Controllable Response Generation for Assistive Use-cases

Shachi H Kumar
shachi.h.kumar@intel.com

Hsuan Su
hsuan.su@intel.com

Ramesh Manuvinakurike
ramesh.manuvinakurike@intel.com

Saurav Sahay
saurav.sahay@intel.com

Lama Nachman
lama.nachman@intel.com

Abstract

Conversational agents have become an integral part of the general population for simple task enabling situations. However, these systems are yet to have any social impact on the diverse and minority population, for example, helping people with neurological disorders (e.g., ALS), and people with speech, language and social communication disorders. Language model technology can play a huge role to help these users carry out daily communication and social interactions. To enable this population, we build a dialog system that can be controlled by users using cues/keywords. We build models that can suggest relevant cues in the dialog response context which is used to control response generation and can speed up communication. We also introduce a keyword-loss to lexically constrain the model output. We show both qualitatively and quantitatively that our models can effectively induce the keyword into the model’s response without degrading the quality of response. In the context of usage of such systems for people with degenerative disorders, we present human evaluation of our cue/keyword predictor and the controllable dialog system and show that our models perform significantly better than models without control. Our study shows that keyword-control on end-to-end response generation models is powerful and can enable and empower users with degenerative disorders to carry out their day-to-day communication.

1 Introduction

Conversational agents, especially systems such as Alexa and Google Home, have become commodity items in people’s homes. Such systems have enabled carrying out one-shot tasks such as setting reminders, playing music and accessing information simpler for the general population. Besides the conversational agents that are popular with IoT and Mobile devices, we also have Personal Computer and Cloud based chatbots that are designed to perform certain goals or tasks, or to just engage in a casual conversation/chat with a user. The latter class of open-domain conversational agents have not yet seen widespread adoption besides mostly research exploration projects for developing conversational agents for long duration sustained and meaningful interactions (Ram et al., 2018). For example, Amazon launched the Alexa Prize challenge to develop Socialbots to converse coherently and engagingly with humans on popular topics such as Sports, Politics, Entertainment, Fashion and Technology for 20 minutes. Prior winning teams have used complex modular building blocks for intent detection, entity resolution, out of scope topic detection, dialog management strategies and a mix of template based and neural response generation methods (Gabriel et al., 2020).

Large language models are also being developed today with end-to-end pre-training. Large-scale pre-training has attained significant performance gains across many tasks within NLP (Devlin et al., 2019; Radford and Narasimhan, 2018). Through self-supervised pre-training on large natural language corpora, these models gain generalized language understanding capabilities that transfer effectively to downstream tasks (Wang et al., 2018), including intent prediction (Castellucci et al., 2019; Chen et al., 2019b) and dialogue state tracking (Heck et al., 2020). Open-domain chatbots are also being trained using generative language modeling objective of minimizing perplexity on next word prediction task using large conversational corpora and transformer based models. These models have demonstrated surprising generality, with models like DialoGPT (Zhang et al., 2020b), Meena (Adiwardana et al., 2020) and Blender (Roller et al., 2020) achieving response generation performance competitive with humans in certain settings. These improving systems still suffer from issues such as repeated responses, hallucinated facts, and lack of grounding and embodiment (See et al., 2019a).
Figure 1: A dialog system for an assistive use-case can listen to a conversation and provide diverse cues to the user. These cues, provide human control to the dialog system that can generate relevant responses that can further be edited. Such a system enables minimum effort and intervention from the user that is critical for people with disabilities.

However, these models serve as a promising basis for further task specific fine-tuning and novel strategies to address issues such as repetitions, hallucinations and grounding.

Science and Engineering advances in Chatbots research make us hopeful for getting close to general purpose personalized AI assistants someday. Right now, with the availability of these pre-trained language enabling models, novel products and applications are emerging in niche domains (Bommasani et al., 2021) such as Communication Systems (e.g. email response completion (Chen et al., 2019a)), Creativity Tools (story writing assistance (Roemmele and Gordon, 2018; Roemmele, 2021)), Human-AI collaboration for Software Engineering (Chen et al., 2021), biosciences (protein structure prediction (Rives et al., 2020) and several other emerging applications (Bommasani et al., 2021). One such accessibility application we are exploring is aimed towards leveraging language modeling technology to support minority group of people with certain disabilities to communicate with others effectively. For example, Amyotrophic Lateral Sclerosis (ALS) is a progressive, degenerative, neurological disorder that destroys the ‘motor neurons’ that are responsible for enabling movement in arms, legs, chest, mouth and throat. People with ALS lose their muscle movement, voice and the ability to carry out a normal day-to-day communication. It takes huge effort and time for these patients to communicate sentences character by character using various data input mechanisms available to them (gaze, fingers, muscle movements).

We want to enable full and faster communication and provide interaction support tools for people with such disabilities by having an intelligent agent be their voice and content assistant. The system should use very limited user input (e.g. gaze, single muscle movement, facial gesture, etc) and suggest cues and cue-based responses that can be interactively chosen and edited for near real time social interactions. Today’s response generation systems are very hard to use as-is for our usage requirements. The system for our usage needs to be context-aware, personalized, should enable minimal user-intervention and most importantly, be assistive and controllable. There has been some recent work on personalization, stylization and controllability of the generative language models, however, current research development tools are not suitable for our assistive usages.

The system goal is to minimize the number of keystrokes input required for continued coherent interactions. Fast response generation with response cues, editing and auto complete features can dramatically reduce the silence gap in the conversation resulting from users slower keystroke by keystroke input. With these goals, we present a technique to control or guide a response generation model to generate a response that is relevant to the conversational context.

