Towards Ecologically Valid Research on Language User Interfaces

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Abstract

Language User Interfaces (LUIs) could improve human-machine interaction for a wide variety of tasks, such as playing music, getting insights from databases, or instructing domestic robots. In contrast to traditional hand-crafted approaches, recent work attempts to build LUIs in a data-driven way using modern deep learning methods. To satisfy the data needs of such learning algorithms, researchers have constructed benchmarks that emphasize the quantity of collected data at the cost of its naturalness and relevance to real-world LUI use cases. As a consequence, research findings on such benchmarks might not be relevant for developing practical LUIs. The goal of this paper is to bootstrap the discussion around this issue, which we refer to as the benchmarks’ low ecological validity. To this end, we describe what we deem an ideal methodology for machine learning research on LUIs and categorize five common ways in which recent benchmarks deviate from it. We give concrete examples of the five kinds of deviations and their consequences. Lastly, we offer a number of recommendations as to how to increase the ecological validity of machine learning research on LUIs.

1 Introduction

In 1991, cognitive scientist Susan E. Brennan wrote the following introduction for one of her papers (Brennan, 1991):

Why is it that natural language has yet to become a widely used modality of human/computer interaction? Visionaries seem to have no difficulty imagining a future where we’ll be able to talk to software applications – or even computer agents – in plain English. And yet the only exposure large numbers of users have had to such interfaces has been through limited question answering systems and keyword interfaces to adventure games.

Nearly three decades later, her observation still holds: Language User Interfaces (LUIs) only play a limited role in our daily interaction with machines. The recent technological advances in Natural Language Processing (NLP) (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017; Devlin et al., 2019), somewhat surprisingly, have not yet moved the needle in terms of LUI adoption. This motivates us to discuss how academic research on LUIs can be made more aligned with the goal of developing practical LUIs.

We are interested in language user interfaces that enhance human capabilities. Specifically, we focus on interfaces that support performing a useful and concrete task, such as searching for information in large collections of documents, booking flights, getting insights from statistical data or instructing domestic robots. In the dialogue literature, these systems are referred to as goal-oriented (Serban et al., 2018) because they facilitate the completion of an unambiguous task, often within a small number of interactions. We distinguish this from the line of work on social chatbots (also known as chit-chat systems) (Ram et al., 2018; Zhou et al., 2020; Adiwardana et al., 2020) whose purpose is to engage and entertain users.

At the time of Brennan’s writing, developing language user interfaces was done by symbolic AI engineers, who analyzed the problem domain and designed linguistic rules for mapping utterances onto formal meaning representations (see, e.g., a survey of early language user interfaces to databases by Androutsopoulos et al. (1995)). While the rule-based paradigm is still widespread (see, e.g., a more recent review by Affolter et al. (2019)), its scalability is limited by the large amounts of expert labor needed to develop, main-
tain and adapt such systems. We therefore focus our analysis on the Machine Learning (ML) approach, in which the bulk of knowledge about natural language is entered as example utterances or dialogues. The use of data instead of expert labor promises better scalability and flexibility, but a key assumption underlying these hopes is that the data is available and appropriate.

Ideally, the data used for training and evaluating the learned LUIs should reflect the intents and linguistic phenomena found in real-world applications and be of reasonable size to accommodate modern data-intensive methods. In certain industrial settings such data might be readily available as logs of users interacting with an existing interface, e.g., Siri or Google Assistant. Such datasets are rarely publicly available both due to customer data privacy needs and their commercial value. For the broader research community, on the other hand, the two requirements of data quality (and in particular its representativeness) and quantity are hard to reconcile.

Earlier literature features data collection efforts of exceptional execution quality, in which researchers attempted to closely simulate the LUI’s anticipated use-case. Some of them were run as user studies (Grosz, 1974; Kelley, 1984; Dahlbäck et al., 1993; Carbonell, 1983), whereas others aimed to collect data for automatic evaluation purposes (Hemphill et al., 1990; Dahl et al., 1994). In both cases, the methods employed to achieve this quality were expensive and hard to scale up. The vast majority of the collected corpora contains anywhere from tens to hundreds of utterances, which is hardly enough for deep-learning-based approaches.

In pursuit of more data, many recent benchmarks opted for cheaper and more scalable methods. For example, it is common these days to use artificial tasks with no naturalistic counterparts or to work with crowd workers that are not representative of the target user population. It is unclear what the consequences of these compromises are for the transferability of research findings. In particular, one can wonder to which extent improvements on these benchmarks translate into more useful language user interfaces.

The questions that we pose above correspond to the notion of external, and more specifically, ecological validity from the psychology literature. The conclusions of an externally valid experiment should hold outside the context of that study (Bronfenbrenner, 1977; Brewer and Crano, 2014). For psychological studies it often indicates whether a causal effect holds up across different populations, environments, or stimuli. Ecological validity is a special case of external validity, specifying the degree to which findings generalize to naturally occurring scenarios. The key strength of studies with high ecological validity is that they generate insights that are practically relevant and useful. Such studies on LUIs are commonly found in the Human Computer Interaction (HCI) community, e.g. by conducting interviews with real-world users of commercial personal assistants (Luger and Sellen, 2016; Cowan et al., 2017).

