A Survey of Intent Classification and Slot-Filling Datasets for Task-Oriented Dialog

Stefan Larson
Vanderbilt University
stefan.larson@vanderbilt.edu

Kevin Leach
Vanderbilt University
kevin.leach@vanderbilt.edu

Interest in dialog systems has grown substantially in the past decade. By extension, so too has interest in developing and improving intent classification and slot-filling models, which are two components that are commonly used in task-oriented dialog systems. Moreover, good evaluation benchmarks are important in helping to compare and analyze systems that incorporate such models. Unfortunately, much of the literature in the field is limited to analysis of relatively few benchmark datasets. In an effort to promote more robust analyses of task-oriented dialog systems, we have conducted a survey of publicly available datasets for the tasks of intent classification and slot-filling. We catalog the important characteristics of each dataset, and offer discussion on the applicability, strengths, and weaknesses of each. Our goal is that this survey aids in increasing the accessibility of these datasets, which we hope will enable their use in future evaluations of intent classification and slot-filling models for task-oriented dialog systems.

1. Introduction

Task-oriented dialog systems are one of the most accessible applications of Natural Language Processing (NLP). Indeed, commercial task-oriented dialog systems in the form of smart devices like Amazon’s Alexa are used by millions of people every day. Within the academic research community, however, task-oriented dialog system models are often benchmarked on relatively few evaluation datasets. This is in spite of the fact that the past few years have seen a substantial growth in the number of available datasets for building and evaluating intent classification and slot-filling models for task-oriented dialog systems. Thus, the goal of this survey is to catalog these intent classification and slot-filling datasets to help facilitate their use in building and evaluating dialog systems and beyond.

Other surveys have discussed dialog datasets in depth (Serban et al. 2018), but exclude almost all intent classification and slot-filling datasets, and model-focused surveys on dialog systems mostly focus on models and pay much less attention to datasets. In this paper, we instead emphasize datasets themselves and present an survey of 40 corpora for developing and evaluating intent classification and slot-filling models. Where appropriate, we discuss the strengths and weaknesses of each dataset, and highlight points of uniqueness for each.

This survey paper consists of the following: In Section 2, we briefly discuss prior surveys related to task-oriented dialog and datasets. Section 3 provides an overview of task-oriented dialog, intent classification, and slot-filling, as well as a discussion of various utterance types and data sources for constructing datasets. Section 4 discusses the various metrics used when evaluating models on intent classification and slot-filling datasets. Sections 5, 6, 7, and 8 are dedicated to introducing and discussing corpora: specifically, joint intent classification and slot-filling¹ (Section 5), intent classification (Section 6), slot-filling (Section 7), and other related corpora (Section 8). Figure 1 presents an overview of the datasets surveyed in Sections 5–7. We distinguish corpora according to several factors: size of the data, problem solved by the

¹ We also refer to this as “joint modeling”.

arXiv:2207.13211v1 [cs.CL] 26 Jul 2022
dataset, and provenance of the dataset. We organize our survey of datasets by dataset task (i.e., joint modeling, intent classification, and slot-filling), as opposed to, e.g., application domain (banking, travel, etc.), as this task typology closely matches how these datasets are consumed by researchers.

However, we also mention dataset domains where appropriate; a visual guide of datasets surveyed in this paper broken down by model task and domain is displayed in Figure 1. Finally, Section 9 provides a discussion of the landscape of the surveyed corpora, with commentary on successes, pitfalls, and lessons learned from the datasets. We also discuss remaining challenge areas that are not currently covered by existing corpora to encourage the development of future research and evaluation of new datasets in this domain.
2. Related Surveys

In this section, we discuss areas of research already addressed by previous surveys to place our own work in context. Existing surveys have addressed (1) dialog systems Chen et al. (2017); Gao, Galley, and Li (2019); McTear (2020); Ni et al. (2021), (2) task-oriented dialog management (Dai et al. 2020), (3) language understanding such as intent classification and slot-filling models (Korpusik, Liu, and Glass 2019; Hou et al. 2019; Tomashenko et al. 2019; Liu, Li, and Lin 2019; Louvan and Magnini 2020; Qin et al. 2021; Razumovskaia et al. 2021; Weld et al. 2022), and (4) semantic parsing Kamath and Das (2019). However, these surveys do not thoroughly discuss evaluation corpora (e.g., discussion is often limited to ATIS and Snips in the cast of Weld et al. (2022)’s survey). While Serban et al. (2018) is an exception with respect to datasets and benchmarks, their survey focuses mostly on end-to-end dialog corpora and does not discuss task-oriented dialog datasets aside from ATIS.

Prior work has also compiled collections of evaluation datasets for task-oriented dialog. This work includes Henderson et al. (2019), Larson, Guldan, and Leach (2020), and Mehri, Eric, and Hakkani-Tur (2020), but none of these are nearly as broad as our survey. Deriu et al. (2020) surveys evaluation methods for dialog systems, but focuses mostly on dialog paradigms outside of intent classification and slot-filling (e.g., open-ended dialog). Prior surveys on building or constructing datasets is limited, but includes Yaghoub-Zadeh-Fard et al. (2020), which surveys data acquisition methods for building “chatbot”-style task-oriented systems. Surveys on datasets outside of dialog systems include those for machine reading comprehension (Dzendzik, Vogel, and Foster 2021), explainable NLP (Wiegreffe and Marasović 2021), and question answering (Wang 2022). Finally, intent classification and slot-filling datasets are often used to evaluate few- and zero-shot learning algorithms, and surveys on this subject include Wang et al. (2020) and Yin (2020). This paper thus fills a gap in the survey literature on dialog systems by surveying and cataloging intent classification and slot-filling datasets.

3. Task-Oriented Dialog Systems, Intent Classification, and Slot-Filling

In this section, we briefly introduce task-oriented dialog systems, intent classification, and slot-filling. We then discuss various utterance types, as well as data sources for creating intent classification and slot-filling datasets.

Task-oriented dialog systems, along with the essential components of intent classification and slot-filling, are particularly relevant in recent years because of the growth of applications for goal-driven dialog systems in areas and industries such as banking and personal finance, e-commerce, technical support, healthcare, travel, etc. (Wen et al. 2019). Typical architectures for task-oriented dialog systems incorporate several modules, including automatic speech recognition (ASR), natural language understanding (NLU), business logic, dialog management, and natural language generation (NLG) modules. Figure 2 illustrates how these components interact. Within the natural language understanding module, text is classified into (an optional) domain as well as a finer-grained intent. This intent frequently maps to a core functionality that the dialog system supports. For example, the user query “find me flights going to Orlando from Detroit on Friday” could map to a system-supported intent class called find_flights. This find_flights intent class might also fall within the travel domain. 2

Identifying the intent of the user’s query is but one of the tasks of the NLU module. An additional step is to extract the important entities from the query, which can then be used as inputs to the subsequent modules. For instance, in our example “find me flights go-

---

2 In this example, we say that the find_flights might fall within the travel domain because different system designers have different requirements — in principle, a system designer could have any intent map to any domain, just as any user query could fall within any intent.
Figure 2: Diagram of typical task-oriented dialog systems. A user’s utterance is first transcribed using speech recognition or is provided directly as textual input form the user. The Natural Language Understanding (NLU) module then extracts semantically meaningful information from the query. In this survey, our focus is on building and evaluating datasets that allow NLU modules to train intent classification and slot-filling models. The extracted information from the NLU module is passed to the Dialog Manager, which may interact with “backend” Business Logic module. The Dialog Manager encodes the “state” of the dialog as well, which gets passed to the Natural Language Generation module, which formulates the system’s response to the user.

According to Orlando from Detroit on Friday”, the important entities are the city names “Orlando” and “Detroit”, as well as the day “Friday”. We call these entities slots. In our hypothetical dialog system, these extracted slots might map to the slot types of destination_location, departure_location, and departure_day. More specifically, “Orlando” is the extracted slot value for the destination_location slot type.

The task of extracting these slots is known interchangeably as slot-filling, slot/entity extraction, or entity/slot tagging. Simple pattern matching systems that look for city names and days of the week might be a straightforward initial solution to the slot-filling task, but such an approach has downsides: First, human users might refer to the departure and destination locations by airport names (like “DTW” and “Love Field”), in which case the list of possible acceptable location names could become very large. Second, the contextual information surrounding the slot values helps indicate the appropriate slot types. In our example, the contextual span “going to” indicate that “Orlando” is the destination, while “from” indicates that “Detroit” is where the user seeks to depart. Standard named entity recognition (NER) models pre-trained to extract locations and dates might also not be appropriate here, as such systems may not be trained to distinguish between a departure and destination location, even though these two locations might be named-entities. Instead, typical machine learning-driven slot extraction modules often rely on sequential models such as stochastic finite state transducers, sequential classifiers, conditional random fields, recurrent neural networks (RNNs) (e.g., (Yao et al. 2013; Mesnil et al.)
Figure 3: Example dialog between a user (U) and a dialog system (S). Utterance U2 is an example of a follow-up query, one that implies information contained in the previous dialog turn. Utterance U3 is an example of an out-of-scope query. Utterance U5 is an example of a simple multi-intent query where two queries (“What was my largest transaction this week” and “what is my withdrawal limit”) are joined by a simple conjunction.