Other possible application of this technology includes supporting people with other conditions such as Social Communication Disorder (SCD) or other pragmatic language impairments such as difficulty in using language for social purposes, appropriately matching communication to the social context, following rules of the communication context (e.g., back and forth of conversation), and understanding nonliteral language (e.g., jokes, idioms, metaphors) (Flax et al., 2019). Those with the diagnosis are impaired in processing implied sentences and indirect uses of language such as metaphors, humor, and aphorisms. They also display nonverbal communication problems along with verbal ones, such as greeting others according to context, waiting for turns in conversations, and modulating their behaviors according to context (Topal et al., 2018). Our system provides cues and prototypical responses that can potentially be used by the community as aids in their interaction support and training.

Our contributions in this work are, i) Minority Group Application: We bring forth a novel usage

---

1According to WHO, there are more than 1 Billion people with disabilities

2According to American Speech-Language-Hearing Association, pragmatic language impairment can exist in as much as 7.5% of kindergarteners based on a sample study
for open-domain chatbots/response generation systems, i.e., designing a response generation system that will represent users with communication disabilities and help them fulfill their day-to-day communication needs. ii) **Minimal user intervention:** We present a technique for fine-grained conversational controllable response generation using keywords/cues. We also build keyword/cue predictor models that further speed up communication time, and present human and automatic evaluation for these. iii) **Keyword Loss:** We introduce a keyword loss to our training objective that further helps in incorporating soft lexical constraints in the form of keywords/similar words in the generated responses. We show through automatic and human evaluation that our models are able to induce the keyword or its semantically similar meaning into the generated responses.

2 Related Work

**Assistive Technologies:** In recent times, AI augmented technologies have been developed that can help blind people better sense the visual world, offer real-time captioning and Sign Language interpretation for people with limited hearing, help augment the capabilities of people with limited mobility using new robotic systems, use brain computer interfaces for helping people communicate and help people with speech impairments better communicate. (Brady et al., 2013; Guo et al., 2020; MacLeod et al., 2017; Elakkiya, 2020; Mišeikis et al., 2020; Ozawa et al., 2020; Ramli et al., 2020; Shor et al., 2019). In ALS, individuals gradually lose their natural speech abilities due to the reduction in speaking rates, rapid deterioration of speaking ability and/or finger movement (Beukelman et al., 2011) and need Augmentative and Alternative Communication (AAC) strategies. AAC strategies support communication related to a large variety of issues, such as personal and medical care, social interaction and closeness, community involvement and employment, maintain emotional connection within families, provide patients with some autonomy and reduce caregiver burden (Linse et al., 2018). Patients work with Speech Language Pathologists to learn to use low-tech to hi-tech AAC interventions to maintain Quality of Life after disease progression (Felgoise et al., 2016). AAC interventions include speech generation (Beukelman et al., 2011), eye-tracking tools (Gibbons and Beneteau, 2010) to BCI interfaces (Wolpaw et al., 2018) for users with various degrees of locked-in states. Current communication systems use well-designed interfaces with inputs via eye-gaze or touch with some predictive text capability for word completion using simpler n-gram based language models (Verbally, 2021; TherapyBox, 2021) and do not exploit the potential of using response generation technology using deep learning based language models. To the best of our knowledge, there aren’t many research explorations for conversational technology based applications that exploit the latest language modeling techniques for people with MND such as ALS.

**Controllable Generation:** Powerful text generation systems (Radford and Narasimhan, 2018), (Brown et al., 2020) have emerged, however they are not controllable. (Keskar et al., 2019) pretrain a conditional transformer model with different types of control codes. (Xu et al., 2020b) presents a keyword controlled technique for generating story endings. While the above involve modifying the language model itself, (See et al., 2019b) present post-processing techniques to control generated text. (Dathathri et al., 2020) show an interesting plug-and-play architecture, where the base large language model is untouched, but one can introduce small attribute models to induce the control. (Madotto et al., 2020) extend the above plug-and-play architecture to dialog, and build attribute models for controls such as styles and topics. (Smith et al., 2020) present techniques for controlling style in dialog and (Gupta et al., 2020) control response generation using semantic exemplars. However, all of these controllable attributes such as ‘topics’, ‘sentiment’ and ‘style’ are too broad and not suitable for our use-case. We need fine-grained control that can enable minimal intervention from users. In the area of fine-grained controllable generation, (Xu et al., 2020a) present a fine-grained guidance to the dialogue system to make the response meet user’s expectation. (Ghazvininejad et al., 2017; See et al., 2019a) propose modifying the decoding procedure with several scoring functions to steer the bag-of-words on poetry generation. Both (Dathathri et al., 2020) and (Ghazvininejad et al., 2017) present techniques for fine-grained generation, but the techniques are very time-consuming and require a lot of computational resources at decoding process which is not applicable to real-time conversation scenarios.

**Similarity-based Loss Function:** To induce the
concept of keyword to the model, several works have focused on addressing the loss functions during model training. (Kovaleva et al., 2018) address the problem of representation learning and they successfully enhance the diversity and meaning in the generated sentence by using similarity-based losses. (Sha, 2020) aims to lexically constrain the language generation, they propose to use the largest gradient between contrained word(keyword) and predictions to find the words that need to be updated. In our work, we aim to compute the loss across the entire sentence to guide keyword generation, rather than at word level. We hence try several variations to enable this.

3 Keyword and Response Modeling

In this work, we modify the HuggingFace TransferTransfo model (Wolf et al., 2019) architecture initializing the decoder with the DialoGPT (Zhang et al., 2020c) weights. We incorporate fine-grained keyword-based control as model inputs and fine-tune the model on the DailyDialog (Li et al., 2017a) dataset with multi-task objective with an additional keyword based loss function. We enable keyword-control by 1) providing automatically generated keywords as auxillary input to the model and 2) by introducing a novel keyword-based loss that encourages the model to generate sentences containing the keyword or words semantically similar to the keyword.