With this paper, we wish to encourage discussions on the ecological validity of LUI research benchmarks. We first discuss several important LUI usecases in Section 2 to make the paper’s scope concrete. In Section 3, we sketch what we think is an ecologically valid research methodology for how valid research on LUI should be conducted. We then review in Section 4 how recently proposed benchmarks deviate from it and
find five common issues—synthetic language, artificial tasks, not working with prospective users, the use of scripts and/or priming, and single-turn interfaces—and show through concrete examples how these issues limit the benchmarks’ ecological validity. We discuss other ecological validity concerns in Section 5 and conclude with recommendations as to how to increase the ecological validity of machine learning research on LUIs in Section 6.

2 Examples of Language User Interfaces

Before we discuss the notion of ecological validity, we will make the concept of language user interfaces more tangible by listing a number of prominent use cases. Note that we intentionally focus on the end user applications and not on the underlying technologies or the corresponding academic “tasks”, such as question answering and semantic parsing, which are more commonly referred to in academic papers. It is the close connection to one of such real-world use cases that makes a task or benchmark ecologically valid.

**Personal assistants** LUIs could aid people in the organisation of their daily lives. For example, such personal assistants can help with obtaining weather forecasts, managing calendar events, and reserving restaurant tables. Google Assistant and Siri are two well-known examples of LUIs that are aiming to provide these services.

**Assistants for the visually impaired** LUIs could aid blind people in overcoming many of their daily challenges. One can, for example, think of an application where visually impaired people could take pictures of their immediate surroundings and ask targeted questions about its content (Gurari et al., 2018). Such assistants could enable them to identify objects, read text labels, or obtain other information that is usually only available to people with good eyesight.

**Customer support assistants** LUIs could provide customer support for purchasing goods and services. Such assistants could, for example, guide the customer through the buying process through a chat-based interface. They can also answer detailed questions about the service provider’s policies, going beyond the lengthy list of Frequently Asked Questions (FAQ).

| An Ecologically Valid Research Procedure |
|------------------------------------------|
| 1. Identify a population of users $P^T$ who would benefit from a language user interface to perform a task $T$. The constructed LUI should increase the user’s productivity in task $T$ compared to alternative interfaces. |
| 2. Collect conversations and corresponding programs/actions through a Wizard-of-Oz simulation of performing task $T$. |
| 3. Train a model |
| 4. Assess how satisfied the user is with the trained model through a $P^T$-in-the-loop evaluation. |

Table 1: Summary of the proposed ecologically valid research procedure on LUIs.

**Assistants for business analysts** LUIs could help analysts obtaining insights into business processes. While this task usually requires writing SQL queries for relational databases or navigating graphical dashboards, LUIs can improve the user experience by enabling natural language requests.

**Domestic appliances and robots** LUIs could aid our interaction with domestic appliances and robots. For example, they would enable controlling TVs or other appliances through natural language instructions. In the longer term, LUIs could also be helpful for interacting with physical robots, e.g. to instruct them to iron shirts or clean the floor.

3 Ecologically Valid Research

By the very definition of the concept, ecologically valid research on LUIs should strive to build LUIs that people would enjoy or benefit from using in their personal or professional life. It should thus start with identifying a population of people $P^T$ in need of assistance with task $T$. Moreover, the developed LUI for this task needs to be more valuable or usable than available alternatives. For example, because users are unable to complete the task with the current interface or would be more satisfied with a language user interface.

Identifying the user and the task is step 1 out of
4 in the ideal methodology that we propose here (see Table 1). Step 2 is to collect data to train the system. For machine learning it is of utmost importance to gather data under conditions that are similar to the deployment setting. Yet the exact deployment setting cannot be simulated until the system is trained and deployed.

To bootstrap out of this chicken and egg problem, the yet-to-be-built LUI can be simulated by a “wizard”. The wizard translates the user’s instructions to programs (e.g., SQL queries) or actions that the machine can execute, often with the help of specifically designed tools for the task (see Figure 1). The described approach is often referred to as Wizard-of-Oz (WoZ) (Kelley, 1984; Fraser and Gilbert, 1991; Maulsby et al., 1993). Ideally, in a WoZ simulation the user should think that they interact with a machine and not know there is a human “behind the curtain”. The argument for maintaining the illusion is that people adjust their language to the characteristics of the listener (Shatz and Gelman, 1973), implying that users interact differently with machines than with human interlocutors. Work from the 80s and 90s puts a lot of emphasis on this aspect of the simulation (Kelley, 1984; Dahlbäck et al., 1993). However, the use of a human wizard is not concealed in Sinha et al. (2002) and it is unclear if, in 2020, people could be easily convinced that they are interacting with a machine despite the unavoidable long response times (for it takes time for the wizard to execute what the user wants and possibly also respond). For this reason, we will not view the user’s awareness of simulation as a deviation, even though strictly speaking it is one.