2013, 2015)), LSTMs (e.g. (Yao et al. 2014)), and transformers and attention-based models (e.g. (Devlin et al. 2019; Wu et al. 2020a,b)).

The extracted slots, along with the query’s predicted intent, are then consumed by the dialog manager, whose role is to determine and construct the system’s response to the user’s query. The dialog manager may interact with a business logic module that might have access to system-specific knowledge bases or APIs (e.g., the business logic module could query a flight booking database). The business logic module may also map extracted slots to specific canonical entities. For instance, knowing that “DTW” and “Detroit” map to the same entity (Detroit Metropolitan Wayne County Airport) can help the business logic module find flights from this specific airport. The dialog manager uses output from both the NLU and business logic modules, as well as knowledge of the conversation history, to produce information that is used by the natural language generation (NLG) module to construct a response to the user. In typical systems, the NLG module may respond to the user using text or text-to-speech with speech synthesis.

3.1 Utterance Types

While not exhaustive, Figure 3 shows examples of several types of utterances, knowledge of which will be helpful for the rest of this survey. For the example in Figure 3, we pretend that the task-oriented dialog system is knowledgeable of the user’s bank account. U1 is the initial, or “root”, user query or utterance. The initial utterance is in-scope with respect to the dialog system, and (assuming there is a corresponding intent for balance queries and that the intent classifier
Suppose you have an intelligent device such as Amazon Alexa, Apple Siri, or Google Assistant. Given an original phrase, provide 5 different ways of saying the same phrase. Original phrase: "what is the weather like in Cleveland"

Don’t use the words "weather" or "what" in your responses.

Determine the type of aircraft used on a flight from Cleveland to Dallas that leaves before noon.

Figure 4: Examples of crowdsourced prompts for data collection. The top two prompts ask crowd workers to paraphrase utterances, and may optionally require or restrict certain lexical features in the paraphrases (prompts adapted from Larson et al. (2020b)). The bottom prompt is an example of a scenario prompt from Dahl et al. (1994).

Correctly identified utterance U1 as a balance query) the system responds accordingly. U2 is a follow-up utterance; one that depends on the previous user query and/or system response. Most of the datasets surveyed in this paper do include initial/root queries, but few have follow-up utterances. The user’s U3 utterance is out-of-scope (or out-of-domain) with respect to the dialog system; assuming the system correctly flags U3 as such, it might respond with an appropriate fallback message in S3. The next utterance worthy of note in this example is U5, which consists of two queries: what was my largest transaction this week; and what is my withdrawal limit. This is a multi-intent utterance. We will see that few of the datasets surveyed in this paper contain multi-intent utterances.

3.2 Sources of Data

As we will see in our survey of various datasets, there are several common ways in which dataset creators collect, gather, or otherwise produce data for their datasets. The survey by Yaghoub-Zadeh-Fard et al. (2020) provides a typology of data source type, which we adopt and adapt here. This typology includes crowdsourcing, wherein crowd workers (e.g., from Amazon Mechanical Turk) are prompted by the dataset designers to respond to certain scenarios or produce paraphrases of example utterances directed towards certain intent categories with optional slots. Figure 4 lists three crowdsourcing prompt examples. We also note that in some cases, the designers of a dataset (or others knowledgeable in the creation of the dataset) may serve as providers of utterances; additionally, experts are often used in translating data from one language to another.

Yaghoub-Zadeh-Fard et al. (2020) also observed that utterances may be generated from templates, an approach used to produce the Leyzer dataset (Sowanski and Janicki 2020), for instance. An example template used to construct a subset of utterances in the Leyzer dataset is shown in Figure 5. Datasets may also be built from existing utterances that were provided to real dialog systems. Finally, we observe that many of the datasets discussed below are derived in some way from prior datasets. This includes datasets that were translated from one dialog dataset’s language to a target language (e.g., Multilingual ATIS (Upadhyay et al. 2018) and MultiATIS++ (Xu, Haider, and Mansour 2020)), or combined from several other prior datasets.
Figure 5: Example grammar for generating utterances for a translate intent (adapted from Sowanski and Janicki (2020)).

4. Common Evaluation Metrics

We will occasionally refer to model performance on certain datasets, so this section defines some commonly used evaluation metrics for evaluating slot-filling and intent classification models.

4.1 Intent Classification Evaluation Metrics

Determining the intent of an utterance is typically framed as a classification problem, and as such, typical evaluation metrics include accuracy, precision, recall, and F1 score. 

Accuracy is the most commonly-used metric, and is the ratio of correct predictions to the number of test utterances, or

$$\text{accuracy} = \frac{\text{# correctly predicted}}{\text{# of test utterances}}.$$ 

Precision and recall are similar to accuracy but with slightly different denominators. Precision computes the ratio of correctly predicted utterances to the number of utterances that were predicted, while recall describes the ratio of correctly predicted utterances to the total number of correct utterances (i.e., those that should have been predicted). In other words, precision measures the number of true positives ($tp$) to the number of true positives and false positives ($fp$), while recall measures the ratio of true positives to true positives and false negatives ($fn$):

$$\text{precision} = \frac{tp}{tp + fp} \quad \text{recall} = \frac{tp}{tp + fn}.$$
Table 1: B/I/O label representation for slot-filling data.

| find  | me    | a     | flight | from | San | Jose | to   | Nashville |
|-------|-------|-------|--------|------|-----|------|------|-----------|
| O     | O     | O     | O      | O    | B-origin | I-origin | O | B-destination |

In multi-class settings (which are very common in intent classification datasets), precision and recall can be micro- or macro-averaged. The *macro-average* of precision is

$$\text{precision}_{\text{macro}} = \frac{\sum_{i=1}^{\mid C \mid} \text{precision}_i}{\mid C \mid}$$

and the *micro-average* of recall is

$$\text{recall}_{\text{micro}} = \frac{\sum_{i=1}^{\mid C \mid} t_p_i}{\sum_{i=1}^{\mid C \mid} t_p_i + f_n_i}$$

where $\mid C \mid$ is the number of classes (i.e., the number of intents) in the dataset, and $i$ represents the $i^{th}$ intent class. The F1 score combines precision and recall into a single metric by computing the harmonic mean of the two:

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

In particular, F1 is often preferred over accuracy when evaluating with datasets that exhibit large class imbalances (meaning the number of test samples per class is unevenly distributed).

### 4.2 Slot-Filling Evaluation Metrics

Most datasets treat slot-filling similarly to that of Named Entity Recognition (NER), and data labels are represented as *Begin*, *Inside*, and *Outside* (or B-I-O) tags. Table 1 shows B/I/O tags on an example utterance. Most evaluations on slot-filling datasets measure the F1 score, where each slot type (e.g., origin, destination, and the null O type) are considered as a classification label.

### 4.3 Joint Model Evaluation Metrics

Evaluations of joint models may use individual metrics for both intent classification and slot-filling tasks. Additionally, *exact match accuracy* is often used as combined measure of intent classification and slot-filling performance. In exact match accuracy, the numerator of the accuracy ratio is the number of utterances whose predicted labels (including intent and all slot predictions) that completely match the ground-truth labels.

### 5. Joint Intent Classification and Slot-Filling Datasets

We begin our survey of datasets by cataloging datasets for the task of joint intent classification and slot-filling. These datasets have intent and slot annotations; while they are suitable for joint modeling tasks, they can also be used as benchmarks for intent classifiers and slot-filling models.

---

3 Often, the O label forms the overwhelming majority of label tags in slot-filling datasets.
Table 2: Example utterances with slots from the ATIS corpus.

| Intent      | Utterance |
|-------------|-----------|
| airfare     | show me the cheapest fare from dallas to baltimore |
| flight      | list the takeoffs and landings at general mitchell international |
| airline     | show me the airlines that fly from denver to san francisco |
| flight      | flights from baltimore to philadelphia please |
| abbreviation| what is ewr airport code |
| ground_service | is there ground transportation from the milwaukee airport to the downtown area |
| aircraft    | list aircraft types that fly between boston and san francisco |
| quantity    | how many airports does oakland have |
| flight      | show me all flights to philadelphia in the evening |
| airline     | what is airline us |
| flight      | find me a flight leaving boston at 12 o’clock |

individually. Datasets surveyed in this section are summarized in Table 3 (English datasets) and Table 4 (non-English datasets).

**ATIS.** The *Air Travel Information System (ATIS)* corpus is by far the oldest dataset for evaluating intent classification and slot-filling models. The *ATIS* dataset—widely-known for the tasks of intent classification and slot-filling—was built from several datasets that were constructed in the early 1990s. The earliest of these is the *ATIS-0* corpus (Hemphill, Godfrey, and Doddington 1990), which consists of transcribed audio recordings of interactions between human users and a flight scheduling system. The system in this case was actually a "wizard" consisting of two experts who transcribed the user’s speech query and then translated the natural language transcription into a database query to retrieve relevant information from the Official Airline Guide (OAG) flight scheduling database. Both the experts and the users were from the Texas Instruments company, and the users were given instructions to use the ATIS system to find airfare that would satisfy certain scenarios. The *ATIS-0* corpus is notable as an early example of a task-oriented wizard-of-oz dialog data collection procedure, where one party (the user) seeks to accomplish a goal (i.e., finding a flight) while the other party (the wizard) imitates a system’s responses.