The model is similar to the Transformer based architecture from (Radford and Narasimhan, 2018) that uses autoregressive and discriminative fine-tuning by optimizing a combination of two loss functions: 1) language modeling loss and 2) next-utterance classification loss. Given a context, the next utterance classification objective picks the next utterance among a set of candidates. We initialize this model with weights of DialoGPT, a large conversational response generation model and fine-tune on popular open domain conversation datasets with fine-grained control information. The DialoGPT model has the same architecture as GPT2 and is pretrained with millions of dialogs from Reddit conversations, making it more suitable for a dialog response generation task.

3.1 Keyword based Control

Given the conversation context, we enable fine-grained control over the responses generated by training the model with important cue words (we will refer to these as keywords for simplicity) automatically generated from the response.

3.1.1 Keywords as context

For a given conversation context, we incorporate keywords into the model by adding new keyword-specific-tokens, in addition to dialog-state/speaker tokens that represent speaker turns in the dialog. We further extend the dialog-state embeddings to add ‘keyword-state-embeddings’ with special keyword separator token to indicate the positions of the keyword tokens.

3.1.2 Keyword-based loss functions

We propose keyword-based loss functions that encourage the occurrence of the input keyword(s) in the generated sentence. We introduce variations to this loss function to enable the generation of semantically similar word to the input keyword as well as incorporate multiple-inputs (where the goal is to induce multiple keywords in the response) as control to the model. With addition of this loss, the overall loss of the model is a combination of: language model loss $L_{lm}$, next sentence prediction loss $L_n$ and keyword loss $L_k$.

$$\text{Overall Loss, } L = \alpha L_{lm} + \beta L_n + \gamma L_k$$

where $\alpha$, $\beta$ and the $\gamma$ are the hyper-parameters. $\alpha$ and $\beta$ are set to 1 as in the original TransferTransfo model.

**Keyword Loss:** In order to encourage the generation of the cue/keyword in a sentence, our goal is to maximize the similarity between the keyword and one of the generated words (at some output position). So to generate a keyword $kw$ at some output timestep, we derive the probability distribution from the generated logits at every timestep $i=1$ to $T$, and compute the negative log of the probability of the $kw$ at each step. We then take the minimum of these scores across the generated sentence. Hence, the loss over the sentence w.r.t the keyword $K$ is equal to,

$$L_k = \min_{i=1}^{T} (- \log p_i(kw)),$$

where $L_k$ is the keyword loss.

**Keyword Loss with similar words:** We incorporate embedding-based similarity scores into the keyword loss computation as shown in equation 3 in order to encourage generation of not just the keywords, but also semantically similar words in
the sentence. Let pool = kw ∪ sim_words(kw). The KeywordLoss $L_k$,

$$L_k = \sum_{j=1}^{N} \min_{i=1}^{T} (-\log p_i(k_j)) \quad (4)$$

### 3.2 Keyword Generation

**Training:** We extract ‘key’ terms from the dataset to fine-tune the model - this data is generated automatically, hence enabling end-to-end automatic pipeline, without the need for any other additional data collection or labeling efforts. Given a conversation context and a response output, keywords are extracted from the response utterance and incorporated into the model. We use keyBERT (Grootendorst, 2020) to extract meaningful keywords from the responses. This technique uses BERT-embeddings and cosine similarity to find the sub-phrases in a document that are most similar to the document itself. We generate top-3 1-gram keywords (rather than key-phrase) for each dialog response, as 1-gram inputs are most suitable for our use-case. We use both single keywords and multiple keywords as inputs to the models in our experiments.

**Inference:** During inference, especially in our use-case where we need to minimize user intervention, the user would greatly benefit from automatic keyword suggestions, rather than having to type it out each time. Hence we build keyword prediction models, given conversation context as input. We build two models for keyword prediction:

1) **Extractive keyword predictor:** Given a conversation context, we use DialoGPT (Zhang et al., 2020d) with diverse beam search (Vijayakumar et al., 2018) to generate multiple responses (we use 10 beams, 2 groups and diversity_penalty of 5.5). We then use keyBERT (Grootendorst, 2020) to extract keywords from the beam outputs and present these as keyword suggestions.

2) **Generative keyword predictor:** We fine-tune a large pretrained language model, GPT2, to generate keywords for a given context, and present these as suggestions. We use the training and validation dataset from DailyDialog to build the keyword predictor. This generative predictor is trained to predict multiple keywords for a given context. For evaluation of these models, we use the top keyword prediction. We further use diverse beam search (same configuration as above) and generate multiple keyword suggestions.

### 4 Methods

We compare our keyword-models (without the keyword loss but containing the keywords as part of dialog context) and keyword-loss-based (with additional keyword loss) models on the DailyDialog dataset (Li et al., 2017b). We initialize the network with weights of DialogPT ‘medium’ model with 345M parameters. We also use 2 candidates for the next utterance prediction task. We use language modeling and multiclass-classification coefficients of 1. We use a batch_size of 64 for training, nucleus sampling for generation with top_p set to 0.9. We fine-tune the model for 3 epochs. We run experiments on 5 main classes of models: i) No-keyword model (no_kw henceforth): Trained without any keyword information ii) Keyword-context (kw_context): Trained with keyword as auxiliary input + dialog context iii) Keyword-loss (kw_loss): Incorporates keyword loss + keyword as auxiliary information. iv) Keyword sim-loss (kw_sim_loss): Incorporate similar words (embedding-based techniques such as Glove (Pennington et al., 2014) (kw_sim_loss_glove) or wordnet-based (kw_sim_loss_wordnet) similarity for loss computation. We experiment with 2 variations, one using the similarity score, and the other using 1. v) Multiple-keyword-loss (multi_kw_loss): Incorporate multiple keywords into the input as well as into the loss computation.