Once the WoZ setup is constructed, one collects a large number of WoZ interactions and records the conversations as well as the programs or actions created by the wizard. Using this dataset, one trains a model to interpret the natural language conversations and predict the programs or actions of the wizard. Finally, one assesses how satisfied the user is with the resulting model and compares it to a traditional interface or a competing model. Ideally, this process measures several aspects of human satisfaction through a human-in-the-loop evaluation with users coming from $P^T$.

| User:  | good morning |
| Wizard:  | hello what can i help you with today |
| User:  | can you book a table in a moderate price range with british cuisine for eight people in rome |
| Wizard:  | i’m on it |
| User:  | SILENCE |
| Wizard:  | ok let me look into some options for you |
| User:  | SILENCE |
| Wizard:  | api_call british rome eight moderate |
| User:  | instead could it be for six people |
| Wizard:  | sure is there anything else to update |
| User:  | instead could it be in bombay |
| Wizard:  | sure is there anything else to update |
| User:  | instead could it be with italian food |
| Wizard:  | sure is there anything else to update |
| User:  | actually i would prefer in a expensive price range |
| Wizard:  | sure is there anything else to update |
| User:  | no |
| Wizard:  | ok let me look into some options for you |
| User:  | SILENCE |
| Wizard:  | api_call italian bombay six expensive |
| User:  | thanks |
| Wizard:  | you’re welcome |

Table 2: Example of the refine API task from the dialog-bAbI dataset (Bordes et al., 2016). The repeated update of the restaurant reservation is repetitive and lacks the diversity found in human dialogues.

4 Deviations
A large majority of recent pure research projects from the ML and NLP communities do not align with the proposed notion of an ecologically valid research procedure. This section describes five common issues—synthetic language, artificial task, not working with prospective user, scripts and priming, single-turn interfaces—and points out their limitations through concrete examples. For many benchmarks, the lack of ecological validity comes from multiple factors which are often hard to disentangle. For that reason, we pick a few example projects that best illustrate the potential impact of this deviation from the ideal data collection methodology.

4.1 Synthetic language
Perhaps the most obvious deviation is to dismiss any form of data collection and instead work with synthetic language. The key difficulty in designing a synthetic language is to obtain broad linguistic coverage while maintaining the natural aspect of language. Some projects intentionally keep the language simple and coverage low. The BabyAI project (Chevalier-Boisvert et al., 2019) defines a context-free grammar to generate simple instructions such as
open the yellow door, then go to the key behind you.

While the BabyAI grammar can generate a large number of instructions, its vocabulary is small and features only a few dozen words. In addition, they need to impose restrictions on the use of “and”, “then”, and “after you” connectors to maintain the readability of the instructions. In general, it is important for grammar-based approaches to carefully limit the operators that can lead to combinatorial explosion, as these are often the source of unnatural utterances. For example, some questions in the Compositional Freebase Questions (CFQ) dataset (Keysers et al., 2019) are hard to understand because of the conjunction of many noun or verb phrases:

Did Patrick Scully’s sibling marry Carolyn Zeifman, influence Tetsuo II: Body Hammer’s art director, director, and executive producer, and influence Christophe Gans?

Especially for larger domains it becomes increasingly difficult and tedious to ensure the readability of all questions or instructions (see, e.g., the effort by Hudson and Manning (2019)).

Long natural-looking questions or dialogues often feature anaphoric references, e.g., the pronoun “them” in the following instruction:

pick up my shoes, then bring them to the living room.

Generating synthetic data containing a wide variety of such references has been studied but remains challenging (Krahmer and van Deemter, 2012). The existing synthetic datasets feature only very restricted use of pronouns and are usually template-based. For example in CLEVR (Johnson et al., 2017), the authors manually write templates for each high-level intent, which contain a number of slots that are filled during instantiation of the question. A drawback of designing templates is that it is labor-intensive and only features relatively few pronouns (namely, the ones that the authors wrote). Producing anaphoric references in a conversational setting is even more challenging as they might refer back to previous dialogue turns (e.g., the pronoun “them” can refer to the object “shoes” in the previous turn). Most synthetic dialogue datasets write templates for each dialogue act independently, which can lead to conversations in which the dialogue acts are not “smoothly” connected. See, for example, the dialog of the bAbI dataset (Bordes et al., 2016) in Table 2, in which the repeated update of the restaurant reservation is repetitive and unnatural.

To summarize, developing a synthetic language that is both natural-looking and covers all necessary linguistic phenomena is highly challenging. Findings on synthetic benchmarks might therefore not be representative of progress on practically relevant LUIs.

4.2 Artificial task

Crafting custom artificial tasks (games) for research purposes is another common deviation from the ideal procedure. Such tasks may be appealing in that they require advanced linguistic human-computer interaction, and the associated data collection efforts often yield diverse and interesting data. Nevertheless, we deem it problematic that these tasks do not correspond to or even resemble a practically relevant LUI setting. For example, Room2Room (Anderson et al., 2018) proposes a LUI task to let robots navigate to (random) locations in the Matterport 3D environment—see Fig. 3 for an example. We expect that robots will be used to e.g., find and pick up objects in a household setting, a task for which navigation is only a subroutine. Human instructions for household tasks are probably more high-level and unlikely to contain detailed information
on the navigation task, such as where to turn left/ right. This mismatch decreases the ecological val-
idity of the Room2Room benchmark.

The vast majority of other artificial tasks are cast as games. One prominent example is the GuessWhat task (De Vries et al., 2017), a 20Q inspired game in which the user aims to find a hidden object in an image. The user can ask a series of yes-no questions to the wizard, who can see the hidden object. See Fig. 2 for an example dialog. Another example is CerealBar (Suhr et al., 2019), where two agents, a leader and a follower, navigate a toy 3D environment in order to collect a set of cards. The leader agent has an overview map of the environment but cannot take as many steps as the follower agent. They therefore delegate the collection of some cards to the follower by providing natural language instructions. Similar to GuessWhat, the CerealBar task is an artificially constructed game that is only meaningful within this virtual environment. We categorize such benchmarks as having low ecological validity because we do not think that people would naturally use these LUIs.

