Liu, R. Lowe, I. V. Serban, M. Noseworthy, L. Charlin, J. Pineau, How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation, arXiv preprint arXiv:1603.08023.

N. Asghar, P. Poupard, J. Hoey, X. Jiang, L. Mou, Affective neural response generation, in: European Conference on Information Retrieval, Springer, 2018, pp. 154–166.

S. Santhanam, S. Shaikh, A survey of natural language generation techniques with a focus on dialogue systems-past, present