### 4.1 Datasets

We use the Dailydialog dataset (Li et al., 2017b), which consists of 13,118 daily conversations involving various topics such as tourism, culture, and education among others. The validation and test sets have 1000 conversations each. For the conversation context, we consider a maximum of upto 5
previous utterances as history for generation. We use the test set, consisting of 6740 context-response pairs, to evaluate our models which will be discussed in the results section. DailyDialog dataset contains daily life communication with the goals of exchanging ideas and information and enhancing social bonding. This dataset contains suitable interactions for building applications to support social communication and daily life interactions and serves as a starting point for AAC applications.

4.2 Automatic Evaluation
We use several automatic metrics to compute the performance of our models. Given the well-discussed fact that word-overlap based metrics do not agree well with human judgment, we utilize other learning based and embedding-based metrics to evaluate the generated response with the reference ground truth.

4.2.1 Metrics for Evaluating Keyword Predictor Models
The keyword predictor model should be able to generate diverse keywords to present varied options for users to choose from. We evaluate the extractive and generative models based on the diversity of keywords generated. We use averaged cosine similarity between generated keywords as a measure of diversity—lower the similarity, higher the diversity. We hypothesize that meaningful keywords will result in generation of meaningful and context-relevant responses. Hence, we compute ‘human-like’ and coherence scores for the generated responses using DialogRPT (Gao et al., 2020), a model trained to predict human feedback dialogue responses.

4.2.2 Metrics for Evaluating Controllable Response Generation Model
Keyword Insertion Accuracy (KIA): The main goal of this work is to provide fine-grained control to the user to have the model induce a keyword (or a word with a similar meaning) in the response. With this in mind, we compute the keyword-insertion accuracy to evaluate the controllable response generation models.

Similarity Based Metrics: For the metrics in this section, we consider the conversation context, generated response and the ground truth for evaluation. Because we intend to generate responses based on keywords, computing measures of similarity between the generated response and ground truth response (in the learnt embedding space) gives a good assessment for the model performance. We use BLEURT, BERTScore (Zhang et al., 2020a) (Sellam et al., 2020), Sentence-BERT (Reimers and Gurevych, 2019) to compute similarity between generated response and ground truth.

Response Quality Metrics: Given the one-to-many nature of open domain dialog, although the above metrics provide a good sense of the generated response, evaluating the quality of response is essential. We only focus on turn level response quality aspects such as fluency, context coherence and diversity. We perform language model based evaluation for fluency and context-coherence and n-gram based diversity evaluation. We also measure the perplexity (PPL) by employing a pretrained GPT-2 "medium" model.

4.3 Human Evaluation
We perform human evaluation via Amazon Mechanical Turk to evaluate the keyword predictor models and controllable response generation models. Towards measuring this we perform evaluations in 3 separate crowd-tasks.

Task 1: Collecting response for automatic and human-entered keywords
We present a conversation context and keywords (from the extractive and generative keyword prediction models) to the turkers and ask them to come up with possible responses relevant to these keywords. The turkers are also asked to answer a question about the relevance of each keyword to the provided context. This information is also used to evaluate the keyword predictor models. To represent human-control in our analysis, the turkers are also asked to enter keywords of their choice, along with the corresponding responses.

Task 2: Overall system interaction and metrics
We use the data obtained in Task 1 (keywords: human and model-generated, and the responses (we treat these as ground truth human responses)). In the interaction flow, the user reads the conversation context, picks a keyword that he/she wants to respond with - which brings up a human response and a model response (kw_loss model). The user can either pick one of the presented responses or edit them partially or type a new response altogether. We present the user with a set of questions based to enables us to understand the reason for the choice made by the user. We analyse
Table 1: Evaluation of keyword predictor models.

| Kw Predictor | Coherence | Human-like | Diversity ↓ |
|--------------|-----------|------------|-------------|
| Generative   | 0.903     | 0.641      | 0.227       |
| Extractive   | 0.891     | 0.595      | 0.265       |

We present the evaluation results on the similar-words generated - lower score indicates higher diversity. We can observe that the generative keyword predictor tends to generate more diverse keywords (lower similarity score), which is very important in our use-case. The responses generated by choosing the keywords from the generative predictor are more coherent and human-like.

Cue/Keyword controlled models: We experiment the keyword-loss models with various values of $\gamma$ ranging between 0 and 1 and see the best performance when $\gamma=0.005$ (details in Appendix). Henceforth, unless otherwise mentioned, we will use $\gamma=0.005$ for all our experiments. Table 2 shows the performance of the response generation models. From the table, the KIA for the no_kw model is negligible, given the one to many nature of open

Figure 2: Shows the responses to the questionnaire. We observe that users significantly felt that they chose the keyword & response as they were most relevant to what was on their mind. We also observe that the users disagree that they chose a response because of it’s length. (One-Sample Wilcoxon Signed Rank Test (mu=0)).

Figure 3: Results from human evaluation. (One-Sample Wilcoxon Signed Rank Test (mu=0) for the statistical tests.*** p<0.001, ** p<0.01, * p<0.05.)

If the users tend to choose a model or a keyword response and also compute the word error rates (WER) for the edits corresponding to the human and model responses.

Task3: Human Evaluation of controllable response generation models: To perform human evaluation of the quality of the responses, we randomly pick 100 dialog contexts and present the context along with the keyword and pairs of responses from the models and ask 3 annotators to rate the responses based on the following criteria: 1) Fluency: how natural and fluent the responses are, 2) Generic: are the responses too generic given the dialog context?, 3) Context relevance: how relevant and coherent is a response to a given dialog context, 4) Keyword relevance: how relevant is a response to the input keyword?