Note that not all game environments are automatically classified as such. Popular game environments, like Minecraft (Szlam et al., 2019), could be an excellent platform for developing LUI tasks with high ecological validity. It should also be noted that, despite the ecological validity concerns, artificial tasks can still serve as an interesting playground for working on conceptual advances in learning and modelling methods. We believe that they are ill-suited for incremental research, as it is unclear how small improvements will find their way to real applications.

4.3 Not working with prospective users

One of the most common issues with existing LUI datasets is that the population that would actually benefit from the language user interface rarely participates in the data collection effort. An example of what this can lead to can be found in the context of visual question answering (VQA). This task gained interest from the research community after the release of the VQA dataset (Antol et al., 2015), consisting of more than 750K open-ended questions. The contextually rich images in VQA are taken from MS COCO (Lin et al., 2014) and natural language questions are gathered on a crowdsourcing platform via the following set of instruc-

We have built a smart robot. It understands a lot about images. It can recognize and name all the objects, it knows where the objects are, it can recognize the scene (e.g., kitchen, beach), people’s expressions and poses, and properties of objects (e.g., color of objects, their texture). Your task is to stump this smart robot! Ask a question about this scene that this smart robot probably cannot answer, but any human can easily answer while looking at the scene in the image.

Although the VQA task was at least partly inspired by the need to help the visually impaired, such questions were not collected from blind people. Instead, human subjects with 20/20 vision were primed to ask questions that would stump a smart robot. As shown by the VizWiz project (Gurari et al., 2018), this decision has had a profound impact on the ecological validity of the dataset. Specifically, their case study found that blind people (1) ask questions that are sometimes incomplete and often conversational in nature, (2) start their questions almost always with “what” (as opposed to words that narrow the answer space, such

Instructions:

Instruction: Head upstairs and walk past a piano through an archway directly in front. Turn right when the hallway ends at pictures and table. Wait by the moose antlers hanging on the wall.
as “how many” or “is it”), and (3) frequently formulate questions that require text-reading capabilities (in 21% of the cases). In addition, blind photographers captured the images using their mobile phone, resulting in many unanswerable questions because of the poor image quality or irrelevant content. Perhaps as a consequence of the differences in the datasets, the authors reported that modern VQA models struggle on the VizWiz dataset, especially when it comes to answering questions that require text-reading capabilities.

In the context of database QA, Spider (Yu et al., 2018) collected questions from 11 computer science students with proficiency in SQL. For each of the 200 databases, they were instructed to write 20–50 questions so as to cover a number of SQL patterns. The students did not have the intention to find information in the database, resulting in questions that might not align with the user population. Looking at the data, we observed that some questions are quite literal translations of the SQL query, sometimes explicitly referring to column names:

What are the names of the customers who bought product "food" at least once?

The SQUAD dataset (Rajpurkar et al., 2016) was collected by having human annotators generate questions about Wikipedia articles. Like the Spider project, these crowdworkers had no information need, which makes it unclear if the resulting questions match the ones from users looking for this information. In all three project examples above, the discrepancy between questions collected from wrong or poorly incentivized users versus target users can make trained models much less useful for the target users than automatic evaluation on the ecologically invalid questions would suggest.

4.4 Scripts and priming

To compensate for the lack of access to potential users and/or to capable wizards, many recent data collection efforts relied on scripts that constrained the flow of human-computer interaction. For example, Budzianowski et al. (2018) collect the MultiWOZ dataset of dialogues for making reservations in hotels, restaurants, etc. For each dialogue, the user is given a script that they are supposed to follow (see Table 4 for an example). The script defines their preferences, such as the type of food and price range of the restaurant, as well as alternatives if their first choice is unavailable.

The use of scripts can cause ecological validity issues, two of which we discuss below. For one, the diversity of user-wizard interactions is limited by the complexity of the script. In the case of MultiWOZ, for example, the search for the right hotel or restaurant cannot take more than two turns. If it is impossible to realize the first set of preferences (e.g., no hotel is available for 3 nights), the prompt suggests an alternative that is feasible (e.g., to book for 2 nights instead, see Table 4 for the complete prompt). In dialogues where a user must inquire about several reservations, each reservation is always completed before the next one is started. For example, the user cannot reconsider their choice of restaurant based on the train schedule. It is possible (and perhaps even likely) that models trained on MultiWOZ data will have trouble generalizing to interaction scenarios that the scripts did not cover.

The second, more direct effect that scripts can have on the collected data is that subjects are primed by the specific wording of the script. In the worst case, users directly copy an automatically generated prompt without rephrasing (e.g., in the first utterance of Table 4: “[sic] am looking for a place to to stay that has cheap price range it should be in a type of hotel”). In a less severe example, the user rephrases the prompt to be more plausible, but the resulting request is still unnatural and heavily influenced by the automatically generated prompt. For example, instead of saying “I need a place to dine at in the south that serves chinese”, most people would probably say “Chinese restaurant” or “Chinese food” (see Table 3 for the complete example).
You are looking for a place to stay. The hotel should be in the cheap price range and should be in the type of hotel.

The hotel should include free parking and should include free wifi.

Once you find the hotel you want to book it for 6 people and 3 nights starting from Tuesday.

If the booking fails how about 2 nights.

Make sure you get the reference number.

Table 4: An example from the MultiWOZ dataset (Budzianowski et al., 2018), illustrating how the scripts limits the search for a hotel to at most 2 attempts.

| Prompt |
|----------------|------------------|
| • Of all the claims, what was the earliest date when any claim was made? |

User: What days were the claims made?