Subsequent iterations of data collection were performed by Hirschman et al. (1992), Hirschman et al. (1993), and Dahl et al. (1994) to produce *ATIS-1, ATIS-2, and ATIS-3*, respectively. Utterances from the ATIS datasets were used to form the ATIS corpus now commonly used by researchers for benchmarking slot-filling and intent classification models. This ATIS benchmark has 26 intent categories and 83 slot types. Examples from ATIS are shown in Table 2. The ATIS benchmark has been translated to several other languages to provide multilingual extensions (we discuss these later in this section).
The ATIS benchmark is the oldest and perhaps the most well-known dataset for evaluating intent classification and slot-filling, and the benchmark is often seen as synonymous with the task-oriented dialog system paradigm introduced in Section 3 (indeed, Niu and Penn (2019) calls such systems "ATIS-based"). There is a concern that the ATIS corpus is now too easy: we plot slot-filling F1 performance against intent classification accuracy for various models surveyed in Weld et al. (2022) on the ATIS benchmark in Figure 6. As can be seen, joint models have been approaching near-optimal performance over the past few years. As Casanueva et al. (2022) remark, "remarkably, ATIS is still considered at present as one of the main go-to datasets in NLU research." Despite its widespread use, several researchers have pointed out weaknesses inherent in the ATIS benchmark. Béchet and Raymond (2018) argued that ATIS is too "shallow" of a dataset to be a valuable benchmark for contemporary deep learning models, and that many of the errors that high-performing models make are due to annotation errors or natural ambiguities. Recent work by Niu and Penn (2019) further states that the ATIS benchmark "offers only a small amount of training data and an overall lack of lexical and syntactic variety"; Niu and Penn (2019) also find that a rule-based parser achieves performance at levels near deep learning models after fixing annotation errors in ATIS. Larson, Guldan, and Leach (2020) also attempt to quantify features of the supposed "shallowness" of ATIS by observing that, for example, that the overwhelming majority of utterances involving the from_loc.city_name and to_loc.city_name slots follow the tokens "from" and "to", respectively. Nevertheless, the ATIS benchmark continues to be a cornerstone in evaluating natural language understanding systems.

**Datasets derived from ATIS.** Most corpora for developing and evaluating intent classification and slot-filling models are in the English language, which makes it harder to develop and evaluate dialog systems for non-English languages. To fill this gap, several versions of ATIS have emerged for non-English languages. In Upadhyay et al. (2018), a subset of the English version of ATIS was translated to Turkish and Hindi to form **Multilingual ATIS**. Translations were performed manually by native speakers of each target language, and slots were then annotated in the target language using crowdsourcing.

Xu, Haider, and Mansour (2020) take inspiration from the Multilingual ATIS corpus and extend ATIS from English to 6 new languages (8 total including Hindi and Turkish). The resulting collection, called **MultiATIS++**, consists of English, Spanish, Portuguese, French, German, Chinese, Japanese, Hindi, and Turkish, which reflect 4 different language families (Indo-
Table 3: Joint intent classification and slot-filling datasets with English language utterances. (Note that we present statistics for the English versions of Leyzer, Facebook, MTOP, and xSID.)

| Dataset                     | Intents | Slots | # Utterances | Source   | License         |
|-----------------------------|---------|-------|--------------|----------|-----------------|
| ATIS (Hemphill, Godfrey, and Doddington (1990), etc.) | 24      | 83    | 5,871        | Crowd    | LDC             |
| ask ubuntu (Braun et al. 2017) | 5       | 3     | 162          | Users    | CC-BY-SA 3.0    |
| Chatbot (Braun et al. 2017)  | 2       | 5     | 206          | Users    | CC-BY-SA 3.0    |
| Web Applications (Braun et al. 2017) | 8       | 3     | 89           | Users    | CC-BY-SA 3.0    |
| Snips (Coucke et al. 2018)   | 7       | 72    | 14,484       | Crowd    | CC0 1.0         |
| TOP (Gupta et al. 2018)      | 25      | 36    | 44,783       | Crowd    | —               |
| HWL-64 (Xingkun Liu and Rieser 2019) | 64      | 54    | 25,716       | Crowd    | CC-BY-SA 3.0    |
| Facebook (Schuster et al. 2019) | 12      | 11    | 43,323       | Crowd    | CC-BY-SA        |
| TOPv2 (Chen et al. 2020)     | 80      | 82    | 181,000      | Crowd    | —               |
| Leyzer (Sowanski and Janicki 2020) | 186     | 86    | 3,892        | Generated| CC-BY-NC-ND 4.0 |
| MixATIS (Qin et al. 2020)    | 24      | 83    | 20,000       | Derived  | —               |
| MixSNIPS (Qin et al. 2020)   | 7       | 72    | 50,000       | Derived  | —               |
| CSTOP (Einolghozati et al. 2021) | 19      | 10    | 5,803        | Expert   | —               |
| MTOP (Li et al. 2021)        | 117     | 78    | 22,288       | Crowd    | —               |
| xSID (van der Goot et al. 2021) | 16      | 41    | 44,405       | Derived  | CC-BY-SA 4.0    |
| NLU++ (Casanueva et al. 2022) | 62      | 17    | 3,080        | Users    | —               |

European, Sino-Tibetan, Japonic, and Turkic). The translations were generated by professional native translators who also annotated the slots in the target languages. ATIS was also translated from English to Indonesian by Susanto and Lu (2017), and from English to Vietnamese (called PhoATIS) by Dao, Truong, and Nguyen (2021).

Braun Collection. Three datasets comprise the Braun Collection (Braun et al. 2017): the Chatbot Corpus, the Web Applications dataset, and the ask ubuntu dataset (the latter two being part of what Braun et al. (2017) call the StackExchange Corpus). Both the Web Applications and ask ubuntu datasets were constructed by scraping queries from various StackExchange forums like askubuntu.com and webapps.stackexchange.com. As such, the utterances in these two datasets were not originally intended for dialog systems, but they are nonetheless dialog-style utterances directed at various intents related to software support. Both the Web Applications and ask ubuntu datasets consist of English utterances. The Chatbot Corpus is composed of real user utterances from a dialog system for public transit queries in Munich, Germany. While the utterances are in English, they do contain many German place names.

The number of intents for each dataset in the Braun Collection is low, ranging from 2 to 8. The number of training samples is also quite low, with the largest training datasets being the Chatbot Corpus with 206 training samples, and the smallest being the Web Applications dataset with 89 samples. (This is compared to the thousands of utterances in the other datasets listed in Table 3). As such, the WebApplications and ask ubuntu datasets offer extreme training scenarios, with WebApplications containing no intent with more than 7 training samples, and ask ubuntu having a maximum of 17 training samples per intent. The number of slot types is also low for each of the datasets, ranging from 3 to 5.

Snips. Like ATIS, the Snips corpus (Coucke et al. 2018) is a commonly-used benchmark for both intent classification and slot-filling (and their joint) tasks. The intents are composed of categories that a user might ask a general purpose artificially intelligent device, like asking for the weather and playing music. Data for Snips was collected using crowdsourcing, in which crowdworkers were asked to respond to scenario-like prompts targeting particular intent categories with certain slot values. For instance, in the example given in Coucke et al. (2018), workers were asked to respond to the following prompt:

Intent: The user wants to switch the lights on; slot: (bedroom)
Figure 7: Multi-intent samples from *MixSnips* and *MixATIS* are formed by joining utterances together with conjunctions like "and".

I want the lights in the bedroom on right now

The composition of the *Snips* corpus is straightforward: In total, *Snips* has 72 slot types—a subset of which appear across multiple intents—and there are 7 intent categories. With an average of around 2,000, there are relatively many training samples per intent class. Like *Atis*, *Snips* is a well-known corpus for benchmarking joint models, and like *ATIS*, joint models have been approaching near-perfection on *Snips* (Figure 6).

**Almawave-SLU.** The *Almawave-SLU* dataset (Bellomaria et al. 2019) is similar to *Multilingual ATIS* insofar as it is translated from an existing English dataset, but instead of using ATIS as the source dataset, *Almawave-SLU* is derived from *Snips*. *Almawave-SLU* consists of 7,142 samples translated from the English *Snips* dataset into Italian. Whereas *Multilingual ATIS* (as well as several *ATIS*-derived multilingual datasets discussed above) were translated manually, samples in *Almawave-SLU* were first translated using machine translation, then verified and—if needed—corrected by human annotators.

**MixATIS and MixSnips.** Noticing a relative lack of multi-intent datasets for evaluating intent classification and slot-filling models, Qin et al. (2020) artificially create multi-intent queries by joining queries from single-intent datasets. They create *MixSnips* and *MixATIS* by joining queries from the *Snips* and *ATIS* datasets, respectively. Multi-intent queries are constructed by joining queries with conjunctions like "and", ",", "(comma), "and also", "and then", etc. Both *MixATIS* and *MixSnips* consist of queries having between 1 and 3 intents (at a ratio of 0.3:0.5:0.2). Figure 7 shows an example of two single-intent utterances joined with a conjunction. While *MixSnips* and *MixATIS* are notable because they are dedicated multi-intent datasets, they are both limited by their parent corpora (*ATIS* and *Snips*) as well as the relatively few conjunctions that are used to connect queries.