We present pairs of responses from models A and B and provide 4 options for for each of the above criteria: A better than B, B better than A, Both and, Neither. We evaluate the pairs, no_keyword vs kw_context, no_keyword vs kw_loss and kw_context vs kw_loss. We compute the scores using a majority vote across 3 annotators.

5 Results

In this section we present the results of human and automatic evaluation on the performance of our keyword-based controllable response generation models and the keyword predictor models.

5.1 Automatic Evaluation Results

We present the evaluation results on the similarity and response-quality metrics computed on the conversation context, generated response and the reference response, on the DailyDialog testset.

Keyword Predictor Models: Table 1 shows the performance of the keyword predictor models based on diversity and the keyword-success-rate (coherence and human-like scores). The diversity of the generated keywords is measured using average cosine-sim computed between pairs of keywords generated - lower score indicates higher diversity. We can observe that the generative keyword predictor tends to generate more diverse keywords (lower similarity score), which is very important in our use-case. The responses generated by choosing the keywords from the generative predictor are more coherent and human-like.
Table 2: Performance of the various controllable models for single and multi-keyword inputs ($\gamma = 0.005$). Label “-1” indicates that we set $\text{sim}(k, kw) = 1$ in equation 3.

|                | KIA    | Similarity | BLEURT | BERT Score | Context | Diversity | Fluency | PPL↓ |
|----------------|--------|------------|--------|------------|---------|-----------|---------|------|
| **Single Keyword** |        |            |        |            |         |           |         |      |
| no_kw          | 0.083  | 0.271      | -1.35  | 0.868/0.836/0.851 | 0.541  | 1.592     | 0.407   | 39.098 |
| kw_context     | 0.672  | 0.539      | -0.67  | 0.844/0.853/0.868 | 0.568  | 1.789     | 0.403   | 41.752 |
| kw_loss        | 0.694  | 0.542      | -0.69  | 0.885/0.852/0.868 | 0.579  | 1.726     | 0.407   | 43.115 |
| kw_sim_loss_glove-1 | 0.684 | 0.541 | -0.606 | 0.884/0.852/0.868 | 0.585 | 1.729 | 0.405 | 42.544 |
| kw_sim_loss_wordnet-1 | 0.686 | 0.540 | -0.615 | 0.884/0.852/0.868 | 0.581 | 1.726 | 0.403 | 42.606 |
| kw_sim_loss_glove | 0.680  | 0.543      | -0.610 | 0.885/0.852/0.868 | 0.570  | 1.741     | 0.403   | 42.362 |
| kw_sim_loss_wordnet | 0.672  | 0.541      | -0.606 | 0.884/0.852/0.867 | 0.576  | 1.733     | 0.403   | 42.301 |
| **Multiple Keywords** |        |            |        |            |         |           |         |      |
| no_kw          | 0.041  | 0.271      | -1.35  | 0.868/0.836/0.851 | 0.541  | 1.592     | 0.407   | 39.098 |
| kw_context     | 0.293  | 0.607      | -0.499 | 0.895/0.857/0.875 | 0.489  | 1.396     | 0.399   | 75.300 |
| kw_loss        | 0.300  | 0.604      | -0.524 | 0.894/0.856/0.874 | 0.492  | 1.354     | 0.412   | 83.971 |
| kw_sim_loss_glove-1 | 0.302 | 0.610 | -0.535 | 0.895/0.857/0.875 | 0.487 | 1.366 | 0.416 | 84.367 |

5.2 Human Evaluation Results

**Task1:** We collect about 1000 responses for the keywords suggested by the two keyword predictors and also collect 1000 additional human keywords and corresponding responses (resulting in about 2000 responses). We also compute keyword-context-relevance from the data provided by users. From Table 1, we see that crowdworkers find keywords generated from generative keyword predictor as more relevant to the conversation context than that generated by the extractive keyword predictor.

**Task2:** Analysing the response choice (human vs model generated) of the turkers, we find that from 121 interactions, 34.7% of the interactions used model response, and 29.7% used human response. We also observe that 60 interactions result in edits of the response by the turkers. Out of this, the WER for edits for a human response is 0.45 while WER for edits is lower when a model response is chosen, at 0.39. This indicates that the model response is relevant and captures the content to be conveyed by the user well. Figure 2 shows some statistics on the responses to the questions asked to the user after the above interaction. The plot shows that most people agree/strongly agree that they picked the keyword/response because it seemed relevant to the context or it resonated with the response in their mind. The plot also shows that people did not choose a response because it was short to edit. This analysis shows that our procedure of suggesting keywords followed by relevant responses is the right strategy for building the controllable response generation system.

**Task3:** Figure 3 shows the scores for the response quality metrics for different model. From human ratings, we observe that the kw_loss and kw_context models outperform the model without control, on all metrics significantly. The keyword-based models generate more fluent and relevant responses while at the same time, generating less generic responses compared to the no_keyword model. We also observe that humans rate kw_context and kw_loss models as very comparable, with kw_loss models being more keyword and context relevant as also established...
by the automatic evaluations.

6 Conclusion

In this paper, we present a novel usage for open domain conversational models - representing differently abled users and enabling them to communicate. In such a use-case, minimizing the need for user intervention is critical, hence the focus of this work has been to develop controllable response generation models that enable fine-grained human control in the form of keyword inputs from the user. We also introduce keyword-based loss functions that encourages the model to generate the keyword or similar words in the response. We show using automatic and human evaluation that these loss functions help in generating more keyword relevant responses. We also extend this to control using multiple keywords, that could further make the models less-restrictive to users. To further improve efficiency and time in interaction, we develop keyword predictors and evaluate them. We show with both automatic and human evaluation that our models outperform the baseline model with no control, at the same time maintaining the response quality. As future work, we plan to broaden the usage of this system to cater to a larger diversity of differently abled population, to help in communication. We are also working with patients to collect feedback and plan to deploy our system as part of a larger AAC system to impact the quality of life of the patients and help the caregivers. Future research direction also involves personalization of these controllable models (both speech and linguistic) that could make these systems more powerful and capable of representing a user.