Wizard (SQL): SELECT Date_Claim_Made FROM Claims

Wizard (Response): There are the dates when all the Claims were made.

User: When was the earliest claim made?

Wizard (SQL): SELECT Date_Claim_Made FROM Claims ORDER BY Date_Claim_Made ASC LIMIT 1

Wizard (Response): The date when the earliest claim was made is 2016-08-02.

User: What day of the week was that claim made?

Wizard (Response): Sorry, I cannot find info about this.

User: What was the claim ID for the earliest claim?

Wizard (SQL): SELECT Claim_ID FROM Claims ORDER BY Date_Claim_Made ASC LIMIT 1

Wizard (Response): The claim id of the earliest claim is 563.

There are many other examples of LUI datasets whose diversity and ecologically validity may be negatively affected by scripting or textual priming. The ALFRED task (Shridhar et al., 2020) collects instructions by having the AMT workers annotate videos of a robot acting in simulated environment. The videos are generated by attaining goals with a planner. There are only 7 kinds of goals (such as “pick & place”, “stack & place”, etc.) and it is unclear if these are representative of the sort of requests that an actual user would want to accomplish. In CoSQL (Yu et al., 2019a), users engage in a dialogue with a conversational database interface that is enacted by a SQL-competent wizard. The users are instructed to explore the DB and also primed by SQL queries coming from the Spider dataset that we discussed earlier. Looking at CoSQL dialogues, we observed that users often asked questions that were close to (or reformulations of) the prompt or its parts (see an example dialogue in Table 5), as opposed to performing curiosity-driven data exploration. The proximity of the dialogue to prompts that originate from SPIDER means that ecological validity concerns regarding Spider queries (see Section 4.3) transfer to CoSQL data.

4.5 Single-turn interfaces

Some recent benchmarks are free of the deviations that we have covered so far as they consider real and useful tasks and involve target users in the data collection effort. For example, the Advising dataset (Finegan-Dollak et al., 2018) collects questions about the course information of the University of Michigan from a department’s Facebook page. Other examples are recent open domain QA benchmarks that extract questions from
User: What is the largest 11780 fixed disk under $40 000?
Wizard: The rp07-aa is a 516MB fixed pack disk that costs $38 000.
User: The largest under $50 000?
Wizard: The rp07-aa.

Table 6: Example taken from Carbonell (1983). “The largest under $50 000?” is an elliptical utterance (because the part about 11780 fixed disk is omitted).

The importance of multi-turn interactions has been established through several Wizard-of-Oz studies (Carbonell, 1983; Bertomeu et al., 2006; Dählback and Jonsson, 1989), suggesting that there are qualitative differences with single-turn interfaces. In a case study simulating a sales assistant, Carbonell (1983) reports that users rely on a rich number of dialog phenomena, such as anaphora, ellipses (see Table 6 for an example), and meta-linguistic utterances (“I should have said ...”). Interestingly, even when users are explicitly instructed to formulate standalone expressions they tend to produce fragmentary utterances. In a database QA setting, Bertomeu et al. (2006) argue that users naturally ask a series of thematically related questions when performing information-seeking tasks. By analyzing a small corpus of QA conversations, they confirm that a large number of questions (36%) are indeed context-dependent. These empirical studies suggest that dialog is the preferred mode of interaction for most LUIs.

5 Other Ecological Validity Concerns

Besides the five common deviations, there are two other ecological validity concerns which we did not discuss so far: (i) the evaluation of machine learning models for LUI benchmarks and (ii) the relevance of speech interfaces.

Evaluation Automatic evaluation procedures are key to enable fast iteration of machine learning models. In the context of language user interfaces, practitioners often evaluate their systems with turn-based metrics which, for example, compare the predicted database query to the groundtruth one (Finegan-Dollak et al., 2018) or assess if the simulated robot has behaved in a desired way. This turn-based evaluation procedure assumes that the system followed the ground-truth conversation up to the \((N - 1)\)th turn and then measures the performance for the \(N\)th response. The key issue with this evaluation procedure is that it does not account for errors that the system makes along the conversation.\(^4\) For example, imagine that the evaluated system makes an error that a human wizard would never make. In the next turn, the user will clarify their intent and thereby diverge to a dialogue that has zero probability under the training distribution (as the wizard would never have made the error). Thus, evaluating under the assumption of ground-truth inputs does not measure how well the system is able to recover from its own mistakes. The only way to measure that is through a human-in-the-loop evaluation that assesses whether the interaction as a whole was successful.

Speech interfaces One aspect that we do not dwell on is the importance of voice-controlled interfaces for the ecological validity of LUI benchmarks. While texting and messaging is very widespread, there are situations in which speech is the preferred interface, such as in settings where people cannot use their hands, e.g., while driving or cooking. Collecting ecologically valid data for such LUI benchmarks will bring additional challenges, including the handling of speech disfluencies, barge-in, and non-verbal cues. We leave these speech-related concerns for future work.

6 Directions for Future Research

Looking forward, there are number of directions that we think deserve more attention from the NLP and ML communities. First, we believe more effort should be put in designing ecologically valid LUI tasks. One approach is to construct LUI tasks for environments that already have many users and which will allow collection of large datasets.