**TOP.** Gupta et al. (2018) argued that the standard manner of representing utterances as intent and slot annotations limits the type of models that can be used in the NLU module of typical task-oriented systems. Instead, Gupta et al. (2018) proposed a hierarchical representation strategy where slots and intents may be nested, and argue that queries such as

```
give me driving directions to the eagles game
```

ought to represented as a composition of two intents: *get_directions* and *get_location*. As such, Gupta et al. (2018) introduced the *TOP* (Task Oriented Parsing) dataset, a corpus of 44,783 utterances across 25 intents and 36 slots labeled using a hierarchical annotation scheme.
Figure 8: Example representation of an utterance in the TOP corpus. (IN: and SL: refer to intent and slot, respectively.)

Figure 8 displays an example annotation for the query *get me driving directions to the oyster festival in San Francisco*. This utterance is annotated with two intents. All utterances in TOP have a top-level intent, and we observed that roughly 35% of all utterances have multiple intents. As such, TOP can be considered as a multi-intent dataset, however all of the multi-intent utterances that we observed have the structure where the nested intent is a direct and only child of a slot annotation, like in the example in Figure 8 where the get_event intent is a direct, only child of the destination slot. (In other words, at least some of the nested intents are redundant with respect to their parent slot annotations.)

**TOPv2.** Chen et al. (2020) built off of the TOP corpus (Gupta et al. 2018) by adding 72 new intents to create TOPv2. In total, the TOPv2 corpus consists of roughly 180,000 utterances across 80 intents and has 82 slot types. Like TOP, the TOPv2 corpus was created by crowdsourcing utterances. The annotation structure of TOPv2 uses the same hierarchical style as TOP, and we estimate that roughly 16% of TOPv2 are multi-intent utterances. A spoken version of TOPv2 exists, called STOP, which consists of 236,477 speech recordings from 885 unique crowd workers from Amazon Mechanical Turk.

**HWU-64.** The HWU-64 joint corpus covers a wide variety of intent types, ranging from home automation, travel, and other general types (e.g., weather queries). In total, this dataset has 64 intent categories and 54 slot types across 25,716 crowdsourced utterances. Like STOP with TOPv2, the HWU-64 corpus has a spoken language extension, SLURP, which has 72,277 speech recordings of utterances from HWU-64 from 177 unique speakers.

**CAIS.** The CAIS (Chinese Artificial Intelligence Speakers) corpus is a Chinese language benchmark consisting of 11 intents and 24 slots (Liu et al. 2019). While not explicitly stated in Liu et al. (2019), CAIS appears to have been constructed from real, spoken user utterances to a production dialog system. CAIS consists of 10,001 samples.

**Facebook.** Like Multilingual ATIS and Almawave-SLU, the Multilingual Task Oriented Dialog dataset (or Facebook, for short) (Schuster et al. 2019) was created to evaluate multilingual transfer learning. This dataset consists of 12 intents across three domain areas related to setting alarms, reminders, and querying the weather. There are 11 slot types. English language utterances were first gathered by prompting crowd workers to provide example commands or questions they would say to a device capable in the three intent categories, then separate crowd workers annotated intent and slot labels for each utterance. A subset of the English utterances were then translated into Spanish and Thai by native speakers.
### Table 4: Non-English joint datasets.

| Dataset                     | Intents | Slots | Language         |
|-----------------------------|---------|-------|------------------|
| Multilingual ATIS (Upadhyay et al. 2018) | 28      | 82    | hi, tr           |
| Facebook (Schuster et al. 2019) | 12      | 11    | en, es, th       |
| Almawave-SLU (Bellomaria et al. 2019) | 7       | 39    | it               |
| CAIS (Liu et al. 2019) | 11       | 24    | zh               |
| MultiATIS++ (Xu, Haider, and Mansour 2020) | 23      | 83    | de, en, es, fr, hi, ja, pt, tr, fr |
| Leyzer (Sowanski and Janicki 2020) | 186     | 86    | en, es, pl       |
| FewJoint (Hou et al. 2020) | 143     | 205   | zh               |
| MTOP (Li et al. 2021)      | 117     | 78    | de, en, es, fr, hi, th |
| PhoATIS (Dao, Truong, and Nguyen 2021) | 28      | 82    | vi               |
| xSID (van der Goot et al. 2021) | 16      | 41    | ar, da, de, de-st, en, id, it, ja, kk, nl, sr, tr, zh |

**MTOP.** Inspired by the nested nature of the queries in many of the TOP dataset’s utterances, the MTOP benchmark was created as a large joint dataset consisting of nested queries in 6 languages: English, Spanish, French, German, Hindi, and Thai (Li et al. 2021). MTOP’s utterances cover 11 different domains and 117 intents (each domain ranges between 3 and 27 intents). There are 78 slot types. The dataset was constructed in several phases: First, crowd workers were prompted to provide English utterances to a hypothetical system given a certain domain. Then, to build the non-English versions of MTOP, professional translators were used to translate the English utterances into each target language, taking care to maintain all slot information.

**Leyzer.** Another multilingual corpus, the Leyzer dataset (Sowanski and Janicki 2020) covers English, Spanish, and Polish. Leyzer pushes the limits in terms of imbalanced datasets, and has between one and 672 samples per intent class. It is also the largest dataset presented in this survey in terms of intents, weighing in at 186 intents covering standard tasks that a hypothetical intelligent device could handle (e.g. news, weather, calendar, web search, etc.). Each intent belongs to one of 20 domain categories. Leyzer contains 86 slot types, with each domain containing between one and seven slot types.

The Leyzer dataset deviates from most of the datasets discussed in this survey in the manner that its sample utterances are generated. While most dialog datasets (i.e., task-oriented dialog in general, and intent classification and slot-filling in particular) are generated by humans using crowdsourcing, experts, or user queries, Leyzer is generated using grammars. In particular, experts defined 20 grammars that produced template utterances, which were then filled in with values sampled from lists. (Figure 5 shows an example of a basic grammar used by Leyzer.) Grammars were built independently for the non-English languages as well, and thus Leyzer is not a parallel corpus (unlike most of the other multilingual corpora discussed in this survey), although there is a small subset of each language’s dataset that is parallel among the three languages.

**FewJoint.** The FewJoint benchmark is a Chinese language benchmark aimed at evaluating few-shot learners. The corpus consists of 143 intent categories and 205 slot types over what Hou et al. (2020) consider to be 59 domains, with 6,694 total utterances. The utterances were sourced from a mix of real user and crowdsourced utterances. Examples from FewJoint are listed in Table 5.

**CSTOP.** The CSTOP corpus (Einolghozati et al. 2021) is a mixed-language Spanish and English language dataset consisting of code-switched (“Spanglish”) queries. These queries target two domains—weather and device—and belong to one of 19 intents and may contain any of 10 slots. While there are several other multilingual intent classification and slot-filling corpora (e.g. Multilingual ATIS, Almawave-SLU, Multilingual Task Oriented Dialog, MultiATIS++, and Leyzer),
Table 5: Example queries from FewJoint (Hou et al. 2020).

| Domain       | Intent          | Utterance                                                                 |
|--------------|-----------------|---------------------------------------------------------------------------|
| message      | sendcontacts    | 把王世怀的号码发给乔丽君                                                   |
| email        | send            | 发一封邮件给张三，内容是晚上来我家吃饭                                   |
| weather      | query           | 合肥今天中午12点温度是多少度                                               |
| cinemas      | score_query     | 大话西游之月光宝盒的评分有多高                                             |
| translation  | translation     | 你今天去了哪里用英文怎么讲                                               |
| home         | turn_on_light   | 打开客厅的吊灯                                                             |

Table 6: Examples from the code-switched language corpus, CSTOP (Einolghozati et al. 2021).

| Intent          | Utterance                                                                 |
|-----------------|---------------------------------------------------------------------------|
| turn_on         | activate mi modo de security                                              |
| open_homescreen | go to la página de inicio                                                  |
| sleep_mode      | pon el dispositivo en sleep mode                                          |
| open_resource   | take me a superframe por favor                                            |
| mute_volume     | pon el speaker en mute                                                    |
| turn_on         | quiero grabar usando la smart camera                                      |
| turn_off        | ponle sonido al speaker                                                   |
| set_brightness  | increase el brillo to 70%                                                 |
| maximize_volume | turn up the volumen a su maxima potencia                                  |
| get_weather     | quiero saber el weather después de las cinco                              |
| get_weather     | dima cuid es el uv index para hoy                                         |
| get_weather     | necesito ponerme un rain jacket                                            |
| get_weather     | tell me the weather para esta tarde                                       |

most of these are derived from existing corpora (i.e, ATIS and Snips). The highly similar semantic parsing field also has a code-switching test set (Duong et al. 2017) for the NLMaps corpus (Haas and Riezler 2016), yet their code-switched corpus was constructed from combining two monolingual data sources. In contrast, CSTOP was constructed from the ground up by workers proficient in code-switched Spanish and English. Examples from CSTOP are shown in Table 6. CSTOP follows the hierarchical annotation style of the other TOP-style datasets. While CSTOP contains some utterances with multiple intent annotations, we estimate that only around 6% have multi-intent annotations, and these appear almost exclusively in CSTOP’s weather domain.

xSID. The xSID corpus seeks to serve as a benchmark for cross-lingual transfer, providing copious amounts of training data (utterances) in English, and limited amounts of evaluation data in 13 different languages: Arabic, Chinese, Danish, Dutch, English, German, Indonesian, Italian, Japanese, Kazakh, Serbian, Turkish, and South Tyrolean (each language has 800 evaluation utterances) (van der Goot et al. 2021). To construct the dataset, the creators of xSID sampled data from Snips and Facebook (both discussed above); these utterances were then translated by experts from English to each target language. xSID consists of 16 intents and 41 slot types.