References

D. Adiwardana, Minh-Thang Luong, D. So, J. Hall, Noah Fiedel, R. Thoppilan, Z. Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, and Quoc V. Le. 2020. Towards a human-like open-domain chatbot. ArXiv, abs/2001.09977.

David Beukelman, Susan Fager, and Amy Nordness. 2011. Communication support for people with als. Neurology research international, 2011:714693.

Rishi Bommasani, Drew A. Hudson, Elhsan Adeli, Russ Altman, et al. 2021. On the opportunities and risks of foundation models.

Erin Brady, Meredith Ringel Morris, Yu Zhong, Samuel White, and Jeffrey P. Bigham. 2013. Visual challenges in the everyday lives of blind people.

In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’13, page 2117–2126, New York, NY, USA. Association for Computing Machinery.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Giuseppe Castellucci, Valentina Bellomaria, A. Favalli, and R. Romagnoli. 2019. Multi-lingual intent detection and slot filling in a joint bert-based model. ArXiv, abs/1907.02884.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe PetroskiSuch, Dave Cummings, MatthiasPlappert, FotosChantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, NikolasTezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and WojciechZaremba. 2021. Evaluating large language models trained on code.

Mia Xu Chen, Benjamin N. Lee, Gagan Bansal, Yuan Cao, Shuyuan Zhang, Justin Lu, Jackie Tsay, Yinan Wang, Andrew M. Dai, Zhifeng Chen, Timothy Sohn, and Yonghui Wu. 2019a. Gmail smart compose: Real-time assisted writing. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’19, page 2287–2295, New York, NY, USA. Association for Computing Machinery.

Qian Chen, Zhu Zhuo, and W. Wang. 2019b. Bert for joint intent classification and slot filling. ArXiv, abs/1902.10909.

Sumanth Datathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2020. Plug and play language models: A simple approach to controlled text generation. In
Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

R. Elakkiya. 2020. Machine learning based sign language recognition: a review and its research frontier. Journal of Ambient Intelligence and Humanized Computing.

Stephanie H. Felgoise, Vincenzo Zacecho, Jason Duff, and Zachary Simmons. 2016. Verbal communication impacts quality of life in patients with amyotrophic lateral sclerosis. Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration, 17(3-4):179–183. PMID: 27094742.

Judy Flax, Christine Gwin, Sherri Wilson, Yuli Fradkin, Steve Buyske, and Linda Brzustowicz. 2019. Social (pragmatic) communication disorder: Another name for the broad autism phenotype? Autism, 23(8):1982–1992. PMID: 30931583.

Raefer Gabriel, Yang Liu, Anna Gottardi, Mihail Eric, Anju Khatri, Anjali Chadha, Qinlang Chen, Behnam Hedayatnia, Pankaj Rajan, Ali Binici, Shui Hu, Kartik Gopalakrishnan, S. Kim, Lauren Stibel, Kate Bland, Arindam Mandal, and Dilek Z. Hakkani-Tür. 2020. Further advances in open domain dialog systems in the third alexa prize socialbot grand challenge.

Xiang Gao, Yizhe Zhang, Michel Galley, Chris Brockett, and Bill Dolan. 2020. Dialogue response ranking training with large-scale human feedback data. In EMNLP.

Marjan Ghazvininejad, Xing Shi, Jay Priyadarshi, and Kevin Knight. 2017. Hafez: an interactive poetry generation system. In Proceedings of ACL 2017, System Demonstrations, pages 43–48, Vancouver, Canada. Association for Computational Linguistics.

Chris Gibbons and Erin Benetou. 2010. Functional performance using eye control and single switch scanning by people with ALS. Perspectives on Augmentative and Alternative Communication, 19(3):64–69.

Maarten Grootendorst. 2020. Keybert: Minimal keyword extraction with bert.

Anhong Guo, Ece Kamar, Jennifer Wortman Vaughan, Hanna Wallach, and Meredith Ringel Morris. 2020. Toward fairness in AI for people with disabilities sbg@a research roadmap. SIGACCESS Access. Comput., (125).

Prakhar Gupta, Jeffrey P. Bigham, Yulia Tsvetkov, and Amy Pavel. 2020. Controlling dialogue generation with semantic exemplars. CoRR, abs/2008.09075.

Michael Heck, Carel van Niekerk, Nurul Lubis, Christian Geishauser, Hsien-Chin Lin, Marco Moresi, and Milica Gasic. 2020. TripPy: A triple copy strategy for value independent neural dialog state tracking. In Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 35–44, 1st virtual meeting. Association for Computational Linguistics.

Nitish Shirish Keskar, Bryan McCann, Lav R. Varshney, Caiming Xiong, and Richard Socher. 2019. CTRL: A conditional transformer language model for controllable generation. CoRR, abs/1909.05858.

Olga Kovaleva, Anna Rumshisky, and Alexey Romanov. 2018. Similarity-based reconstruction loss for meaning representation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4875–4880, Brussels, Belgium. Association for Computational Linguistics.

Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017a. Dailydialog: A manually labelled multi-turn dialogue dataset.

Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017b. Dailydialog: A manually labelled multi-turn dialogue dataset. In Proceedings of the Eighth International Joint Conference on Natural Language Processing, IJCNLP 2017, Taipei, Taiwan, November 27 - December 1, 2017 - Volume 1: Long Papers, pages 986–995. Asian Federation of Natural Language Processing.