\(^4\)In the machine translation community, researchers refer to this issue as the “exposure bias” (Wiseman and Rush, 2016).
| Deviation                          | Project                                                                 |
|-----------------------------------|--------------------------------------------------------------------------|
| Synthetic language                | BabyAI (Chevalier-Boisvert et al., 2019)                                 |
|                                   | CLEVR (Johnson et al., 2017)                                            |
|                                   | CFQ (Keysers et al., 2019)                                              |
|                                   | GQA (Hudson and Manning, 2019)                                          |
| Artificial task                   | GuessWhat (De Vries et al., 2017)                                       |
|                                   | CerealBar (Suhr et al., 2019)                                           |
|                                   | CoDraw (Kim et al., 2019)                                               |
|                                   | VisionAndLanguage (Anderson et al., 2018)                               |
| Not working with prospective users| Visual Question Answering (Antol et al., 2015)                          |
|                                   | Visual Dialog (Das et al., 2017)                                        |
|                                   | Spider (Yu et al., 2018)                                                |
|                                   | SQuAD (Rajpurkar et al., 2016)                                          |
| Scripts and priming               | MultiWOZ (Budzianowski et al., 2018)                                    |
|                                   | ALFRED (Shridhar et al., 2020)                                          |
|                                   | CoSQL (Yu et al., 2019a)                                                |
|                                   | Sparc (Yu et al., 2019b)                                                |
|                                   | AirDialogue (Wei et al., 2018)                                          |
|                                   | Overnight (Wang et al., 2015)                                           |
| Single-turn interfaces            | Advising (Finegan-Dollak et al., 2018)                                  |
|                                   | MS Marco (Bajaj et al., 2016)                                           |
|                                   | Natural Questions (Kwiatkowski et al., 2019)                            |
|                                   | DuReader (He et al., 2018)                                               |

Table 7: Five common deviations from the proposed ecologically valid research procedure. For each deviation we list a number of recent LUI benchmarks that suffer from it.

Promising proposals are the development of LUI benchmarks for popular video game environments like Minecraft (Szlam et al., 2019) or for platforms that bundle user services on the Internet of Things (Campagna et al., 2019). A more ambitious direction is to create LUIs that have the potential to attract a big user audience. For example, the academic community could work on LUIs that enable citizens to easily access statistical information published by governments.

Our second recommendation is that, as a first step, the community could focus on ecologically valid evaluation. As collecting large amounts of ecologically valid training data remains expensive, it would be easier to start with smaller amounts of data for testing purposes. Such an evaluation procedure would directly measure to what extent the trained model generalizes to a practical NLI use case. For training, one could still use data with low ecological validity—e.g., by data augmentation on real language (Andreas, 2019)—so as to meet the big data requirements of deep learning methods.

Finally, as many current LUI benchmarks suffer from low ecological validity, we recommend researchers not to initiate incremental research projects on them. Benchmark-specific advances are less meaningful when it is unclear if they transfer to real LUI use cases. Instead, we suggest the community to focus on conceptual research ideas that can generalize well beyond the current datasets.

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References

Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, and others. 2020. Towards a human-like open-domain chatbot. arXiv preprint arXiv:2001.09977.

Katrin Affolter, Kurt Stockinger, and Abraham Bernstein. 2019. A Comparative Survey of Recent Natural Language Interfaces for Databases. The VLDB Journal, 28(5):793–819. ArXiv:1906.08990.

Peter Anderson, Qi Wu, Damien Teney, Jake Bruce, Mark Johnson, Niko Sunderhauf, Ian Reid, Stephen Gould, and Anton Van Den Hengel. 2018. Vision-and-Language Navigation: Interpreting Visually-Grounded Navigation Instructions in Real Environments. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pages 3674–3683. IEEE Computer Society.

Jacob Andreas. 2019. Good-enough compositional data augmentation. arXiv preprint arXiv:1904.09545.

Ion Androutsopoulos, Graeme Ritchie, and Peter Thanisch. 1995. Natural language interfaces to databases â€” an introduction. Natural Language Engineering, 1(1):29–81.

Stanislaw Antol, Ashwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. VQA: Visual Question Answering. In Proceedings of the IEEE International Conference on Computer Vision (ICCV).

Dzmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings. International Conference on Learning Representations, ICLR.

Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, and others. 2016. Ms marco: A human generated machine reading comprehension dataset. arXiv preprint arXiv:1611.09268.

Nâźria Bertomeu, Hans Uszkoreit, Anette Frank, Hans-Ulrich Krieger, and Brigitte Jörg. 2006. Contextual phenomena and thematic relations in database QA dialogues: results from a Wizard-of-Oz experiment. In Proceedings of the Interactive Question Answering Workshop at HLT-NAACL 2006, pages 1–8.

Antoine Bordes, Y-Lan Boureau, and Jason Weston. 2016. Learning End-to-End Goal-Oriented Dialog. 5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings.

Susan E. Brennan. 1991. Conversation with and through computers. User Modeling and User-adapted Interaction, 1(1):67–86.

Marilynn B. Brewer and William D. Crano. 2014. Research Design and Issues of Validity. In Handbook of Research Methods in Social and Personality Psychology, pages 11–26. Cambridge University Press.

Urie Bronfenbrenner. 1977. Toward an experimental ecological of human development. American Psychologist, 32:513–531.

PaweÅ‡ Budzianowski, Tsung Hsien Wen, Bo Hsiang Tseng, IĂśigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWoz - A large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018.