NLU++. The NLU++ (Casanueva et al. 2022) benchmark consists of two individual joint-task datasets: Banking (consisting of 48 intents and 13 slots) and Hotels (consisting of 40 intents and 14 slots). Together, these two datasets form NLU++, which has 62 intents, 17 unique slots, and a total of 3,080 user-generated utterances, many of which are multi-intent. The annotation scheme
used by NLU++ is unique: instead of annotating spans to indicate separate intent segments, a set of intent labels is applied to each utterance. The intent labels can have varying degrees of granularity: for instance, the cancel intent category can be applied to a wide variety of utterances across both the Banking and Hotel domains, while the account intent applies only to the Banking domain. Together, both cancel and account can be applied to utterances like please cancel my bank account without the need for an explicit cancel_bank_account intent category.

6. Intent Classification Datasets

Intent classification datasets are typically similar to joint intent classification and slot-filling datasets, except they lack slot-filling annotations. Such datasets are usually designed with the goal of evaluating only classification models, but they can also be used for evaluating tasks like clustering as well. The datasets discussed in this section are summarized in Table 10.

**SMP-ECDT Task 1.** The SMP-ECDT Task 1 dataset consists of 3,736 utterances in Chinese (Zhang et al. 2017). SMP-ECDT Task 1 has relatively few utterances per intent. The dataset has 31 intent categories, covering a wide breadth of topics. Example utterances from this corpus are listed in Table 8. Utterances in SMP-ECDT Task 1 were sourced from real user utterances and provided by the iFlytek corporation.

**Outlier Collection.** The Outlier Collection (Larson et al. 2019a) was not designed to be a benchmark for comparing intent classification models, but rather a way to compare data collection methods. The Outlier Collection consists of three datasets, Same, Random, and Unique, but each dataset contains the same 10 intent classes. The difference between the three sets is the manner in which they were crowdsourced.

Each dataset was collected using three iterations of paraphrase crowdsourcing prompts, using the Amazon Mechanical Turk crowdsourcing platform. The first round of data collection
Table 9: Sample utterances from the Clinc-150 dataset (Larson et al. 2019b).

| Domain       | Intent            | Utterance                                                                 |
|--------------|-------------------|---------------------------------------------------------------------------|
| credit_cards | card_declined     | my card was rejected at shakey's and i am wondering why                   |
| kitchen_and_dining | restaurant_reservation | i need a table for 3 at 5pm at andrea's steakhouse under wheeler          |
| auto_and_commute | traffic          | what is the traffic like on the way to north shore                        |
| utility      | time              | what time is in ever there in pacific standard time                       |
| travel       | flight_status     | could you tell me the status of flight dl123                             |
| work         | schedule_meeting  | i'd like to schedule a meeting room from 1:00 pm until 2:00 pm            |
| meta         | change_language   | please respond to me in english from now on                               |
| home         | shopping_list_update | i'm out of kleenex so will you put that on my shopping list              |
| small_talk   | are_you_a_bot     | tell me if you are a human or a computer                                  |
| banking      | transfer          | move 100 dollars from my savings to my checking                           |
|              | out-of-scope      | how long does it take to become an architect                              |
|              | out-of-scope      | is the united states a democracy                                           |
|              | out-of-scope      | how much oer will overdraft protection cover                              |
|              | out-of-scope      | what were the top stories this week                                       |
|              | out-of-scope      | how much has microsoft's stock changed over the last year                 |

contributed to all three datasets, but the Same dataset used the same prompts for the second and third rounds, the Random dataset used randomly selected utterances from the previous round as paraphrase prompts for the next round of data collection, and the Unique dataset used outlier detection to select the most unique (but semantically correct) utterances from each intent from the previous round as prompts for the next round. In this way, the manner in which the Unique version of Outlier is generated is inspired by Negri et al. (2012), which uses a method similar to the "Chinese whispers" or "telephone" game of iterative paraphrase generation. All 10 intents for each Outlier dataset belong to the banking domain, and there is a large amount of samples per intent, with a total of 6,079 samples across all intents (in the case of the Unique dataset).

**Clinc-150.** The Clinc-150 dataset (Larson et al. 2019b) was designed to target several dimensions of intent classification evaluation. First, to test the limits of intent classifiers by providing a large number (150) of intent classes. These intent categories each belong to one of 10 domains, including banking, travel, kitchen & dining, and work. The large number of intents in Clinc-150 stands in contrast with older datasets, like Snips (7 intents) and ATIS (18 intents).

Data for Clinc-150 was collected using crowdsourcing with Amazon Mechanical Turk. Crowd workers were prompted several ways: (1) With open-ended prompts that asked workers to brainstorm what they might reasonably ask (or command) an artificially intelligent system that is knowledgeable in a certain domain. The authors then reviewed this data and manually clustered the data into several intents. The dataset designers also brainstormed intents and added them to this initial intent set. Additional data was added to all intents using (2) paraphrase and scenario prompts, which asked crowd workers to paraphrase utterances from these intents or respond to scenarios that would lead them to target these intents. Table 9 lists example utterances from the Clinc-150 dataset.

The second motivation—and main novelty—of the design of Clinc-150 was to include numerous out-of-scope utterances, which are intended to test an intent classifier's ability to distinguish queries that belong to the 150-intent in-scope set, and those that do not. This notion of out-of-scope is similar to out-of-distribution (e.g., Hendrycks and Gimpel (2017)) and out-of-domain (e.g., Tur, Deoras, and Hakkani-Tür (2014), Tan et al. (2019), and Zheng, Chen, and Huang (2020))
Table 10: Intent Classification datasets.

| Dataset                      | Intents | # Utterances | Source | Lang. | License       |
|------------------------------|---------|--------------|--------|-------|---------------|
| SMP-EDCT Task 1 (Zhang et al. 2017) | 31      | 3,736        | Users  | zh    | —             |
| Outlier (Larson et al. 2019a)   | 10      | 6,079        | Crowd  | en    | CC BY-NC 3.0  |
| Clinc-150 (Larson et al. 2019b)  | 150     | 23,700       | Crowd  | en    | CC BY 3.0     |
| Banking-77 (Casanueva et al. 2020) | 77      | 13,082       | Crowd  | en    | CC BY-NC 4.0  |
| ACID (Acharya and Fung 2020)    | 174     | 22,172       | Users  | en    | —             |
| Curekart (Arora et al. 2020)    | 28      | 1,590        | Experts, Users | en | ODBL 1.0 |
| Powerplay11 (Arora et al. 2020) | 59      | 1,454        | Experts, Users | en | ODBL 1.0 |
| SOFMattress (Arora et al. 2020) | 21      | 710          | Experts, Users | en | ODBL 1.0 |
| ROSTD (Gangal et al. 2020)      | —       | 4,590        | Experts | en | —             |
| Redwood (Larson and Leach 2022) | 451     | 62,216       | Crowd, Mixed | en | —             |

However, the Clinc-150 out-of-scope set includes utterances from within the 10 in-scope domains, as well as from outside these domains.

**Banking-77.** While the Clinc-150 dataset pushed the limits on the number of intents in an intent classification dataset, these intents are distributed across 10 disparate domains. In contrast, the Banking-77 dataset (Casanueva et al. 2020) consists of only one domain—banking—but has 77 intents. The rationale behind this design choice is that distinguishing between 77 closely-related intents is a more challenging intent classification task than if the intents were distributed across several distinct domain categories. That is, the Banking-77 dataset seeks to evaluate a model’s ability to distinguish among fine-grained intent classes. Data for the Banking-77 dataset was generated using crowdsourcing in a manner similar to the Clinc-150 dataset.

**ACID.** The Amfam Chatbot Intent Dataset (ACID) (Acharya and Fung 2020) follows Banking-77 by providing a large number of intents from a single domain. ACID has 174 intents all belonging to the insurance domain, more than double the number of intents from Banking-77. Unlike Clinc-150 and Banking-77, ACID consists of utterances sourced from real customer interactions with human customer service representatives from American Family Insurance (Amfam) company. Similar to Clinc-150, subject matter experts organized the sourced customer interactions into intents.

**HINT3.** The HINT3 corpora (Arora et al. 2020) consist of 3 datasets each from a single domain. These datasets are named SOFMattress (21 intents), Curekart (28 intents), and Powerplay11 (59 intents). Notably, the HINT3 datasets also include a sizeable amount of out-of-scope test samples. Unique among the datasets discussed thus far, the HINT3 datasets have training data sourced from domain experts who imitate real users, based on historical user queries from deployed systems. The HINT3 test sets—including the out-of-scope data—consist of user data from deployed systems.