Katharina Linse, Elisa Aust, Markus Joos, and Andreas Hermann. 2018. Communication matters—pitfalls and promise of high-tech communication devices in palliative care of severely physically disabled patients with amyotrophic lateral sclerosis. Frontiers in Neurology, 9:603.

Haley MacLeod, Cynthia L. Bennett, Meredith Ringel Morris, and Edward Cutrell. 2017. Understanding blind people’s experiences with computer-generated captions of social media images. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, CHI ’17, page 5988–5999, New York, NY, USA. Association for Computing Machinery.

Andrea Madotto, Etsuko Ishii, Zhaojiang Lin, Sumanth Dathathri, and Pascale Fung. 2020. Plug-and-play conversational models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, EMNLP 2020, Online Event, 16-20 November 2020, pages 2422–2433. Association for Computational Linguistics.

J. Mišek, P. Caroni, P. Duchamp, A. Gasser, R. Marko, N. Mišek, F. Zwilling, C. de Castelbajac, L. Eicher, M. Früh, and H. Früh. 2020. Lio-a...
personal robot assistant for human-robot interaction and care applications. *IEEE Robotics and Automation Letters*, 5(4):5339–5346.

Kuniaki Ozawa, Masayoshi Naito, Naoki Tanaka, and Shiryu Wada. 2020. A word communication system with caregiver assist for amyotrophic lateral sclerosis patients in completely and almost completely locked-in state.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global vectors for word representation. In *Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543.

A. Radford and Karthik Narasimhan. 2018. Improving language understanding by generative pre-training.

Ashwin Ram, Rohit Prasad, Chandra Khatri, Anu Venkatesh, Raefer Gabriel, Qing Liu, Jeff Nunn, Behnam Hedayatnia, Ming Cheng, Ashish Nagar, Eric King, Kate Bland, Amanda Wartick, Yi Pan, Han Song, Sk Jayadev, Gene Hwang, and Art Petrigue. 2018. Conversational ai: The science behind the alexa prize.

A. Radford, Ilya Sutskever, and K. Lux. 2020. MRK: Biological structure and function emerge from scaling unsupervised learning to 250 million protein sequences.

Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019*, pages 3980–3990. Association for Computational Linguistics.

Alexander Rives, Joshua Meier, Tom Sercu, Siddharth Goyal, Zeming Lin, Jason Liu, Demi Guo, Myle Ott, C. Lawrence Zitnick, Jerry Ma, and Rob Fergus. 2020. Biological structure and function emerge from scaling unsupervised learning to 250 million protein sequences. *bioRxiv*.

Melissa Roemmele. 2021. Inspiration through observation: Demonstrating the influence of automatically generated text on creative writing. *arXiv preprint arXiv:2107.04007*.

Melissa Roemmele and Andrew S Gordon. 2018. Automated assistance for creative writing with an rnn language model. In *Proceedings of the 23rd International Conference on Intelligent User Interfaces Companion*, pages 1–2.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric Smith, Y-Lan Boureau, and Jason Weston. 2020. Recipes for building an open-domain chatbot.

Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019a. What makes a good conversation? how controllable attributes affect human judgments. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1702–1723, Minneapolis, Minnesota. Association for Computational Linguistics.

Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019b. What makes a good conversation? how controllable attributes affect human judgments. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 1702–1723. Association for Computational Linguistics.

Thibault Sellam, Dipanjan Das, and Ankur P. Parikh. 2020. BLEURT: learning robust metrics for text generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online. July 5-10, 2020*, pages 7881–7892. Association for Computational Linguistics.

Lei Sha. 2020. Gradient-guided unsupervised lexically constrained text generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8692–8703. Online. Association for Computational Linguistics.

Joel Shor, Dotan Emanuel, Oran Lang, Omry Tuval, Michael Brenner, Julie Cattiau, Fernando Vieira, Maeve McNally, Taylor Charbonneau, Melissa Nollstadt, and et al. 2019. Personalizing asr for dysarthric and accented speech with limited data. *Interspeech 2019*.

Eric Michael Smith, Diana Gonzalez-Rico, Emily Dinan, and Y-Lan Boureau. 2020. Controlling style in generated dialogue. *CoRR*, abs/2009.10855.

TherapyBox. 2021. Predictable: Text-to-speech aac app (accessed sept 2021).

Zehra Topal, Nuran Demir, Sarper Taskiran, Ali Evren Tufan, and Bengi Semerci. 2018. Social communication disorder: A narrative review on current insights. *Neuropsychiatric Disease and Treatment*, Volume 14:2039–2046.

Verbally. 2021. Verbally app (accessed sept 2021).

Ashwin Vijayakumar, Michael Cogswell, Ramprasaath Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2018. Diverse beam search for improved description of complex scenes. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1).

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018.
Appendix

A Human Evaluation Setup Details

Human evaluation of our system is split into three tasks: task 1 for collecting keywords and corresponding responses from humans. Task 2 involved the crowd workers on Amazon Mechanical Turk interact with our system. We used the keyword suggestions from our extractive and generative keyword predictor models and also the human-generated keywords. We run our controlled response generation pipeline on these keywords to obtain relevant responses. In this task, we first present the turkers with the conversation context as shown in 4. We also present 9 keyword suggestions - 3 from the extractive keyword predictor, 3 from the generative keyword predictor and 3 keywords generated by humans (from task 1). Figure 5 shows this step. Choosing one of these keywords, brings up responses from the human responses generated from Task1, and our controllable response generation model. We use \( kw \_loss \) model with \( \gamma = 0.005 \) and diverse beam search to generate the responses. The users can choose one of the responses and further edit, or enter his/her own response in the box provided. We then present a questionnaire to the turkers - asking them to answer on a likert scale, some questions about why they chose a particular keyword/responses. At the end, turkers are shown a virtual keyboard as you can see in Figure 6 and asked to type in the response that they chose/edited. Their physical keyboard is disabled for this part of the task - this is to ensure that the turkers use the virtual keyboard and generate the given text. This data enables us to compare the time it
Figure 5: Shows the step 2 for Task 2 on the MTurk study. Here the turkers are shown 9 keywords (generated from keyword predictor models and humans from task 1). Choosing one of them allows them to see the response generated from our models, and human-generated ground truth response, that can be chosen.