Giovanni Campagna, Silei Xu, Mehrad Moradshahi, Richard Socher, and Monica S Lam. 2019. Genie: A Generator of Natural Language Semantic Parsers for Virtual Assistant Commands. In Proceedings of the 40th ACM SIGPLAN Conference on Programming Language Design and Implementation, PLDI 2019, pages 394–410, New York, NY, USA. Association for Computing Machinery.

Jaime G. Carbonell. 1983. Discourse Pragmatics and Ellipsis Resolution in Task-Oriented Natural Language Interfaces. In Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference, pages 164–168, Morristown, NJ, USA. Assoc for Computational Linguistics.
Maxime Chevalier-Boisvert, Dzmitry Bahdanau, Salem Lahlou, Lucas Willems, Chitwan Saharia, Thien Huu Nguyen, and Yoshua Bengio. 2019. BabyAI: First Steps Towards Grounded Language Learning With a Human In the Loop. In International Conference on Learning Representations.

Benjamin R. Cowan, Nadia Pantidi, David Coyle, Kellie Morrissey, Peter Clarke, Sara Al-Shehri, David Earley, and Natasha Bandeira. 2017. “what can I help you with?”: Infrequent users’ experiences of intelligent personal assistants. In Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services, pages 1–â€S12.

Deborah A. Dahl, Madeleine Bates, Michael Brown, William Fisher, Kate Hunnicke-Smith, David Pallett, Christine Pao, Alexander Rudnicky, and Elizabeth Shriberg. 1994. Expanding the scope of the ATIS task: the ATIS-3 corpus. In Proceedings of the workshop on Human Language Technology, HLT ’94, pages 43–48, Plainsboro, NJ. Association for Computational Linguistics.

Nils Dahlbäck and Arne Jönsson. 1989. Empirical Studies of Discourse Representations for Natural Language Interfaces. In Fourth Conference of the European Chapter of the Association for Computational Linguistics, Manchester, England. Association for Computational Linguistics.

Nils Dahlbäck, Arne Jönsson, and Lars Ahrenberg. 1993. Wizard of Oz studies. In Proceedings of the 1st international conference on Intelligent user interfaces - IUI ’93, pages 193–200, New York, New York, USA. Association for Computing Machinery (ACM).

Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, JosÃf M F Moura, Devi Parikh, and Dhruv Batra. 2017. Visual Dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Harm De Vries, Florian Strub, Sarath Chandar, Olivier Pietquin, Hugo Larochelle, and Aaron Courville. 2017. Guesswhat!! visual object discovery through multi-modal dialogue. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5503–5512.

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.

Catherine Finegan-Dollak, Jonathan K Kummerfeld, Li Zhang, Karthik Ramanathan, Sesh Sadasivam, Rui Zhang, and Dragomir Radev. 2018. Improving Text-to-SQL Evaluation Methodology. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 351–360, Melbourne, Australia. Association for Computational Linguistics.

Norman M. Fraser and G. Nigel Gilbert. 1991. Simulating speech systems. Computer Speech and Language, 5(1):81–99.

Barbara Grosz. 1974. The structure of task oriented dialogs. In IEEE Symposium on Speech Recognition: Contributed Papers. Carnegie Mellon University Computer Science Dept., Pittsburgh, Pennsylvania, volume 10.

Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. 2018. Vizwiz grand challenge: Answering visual questions from blind people. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3608–3617.

Wei He, Kai Liu, Jing Liu, Yajuan Lyu, Shiqi Zhao, Xinyan Xiao, Yuan Liu, Yizhong Wang, Hua Wu, Qiaoqiao She, Xuan Liu, Tian Wu, and Haifeng Wang. 2018. DuReader: a Chinese Machine Reading Comprehension Dataset from Real-world Applications. In Proceedings of the Workshop on Machine Reading for Question Answering, pages 37–46, Melbourne, Australia. Association for Computational Linguistics.
Charles T Hemphill, John J Godfrey, and George R Doddington. 1990. The ATIS Spoken Language Systems Pilot Corpus. In Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27,1990.

Drew A. Hudson and Christopher D. Manning. 2019. GQA: A New Dataset for Real-World Visual Reasoning and Compositional Question Answering. Proceedings of the 2019 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019. ArXiv: 1902.09506.

Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. 2017. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2901–2910.

J. F. Kelley. 1984. An iterative design methodology for user-friendly natural language office information applications. ACM Transactions on Information Systems, 2(1):26–41.

Daniel Keysers, Nathanael Schärli, Nathan Scales, Hylke Buisman, Daniel Furrer, Sergii Kushubin, Nikola Momchev, Danila Sinopalnikov, Lukasz Stafiniak, Tibor Tihon, Dmitry Tsarkov, Xiao Wang, Marc van Zee, and Olivier Bousquet. 2019. Measuring Compositional Generalization: A Comprehensive Method on Realistic Data. In International Conference on Learning Representations (ICLR).

Jin-Hwa Kim, Nikita Kitaev, Xinlei Chen, Marcus Rohrbach, Yuandong Tian, Dhruv Batra, and Devi Parikh. 2019. CoDraw: Collaborative Drawing as a Testbed for Grounded Goal-driven Communication. arXiv preprint arXiv:1712.05558.

Emiel Krahmer and Kees van Deemter. 2012. Computational Generation of Referring Expressions: A Survey. Computational Linguistics, 38(1):173–218.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural Questions: A Benchmark for Question Answering Research. Transactions of the Association for Computational Linguistics, 7:453–466.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755.