**ROSTD.** Gangal et al. (2020) created ROSTD (Real Out-of-Domain Sentences from Task-Oriented Dialog) as a companion out-of-domain benchmark to the Facebook corpus (Schuster et al. 2019)). In this way, ROSTD is similar to the out-of-scope set provided with the Clinc-150 benchmark. To create ROSTD, several workers first familiarized themselves with the in-domain intent categories from Facebook, then worked to produce realistic utterances that are out-of-domain

---

4 Prior work has also called this the out-of-application problem (e.g. Bohus and Rudnicky 2005). Out-of-scope utterances were called “orphan” utterances in Tur, Deoras, and Hakkani-Tür (2014).

5 Determined via author correspondence.
with respect to Facebook’s intent categories. ROSTD consists of 4,590 utterances; there are no slot annotations.

Redwood. Larson and Leach (2022) observed that many of the published intent classification and joint-task datasets have overlapping intents (e.g., Snips and Clinc-150 both have intents for asking about the weather), as well as intent categories that are unique to a particular dataset. Larson and Leach (2022) then developed automated tools to detect “colliding” intents between datasets (i.e., intent categories from individual datasets that overlap semantically with intents from other datasets) in order to join 12 intent classification datasets together into a single intent classification dataset, Redwood. The Redwood dataset consists of 451 intents, with each intent consisting of at least 50 samples. The 12 individual datasets that were used to build Redwood are: ACID, Clinc-150, MTOP, Banking-77, HWU, MetalWoz, DSTC-8, ATIS, Outlier, Snips, Jobs640, Talk2Car. Redwood also includes intent categories not found in those 12 datasets; the authors crowdsourced this data.

7. Slot-Filling Datasets

This section surveys slot-filling datasets, which are summarized in Table 11. These are typically datasets that consist of utterances with only slot-level annotations.

MIT Collection. The MIT Collection (Liu et al. 2013) consists of two datasets, MIT Movie and MIT Restaurant. The former dataset consists of utterances directed at a hypothetical movie database, while the latter is composed of phrases targeting a restaurant search application. Two crowdsourcing strategies were used to generate utterances for both datasets. The first, called frame-based, sees crowd workers create utterances given one or several provided slot values. The second, called free-form, asks workers to generate queries and does not provide any pre-defined slot values (workers are free to make up their own slot values, or none). The MIT Movie dataset contains 12,218 samples and 12 slots, and the MIT Restaurant dataset has 9,181 samples and 8 slots.

Jaech Collection. The Jaech Collection (Jaech, Heck, and Ostendorf 2016) consists of four datasets, all of which consist of queries targeting travel and restaurant apps. These datasets are named Airbnb, United (i.e., United Airlines), Greyhound, and OpenTable, and the corresponding app actions that a hypothetical user could take are booking lodging, booking flights, booking bus travel, and reserving a table at a restaurant. The creators of the Jaech Collection were motivated to develop these four datasets in order to evaluate multi-task learning slot-filling models.

Data for the Jaech Collection was collected using crowdsourcing. With the exception of the United dataset, users were asked to pretend they were interacting with a friend (as opposed to an artificially intelligent app) in an attempt to prompt the crowd workers to use more natural language. The dataset creators also made an effort to inject a diverse array of slot values into the dataset by sampling values from curated entity lists. In contrast to most of the datasets discussed thus far, the Jaech Collection contains sample utterances from non-root states of a dialog. Contextual information is not provided in the dataset, however, and thus models trained on the Jaech Collection must rely solely on the textual features of single utterances.

Restaurants-8k. In contrast to the Jaech Collection, the Restaurants-8k dataset (Coope et al. 2020) contains contextual annotations indicating which slots were requested by the system in a dialog. For instance, the utterance “for just one person” has “one person” annotated with the people slot, but also has the people labeled as a requested slot. The requested slot annotations thus provide contextual information to help disambiguate slot predictions (e.g. “7” could be the number of people or the time for booking a restaurant). The precise dialog turns are not annotated or included in the dataset, however, nor are system responses provided. The Restaurants-8k dataset
Table 11: Summary of slot-filling datasets. All datasets listed in this table consist of English utterances.

| Dataset                  | Slots | # Utterances | Source      | License      |
|--------------------------|-------|--------------|-------------|--------------|
| MIT Movie (Liu et al. 2013) | 12    | 12,218       | Crowd       | —            |
| MIT Restaurant (Liu et al. 2013) | 8     | 9,181        | Crowd       | —            |
| Airbnb (Jaech, Heck, and Ostendorf 2016) | 5     | 4,663        | Crowd       | —            |
| Greyhound (Jaech, Heck, and Ostendorf 2016) | 5     | 4,952        | Crowd       | —            |
| OpenTable (Jaech, Heck, and Ostendorf 2016) | 5     | 3,146        | Crowd       | —            |
| United (Jaech, Heck, and Ostendorf 2016) | 5     | 20,696       | Crowd       | —            |
| Restaurants-8k (Coope et al. 2020) | 5     | 20,093       | Users       | CC-BY 4.0    |
| Pizza (Arkoudas et al. 2021) | 10    | 2,458,151    | Generated, Crowd | CC-BY-NC 4.0 |
| Burrito (Rubino et al. 2022) | 11    | 10,173       | Generated   | CC-BY-NC 4.0 |
| Sub (Rubino et al. 2022) | 8     | 10,161       | Generated   | CC-BY-NC 4.0 |
| Coffee (Rubino et al. 2022) | 9     | 104          | Generated   | CC-BY-NC 4.0 |
| Burger (Rubino et al. 2022) | 9     | 161          | Generated   | CC-BY-NC 4.0 |

contains 8,198 utterances, and was sourced from real users interacting with a deployed dialog system in the restaurant booking domain.

Pizza. The Pizza dataset (Arkoudas et al. 2021) is a large corpus consisting of 2,456,446 generated training utterances and 1,705 human-generated test and validation utterances. The synthetically generated utterances were done so by using human-crafted templates. All samples in the Pizza corpus have been annotated in the TOP hierarchical fashion, and all utterances in the corpus are related to ordering food and drink from a hypothetical pizza restaurant.

FoodOrdering Collection. The FoodOrdering collection was introduced in Rubino et al. (2022) and consists of 4 distinct datasets: Burrito, Sub, Coffee, and Burger, all of which are similar to the Pizza dataset (described previously) and consist of TOP-style annotated utterances directed at hypothetical food ordering scenarios. Like Pizza, the Burrito and Sub datasets consist of synthetically-generated training data, but all four of the FoodOrdering corpora consist of crowd-generated utterances. Coffee and Burger have no training data, and are intended to be used as evaluation benchmarks for zero-shot learners.

8. Other Datasets

In this section, we highlight datasets that do not belong to any of the three discussed dataset categories (intent classification, slot-filling, and joint intent classification and slot-filling), but are nonetheless relevant to the task-oriented dialog tasks of intent classification and slot-filling. The datasets discussed in this section are relevant because they contain dialog-style queries, commands, or utterances typically directed towards automated systems.

8.1 Turn-Based Dialog Datasets

While this survey focuses on intent classification and slot-filling datasets, turn-based datasets—which include dialogs consisting of a sequence of utterances between two parties—are also relevant. For instance, the Redwood intent classification dataset (discussed in Section 6) incorporated the "root" utterances from several turn-based dialog datasets, including MetalWOz (Lee et al. 2019) and SGD (Rastogi et al. 2020). The MetalWOz dialog corpus consists of 37,884 dialogs, and the root-level utterances are distributed across 51 intents (according to Larson and Leach (2022)). The Schema-Guided Dataset (or SGD) consists of 16,142 dialogs collected using crowdsourcing,
and Larson and Leach (2022) estimate that the root-level utterances are distributed across 34 intents. Other turn-based dialog dataset include MultiWOZ (Budzianowski et al. 2018) (and its extensions MultiWOZ 2.1 (Eric et al. 2020), MultiWOZ 2.2 (Zang et al. 2020), MultiWOZ 2.3 (Han et al. 2021), and MultiWOZ 2.4 (Ye, Manotumruksa, and Yilmaz 2021)), M2M (Shah et al. 2018), Frames (El Asri et al. 2017), WOZ 2.0 (Wen et al. 2017). Less task-oriented and more open-ended dialog datasets are also valuable, for instance the root level utterances from the open-ended crowdsourced dialog dataset from Vertanen (2017) was used as out-of-domain data in Redwood (Larson and Leach 2022).

8.2 Short Text Classification Corpora

Intent classification is inherently a text classification problem, thus corpora used to evaluate text classifiers are relevant here. One widely-used text classification corpus is the TREC corpus (Li and Roth 2002), which consists of natural language queries taken from the 2001 Text Retrieval Conference (TREC) Question Answering challenge. The TREC corpus has two target label sets, one consisting of six question types, each pertaining to the intended answer content sought after in the question. For example, location and quantity are both question types. The second target label set consists of 50 fine-grained question categories (e.g., the location question type has the fine-grained sub-categories of city, country, mountain, state, and other). The TREC corpus consists of 5,952 questions.

Other widely used text classification corpora include Movie Reviews (Pang and Lee 2005), SST (Socher et al. 2013), etc., but these are sentiment analysis datasets consisting of product or movie reviews meant to communicate information to other humans rather than utterances directed toward a non-human system.

8.3 Semantic Parsing and Natural Language to Database Corpora

The NLP task of semantic parsing aims to convert human language into a machine-readable logical representation (an example application is converting a natural language utterance to a database query). Semantic parsing has substantial overlap with slot-filling and joint modeling, but we discuss semantic parsing datasets separately here since they are not typically used in dialog evaluation.