Figure 6: Shows the step 4 for Task 2 on the MTurk study. Step 3 is questionnaire with radio button options which is not shown above.

took to complete a single interaction and the time it takes to actually type in the entire response (future work).

B Experiments

We present the effect of varying the $\gamma$ coefficient in the keyword-based loss models. These results are presented in table 3. Please note that when $\gamma = 0$, the model is the $\text{kw}_{\text{context}}$ model. We see from the table that increasing $\gamma$ increases the KIA, which matches our intuition, and reaches close to 75% when $\gamma = 1$. However, we see that this is optimal when $\gamma = 0.005$. Similarity metrics such as BLEURT see a drop as we increase $\gamma$ with the lowest at 1. Also, Response Quality deteriorates heavily with context coherence, diversity and fluency metrics. While the higher $\gamma$ tries to increasingly encourage the model to generate the keyword in the sentence, this is at the cost of the overall quality of the response. Hence, in all of the experiments and results reported in the paper, we fix $\gamma = 0.005$, unless otherwise specified.

C Sample Model Outputs

In Table 4, we present the outputs from the various models - for a given context and keyword. We show the sample outputs from the $\text{no_kw}$, $\text{kw}_{\text{context}}$, $\text{kwloss}_{0.005}$, $\text{kwloss}_{\text{sim}}_{\text{loss}}_{\text{glove}}$ models and the ground truth. We see that the keyword-based models are able to effectively induce the keywords into the generated sentence.

D Keyword Control with Multiple Inputs

Table 5 shows the results from our experiments with training the models with multiple keywords as control. We see that $\text{kw}_{\text{sim}}_{\text{loss}}_{\text{wordnet}} - 1$ performs well on several metrics. We plan to look into these models further as part of future work.
**Table 3:** Examining the effect of $\gamma$

| coeff=0  | KWI Accuracy | Similarity | BLEURT | Context | Diversity | Fluency | PPL   |
|----------|---------------|------------|--------|---------|-----------|---------|-------|
| 0.672    | 0.539         | **-0.607** | 0.568  | 1.789   | 0.403     | 41.752  |
| coeff=0.005 | 0.694  | 0.542        | -0.609 | 0.579   | 1.726     | **0.407** | 43.115 |
| coeff=0.01 | 0.681   | 0.538        | -0.629 | **0.581** | 1.641     | 0.406   | 45.749 |
| coeff=0.1  | 0.690   | 0.508        | -0.846 | 0.519   | 0.888     | 0.397   | 92.567 |
| coeff=1    | **0.746**  | 0.527        | -0.826 | 0.468   | 0.695     | 0.373   | 90.070 |

**Context**

**Speaker1:** John, I'd like you to meet Charles Brown, our new manager at the airport.

**Speaker2:** Yes, certainly. How can I recognize him?

**Speaker1:** He is short, well-built, and he's got light blond hair.

**Speaker2:** Is there anything else?

**Speaker1:** Please tell me something about your insurance background.

**Speaker2:** I majored in international banking at college so I took many insurance courses. And I worked at an insurance company for my graduation field work.

**Speaker1:** Why do you want to be an insurance agent?

**Speaker2:** I care about people and I know the importance of insurance.

**Speaker1:** Do you have any work experience in promotion?

**Keyword**

**NoKeyword**

Yes, he is tall, but he is slim.

**Keyword**

**mustache**

He has a rather bushy facial beard and a moustache.

**NoKeyword**

He has a rather light mustache, too.

**Keyword**

No, he has a very nice mustache.

**NoKeyword**

Yes, I have been promoted twice. I have been promoted twice as well.

**GroundTruth**

He has a mustache, if I remember correctly, and a light complexion.

Yes, I do. I have worked as a salesman for P and G Company Ltd.

**Context**

**Speaker1:** Were you in a leadership position when you were a college student?

**Speaker2:** Yes. I was president of the Student Council of our university.

**Speaker1:** Did you get any honors or awards at your university?

**Speaker2:** Yes. I was elected Excellent Party Member for four academic years.

**Speaker1:** Were you involved in any club activities at your university?

**Speaker2:** Yes. I was a member of the Student Poetry Society. I like writing poems in my spare time.

**Speaker1:** Do you have a free moment?

**Speaker2:** Sure. What do you need?

**Speaker1:** I’m having some trouble. How do you use this printer?

**Speaker2:** Well, first you have to turn this switch on.

**Speaker1:** Silly me.

**Keyword**

**extracurricular**

What kinds of poems did you write?

**NoKeyword**

It's not complicated.

**Keyword**

**button**

Did you have any extracurricular activities?

**NoKeyword**

Then press the button.

**Keyword**

**KwLoss_0.005**

Were you involved in any extracurricular activities?

**NoKeyword**

Now press this button.

**Keyword**

**kwloss_sim_glove**

What was your extracurricular activities?

**NoKeyword**

Then press the button.

**Keyword**

**GroundTruth**

What extracurricular activities did you usually take part in at your college?

**NoKeyword**

Now press this button.

**Table 4:** Sample conversation contexts and comparison of different model outputs
Table 5: Performance of the various controllable models for multiple keyword input ($\gamma = 0.005$). Label "-1" indicates that we set $\text{sim}(k, kw) = 1$ in equation 3.