Ewa A. Luger and Abigail J. Sellen. 2016. “like having a really bad pa”: The gulf between user expectation and experience of conversational agents. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, pages 5286â ˘ÁŠ–5297.

David Maulsby, Saul Greenberg, and Richard Mander. 1993. Prototyping an intelligent agent through Wizard of Oz. In Conference on Human Factors in Computing Systems - Proceedings, pages 277–284, New York, New York, USA. Publ by ACM.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Ashwin Ram, Rohit Prasad, Chandra Khatri, Anu Venkatesh, Raefar Gabriel, Qing Liu, Jeff Nunn, Behnarn Hedayatnia, Ming Cheng, Ashish Nagar, and others. 2018. Conversational ai: The science behind the alexa prize. arXiv preprint arXiv:1801.03604.

Karthik Raman, Paul N. Bennett, and Kevyn Collins-Thompson. 2013. Toward whole-session relevance: Exploring intrinsic diversity in web search. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval (SIGIR), page 463â ˘ÁŠ472.

Iulian Vlad Serban, Ryan Lowe, Peter Henderson, Laurent Charlin, and Joelle Pineau. 2018. A survey of available corpora for building data-driven dialogue systems: The journal version. Dialogue & Discourse, 9(1):1–49.
Marilyn Shatz and Rochel Gelman. 1973. The Development of Communication Skills: Modifications in the Speech of Young Children as a Function of Listener. *Monographs of the Society for Research in Child Development*, 38(5):1.

Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roobbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. 2020. Alfred: A benchmark for interpreting grounded instructions for everyday tasks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10740–10749.

Anoop K. Sinha, Scott R. Klemmer, and James A. Landay. 2002. Embarking on spoken-language NL interface design. *International Journal of Speech Technology*, 5:159–169.

Alane Suhr, Ming-Wei Chang, Peter Shaw, and Kenton Lee. 2020. Exploring Unexplored Generalization Challenges for Cross-Database Semantic Parsing. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8372–8388. Online. Association for Computational Linguistics.

Alane Suhr, Claudia Yan, Jack Schluger, Stanley Yu, Hadi Khader, Marwa Mouallem, Iris Zhang, and Yoav Artzi. 2019. Executing Instructions in Situated Collaborative Interactions. 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)*, pages 2119–2130, Hong Kong, China. Association for Computational Linguistics.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to Sequence Learning with Neural Networks. *Advances in Neural Information Processing Systems*, 4(January):3104–3112.

Arthur Szlam, Jonathan Gray, Kavya Srinet, Yacine Jernite, Armand Joulin, Gabriel Synnaeve, Douwe Kiela, Haonan Yu, Zhuoyuan Chen, Siddharth Goyal, and others. 2019. Why Build an Assistant in Minecraft? *arXiv preprint arXiv:1907.09273*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, ÂAukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 2017-December, pages 5999–6009. Neural information processing systems foundation.

Yushi Wang, Jonathan Berant, and Percy Liang. 2015. Building a semantic parser overnight. In *ACL-IJCNLP 2015 - 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing of the Asian Federation of Natural Language Processing. Proceedings of the Conference*, volume 1, pages 1332–1342. Association for Computational Linguistics (ACL).

Wei Wei, Quoc Le, Andrew Dai, and Jia Li. 2018. AirDialogue: An Environment for Goal-Oriented Dialogue Research. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3844–3854, Stroudsburg, PA, USA. Association for Computational Linguistics.

Sam Wiseman and Alexander M. Rush. 2016. Sequence-to-Sequence Learning as Beam-Search Optimization. *EMNLP 2016 - Conference on Empirical Methods in Natural Language Processing, Proceedings*, pages 1296–1306.

Tao Yu, Rui Zhang, Heyang Er, Suyi Li, Eric Xue, Bo Pang, Xi Victoria Lin, Yi Chern Tan, Tianze Shi, Zihan Li, Youxuan Jiang, Michihiro Yasonaga, Sungruk Shim, Tao Chen, Alexander Fabbri, Zifan Li, Luyao Chen, Yuwen Zhang, Shreyas Dixit, Vincent Zhang, Caiming Xiong, Richard Socher, Walter Lasecki, and Dragomir Radev. 2019a. CoSQL: A Conversational Text-to-SQL Challenge Towards Cross-Domain Natural Language Interfaces to Databases. 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)*, pages 1962–1979, Hong Kong, China. Association for Computational Linguistics.

Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasonaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir Radev. 2018. Spider: A Large-Scale Human-Labeled Dataset for Complex and Cross-Domain Semantic Parsing and
Text-to-SQL Task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3911–3921, Brussels, Belgium. Association for Computational Linguistics.

Tao Yu, Rui Zhang, Michihiro Yasunaga, Yi Chern Tan, Xi Victoria Lin, Suyi Li, Heyang Er, Irene Li, Bo Pang, Tao Chen, Emily Ji, Shreya Dixit, David Proctor, Sungrok Shim, Jonathan Kraft, Vincent Zhang, Caiming Xiong, Richard Socher, and Dragomir Radev. 2019b. SParC: Cross-Domain Semantic Parsing in Context. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4511–4523, Florence, Italy. Association for Computational Linguistics.

Li Zhou, Jianfeng Gao, Di Li, and Heung-Yeung Shum. 2020. The design and implementation of xiaoice, an empathetic social chatbot. Computational Linguistics, 46(1):53–93.