Such datasets include GeoQuery (Zelle and Mooney 1996) and its extensions to Spanish, Japanese, and Turkish (Wong and Mooney 2006) and to German, Greek, and Thai (Jones, Johnson, and Goldwater 2012), Jobs640 (Califf and Mooney 1997), Restaurants (Tang and Mooney 2000), Free917 (Cai and Yates 2013), WebQuestions (Berant et al. 2013), NLLmaps (Haas and Riezler 2016), NNLIDB (Brad et al. 2017), Scholar (Iyer et al. 2017), MAS (Li and Jagadish 2014), IMDB and Yelp (Yaghmazadeh et al. 2017), WikiSQL (Zhong, Xiong, and Socher 2017), Advising (Finegan-Dollak et al. 2018), Spider (Yu et al. 2018), NL2Bash (Lin et al. 2018), and Talk2Car (Deruyttere et al. 2019).

9. Discussion and Future Directions

In this section we reflect on the nature of the datasets surveyed above. We identify several areas that are ripe for future research directions.

9.1 Language Representation

Within NLP there is a risk of focusing solely on the English language. As we have seen, though, there are ample non-English language datasets for benchmarking joint tasks. However, many of these datasets were produced by automatic translation, and hence may be limited in
representing realistic language phenomena. Moreover, non-English datasets for the solo tasks of intent classification and slot-filling number far fewer.

9.2 Sources of Data

We observe that most of the datasets surveyed here use crowdsourcing or data generation to produce utterances, and many of the non-English datasets are derived in the form being translations of parent corpora into target languages. While derived datasets are seen in other NLP fields (e.g., ASR (Chan et al. 2021), open information retrieval (Solawetz and Larson 2021)), the intent classification and slot-filling landscape—especially for joint datasets—is becoming quite populated with derived corpora. Far fewer datasets surveyed here consist of utterances from real users, and it would be interesting to investigate whether models trained on real user data outperform generated (either synthetic or by crowdsourcing) or derived datasets.

9.3 Out-of-Domain Data

It may be unreasonable to expect a human user to limit their queries to those that fall within the scope or domain of a task-oriented dialog system’s supported intents. Despite this, almost all of the datasets surveyed in this paper do not include dedicated out-of-scope or out-of-domain samples with which to evaluate a model’s ability to recognize out-of-domain utterances. The Clinc-150 and ROSTD benchmarks are a notable exception to this—as they have large amounts of out-of-scope utterances—but Clinc-150 is an intent-only dataset. Researchers and practitioners wishing to evaluate out-of-scope performance for their models may find that some of the datasets surveyed herein can be used as pseudo-out-of-scope utterances (for instance, a model could be trained on ATIS, and then evaluated on Snips). However, to be more thorough, we recommend creators of new datasets to include out-of-scope queries to facilitate more realistic evaluation.

9.4 Multi-Intent Corpora

Out of the datasets surveyed in this paper, only Task Oriented Parsing (TOP) (Gupta et al. 2018), MixATIS and MixSNIPS (Qin et al. 2020), and NLU++ (Casanueva et al. 2022) datasets contain multi-intent utterances. MixATIS and MixSNIPS were each constructed from already existing source datasets (ATIS and Snips, respectively) by joining queries from the source datasets using simple conjunction words like "and" and "and also". These two datasets are therefore quite limited in the way that multi-intent utterances appear. Moreover, randomly joining two utterances from a dataset like Snips might not sufficiently represent the way in which human users interact with dialog systems. For example, a human user might be unlikely to ask about the weather and tell a system to rate a book in the same query, as these two intents (get_weather and rate_book) are rather different. To help improve the capabilities of task-oriented dialog systems, we recommend creators of new datasets to include realistic multi-intent utterances.

9.5 Challenge Corpora

As seen in figures 6a and 6b, model performance on the ATIS and Snips datasets has increased to near perfect levels over recent years. This might indicate that the tasks of intent classification and slot-filling are close to being solved. On the contrary, recent work on model evaluation has shown that models trained on standard evaluation datasets but tested on challenge datasets often exhibit substantially worse performance.

In Larson et al. (2020b), crowdsourcing was used to generate paraphrases of test samples from the ATIS, Snips, Clinc-150, and TOP datasets (among others). Importantly, when the crowd workers were made to avoid using certain key words in their paraphrases, they produced test
data that models trained on the standard datasets struggled on in comparison. Inspired by Ribeiro et al. (2020), who developed an automated framework for modifying test data in order to probe model robustness on sentiment analysis and machine comprehension tasks, several recent efforts have developed mixes of automated and crowdsourced frameworks for altering intent classification and slot-filling data in order to evaluate model robustness. For instance, Peng et al. (2021), Liu et al. (2021), and Krone, Sengupta, and Mansoor (2021) all introduce methods for injecting noise (e.g., spelling and ASR errors, speech disfluencies) into and producing modifications (e.g., paraphrases; punctuation, casing, and morphological changes) of utterances. These types of efforts typically find that models trained on standard, clean data often struggle to generalize to these noisier inputs. A related work also introduces new train-test splits on the related task of semantic parsing in order to reduce overlap between train and test sets (Finegan-Dollak et al. 2018). In all, investigating datasets with a critical eye and a goal of producing diverse and realistic training and test sets is likely to increase in importance in the coming years.

9.6 Analysis of Datasets

Our survey of intent classification and slot-filling corpora for task-oriented dialog systems has used fairly straightforward metrics of comparison: number of intents and slots, number of utterances, language, data source, etc. Other more detailed comparison metrics could be used, like the word-based vocabulary size and token type ratio (Templin 1957) metrics. Going further, future work could aim to quantify notions like correctness, difficulty, and generalizability of datasets. By correctness, we mean metrics and tools for ensuring that corpora are free from annotation inconsistencies and errors (e.g., Larson et al. (2020a), Klie, Webber, and Gurevych (2022)). By difficulty, recall our discussion of the ATIS benchmark and "shallowness" notion from Béchet and Raymond (2018) and Niu and Penn (2019); what metrics and tools can be developed to quantify how difficult a benchmark is, in addition to simply computing accuracy and F1 scores on models? Moreover, as we discussed in the previous subsection, prior work (e.g., Krone, Sengupta, and Mansoor 2021; Larson et al. 2020b; Peng et al. 2021) has raised doubts as to whether models trained on the benchmarks surveyed herein can generalize well to real-world or "long tail" inputs. For this reason, tools and metrics to help determine the quality of a corpus in regards to difficulty and generalizability could be very valuable.

10. Conclusion

The interest in and application of task-oriented dialog systems has grown within the past decade, and will likely grow more in the near future. To develop such systems, the essential intent classification and slot-filling components must be benchmarked and evaluated. In this survey, we have cataloged evaluation datasets for intent classification, slot-filling, and joint modeling tasks. Our hope is that researchers, developers, and dialog system designers will find this survey useful when selecting datasets to use for benchmarking these types of models.

11. Acknowledgments

We thank Deborah Dahl for detailed discussion on the origins and development of ATIS.

References

Acharya, Shailesh and Glenn Fung. 2020. Using optimal embeddings to learn new intents with few examples: An application in the insurance domain. In Proceedings of the KDD 2020 Workshop on Conversational Systems Towards Mainstream Adoption (KDD Converse 2020).

Arkoudas, Konstantine, Nicolas Guenon des Mesnards, Melanie Rubino, Sandesh Swamy, Saarthak Khanna, and Weiqi Sun. 2021. Pizza: a task-oriented semantic parsing dataset.
Arora, Gaurav, Chirag Jain, Manas Chaturvedi, and Krupal Modi. 2020. HINT3: Raising the bar for intent detection in the wild. In Proceedings of the First Workshop on Insights from Negative Results in NLP, pages 100–105, Association for Computational Linguistics, Online.

Béchet, Frédéric and Christian Raymond. 2018. Is atis too shallow to go deeper for benchmarking spoken language understanding models? In Proceedings of Interspeech.

Bellomaria, Valentina, Giuseppe Castellucci, Andrea Favalli, and Raniero Romagnoli. 2019. Almawave-slu: A new dataset for SLU in Italian. In Proceedings of the Sixth Italian Conference on Computational Linguistics, Bari, Italy, November 13-15, 2019, volume 2481 of CEUR Workshop Proceedings, CEUR-WS.org.

Berant, Jonathan, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Association for Computational Linguistics, Seattle, Washington, USA.

Bohus, Dan and Alexander I. Rudnick. 2005. Sorry and I didn’t catch that! - an investigation of non-understanding errors and recovery strategies. In Proceedings of the 6th SIGdial Workshop on Discourse and Dialogue, pages 128–143, Special Interest Group on Discourse and Dialogue (SIGdial), Lisbon, Portugal.

Brad, Florin, Radu Cristian Alexandru Iacob, Ionel Alexandru Hosu, and Traian Rebedea. 2017. Dataset for a neural natural language interface for databases (NNLIDB). In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 906–914, Asian Federation of Natural Language Processing, Taipei, Taiwan.

Braun, Daniel, Adrian Hernandez Mendez, Florian Matthes, and Manfred Langen. 2017. Evaluating natural language understanding services for conversational question answering systems. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 174–185, Association for Computational Linguistics, Saarbrücken, Germany.

Budzianowski, Pawel, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo 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, pages 5016–5026, Association for Computational Linguistics, Brussels, Belgium.

Cai, Qingqing and Alexander Yates. 2013. Large-scale semantic parsing via schema matching and lexicon extension. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 423–433, Association for Computational Linguistics, Sofia, Bulgaria.

Califf, Mary Elaine and Raymond J. Mooney. 1997. Relational learning of pattern-match rules for information extraction. In CoNLL97: Computational Natural Language Learning.

Casanueva, Inigo, Tadas Temčinas, Daniela Gerz, Matthew Henderson, and Ivan Vulić. 2020. Efficient intent detection with dual sentence encoders. In Proceedings of the 2nd Workshop on Natural Language Processing for Conversational AI, pages 38–45, Association for Computational Linguistics, Online.

Casanueva, Inigo, Ivan Vulić, Georgios Spithourakis, and Pawel Budzianowski. 2022. NLU++: A multi-label, slot-rich, generalisable dataset for natural language understanding in task-oriented dialogue. In Findings of the Association for Computational Linguistics: NAACL 2022, pages 1998–2013, Association for Computational Linguistics, Seattle, United States.

Chan, William, Daniel Ś. Park, Chris Lee, Yu Zhang, Quoc V. Le, and Mohammad Norouzi. 2021. Speechstew: Simply mix all available speech recognition data to train one large neural network. arXiv preprint arXiv:2104.02133.

Chen, Hongshen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. 2017. A survey on dialogue systems: Recent advances and new frontiers. SIGKDD Explor. Newsl., 19(2):25–35.

Chen, XiLun, Asish Ghoshal, Yashar Mehdad, Luke Zettlemoyer, and Sonal Gupta. 2020. Low-resource domain adaptation for compositional task-oriented semantic parsing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5090–5100, Association for Computational Linguistics, Online.

Coope, Samuel, Tyler Farghly, Daniela Gerz, Ivan Vulić, and Matthew Henderson. 2020. Span-ConverseRT: Few-shot span extraction for dialog with pretrained conversational representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 107–121, Association for Computational Linguistics, Online.

Coullicke, Alice, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibault Lavril, Maël Primet, and Joseph Dureau. 2018. Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. CoRR, abs/1805.10190.

Dahl, Deborah A., 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 Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994.
Dai, Yinpei, Huihua Yu, Yixuan Jiang, Chengguang Tang, Yongbin Li, and Jian Sun. 2020. A survey on dialog management: Recent advances and challenges. arXiv preprint arXiv:2005.02233.

Dao, Mai Hoang, Thinh Hung Truong, and Dat Quoc Nguyen. 2021. Intent Detection and Slot Filling for Vietnamese. In Proceedings of the 22nd Annual Conference of the International Speech Communication Association (INTERSPEECH).

Deriu, Jan, Alvaro Rodrigo, Arantxa Otegi, Guillermo Echeugoyen, Sophie Rosset, Eneko Agirre, and Mark Cieliebak. 2020. Survey on evaluation methods for dialogue systems. Artificial Intelligence Review, page 56p.

Deruyttere, Thierry, Simon Vandenhende, Dusan Grujicic, Luc Van Gool, and Marie-Francine Moens. 2019. Talk2Car: Taking control of your self-driving car. 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 2088–2098, Association for Computational Linguistics, Hong Kong, China.

Devlin, Jacob, 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, Association for Computational Linguistics, Minneapolis, Minnesota.

Duong, Long, Hadi Afshar, Dominique Estival, Glen Pink, Philip Cohen, and Mark Johnson. 2017. Multilingual semantic parsing and code-switching. In Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017), pages 379–389, Association for Computational Linguistics, Vancouver, Canada.

Dzendzik, Daria, C. Vogel, and Jennifer Foster. 2021. English machine reading comprehension datasets: A survey. arXiv preprint arXiv:2101.10421.

Einolghozati, Arash, A. Arora, Lorona Sainz-Maza Lecanda, A. Kumar, and Sonal Gupta. 2021. El volumen louder por favor: Code-switching in task-oriented semantic parsing. arXiv preprint arXiv:2101.10524.

El Asri, Layla, Hannes Schulz, Shikhar Sharma, Jeremie Zumer, Justin Harris, Emery Fine, Rahul Mehrotra, and Kaheer Suleman. 2017. Frames: a corpus for adding memory to goal-oriented dialogue systems. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 207–219, Association for Computational Linguistics, Saarbrücken, Germany.

Eric, Mihail, Rahul Goel, Shachi Paul, Abhishek Sethi, Sanchit Agarwal, Shuyang Gao, Adarsh Kumar, Anuj Goyal, Peter Ku, and Dilek Hakkani-Tur. 2020. MultiWOZ 2.1: A consolidated multi-domain dialogue dataset with state corrections and state tracking baselines. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 422–428, European Language Resources Association, Marseille, France.

Finegan-Dollak, Catherine, 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, Association for Computational Linguistics, Melbourne, Australia.

Gangal, Varun, Abhinav Arora, Arash Einolghozati, and Sonal Gupta. 2020. Likelihood ratios and generative classifiers for unsupervised out-of-domain detection in task oriented dialogue. In Proceedings of the AAAI Conference on Artificial Intelligence.

Gao, Jianfeng, Michel Galley, and Lihong Li. 2019. Neural approaches to conversational ai. arXiv preprint arXiv:1809.08267.

van der Goot, Rob, Ibrahim Sharaf, Aizhan Imankulova, Ahmet Üstün, Marija Stepanović, Alan Ramponi, Siti Oryza Khaireunnisa, Mamoru Komachi, and Barbara Plank. 2021. From masked language modeling to translation: Non-English auxiliary tasks improve zero-shot spoken language understanding. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2479–2497, Association for Computational Linguistics, Online.

Gupta, Sonal, Rushin Shah, Mrinal Mohit, Anuj Kumar, and Mike Lewis. 2018. Semantic parsing for task oriented dialog using hierarchical representations. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2787–2792, Association for Computational Linguistics, Brussels, Belgium.

Haas, Carolin and Stefan Riezler. 2016. A corpus and semantic parser for multilingual natural language querying of OpenStreetMap. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 740–750, Association for Computational Linguistics, San Diego, California.

Han, Ting, Ximing Liu, Ryuichi Takanabu, Yixin Lian, Chongxuan Huang, Dazhen Wan, Wei Peng, and Minlie Huang. 2021. Multiwoz 2.3: A multi-domain task-oriented dialogue dataset enhanced with annotation corrections and co-reference annotation. In Natural Language Processing and Chinese
Hirschman, L., M. Bates, D. Dahl, W. Fisher, J. Garofolo, D. Pallett, K. Hunicke-Smith, P. Price, A. Rudnicky, and E. Tzoukermann. 1993. Multi-site data collection and evaluation in spoken language understanding. In Human Language Technology: Proceedings of a Workshop Held at Plainsboro, New Jersey, March 21-24, 1993.

Hirschman, Lynette, Madeleine Bates, Deborah Dahl, William Fisher, Kate Hunicke-Smith, David Pallett, Christine Pao, Patti Price, and Alexander Rudnicky. 1992. Multi-site data collection for a spoken language corpus. In Speech and Natural Language: Proceedings of a Workshop Held at Harriman, New York, February 23-26, 1992.

Hou, Lixian, Yanling Li, Chengcheng Li, and Min Lin. 2019. Review of research on task-oriented spoken language understanding. Journal of Physics: Conference Series, 1267:012023.

Klie, Jan-Christoph, Bonnie Webber, and Iryna Gurevych. 2022. Annotation error detection: Analyzing the past and present for a more coherent future. arXiv preprint arXiv:2206.02280.

Korpusik, Mandy, Zoe Liu, and James Glass. 2019. A Comparison of Deep Learning Methods for Language Understanding. In Proc. Interspeech 2019, pages 849–853.

Krone, Jason, Sailik Sengupta, and Saab Mansoor. 2021. On the robustness of goal oriented dialogue systems to real-world noise. arXiv preprint arXiv:2104.07149.

Larson, Stefan, Adrian Cheung, Anish Mahendran, Kevin Leach, and Jonathan K. Kummerfeld. 2020a. Inconsistencies in crowdsourced slot-filling annotations: A typology and identification methods. In Proceedings of the 28th International Conference on Computational Linguistics, pages 5035–5046, International Committee on Computational Linguistics, Barcelona, Spain (Online).

Larson, Stefan, Eric Guldan, and Kevin Leach. 2020. Data query language and corpus tools for slot-filling and intent classification data. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 7060–7068, European Language Resources Association, Marseille, France.

Larson, Stefan and Kevin Leach. 2022. Redwood: Using collision detection to grow a large-scale intent classification dataset. arXiv preprint arXiv:2204.05483.

Larson, Stefan, Anish Mahendran, Andrew Lee, Jonathan K. Kummerfeld, Parker Hill, Michael A. Laurenzano, Johann Hauswald, Lingjia Tang, and Jason Mars. 2019a. Outlier detection for improved data quality and diversity in dialog systems. 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 517–527, Association for Computational Linguistics, Minneapolis, Minnesota.

Larson, Stefan, Anish Mahendran, Joseph J. Peper, Christopher Clarke, Andrew Lee, Parker Hill, Jonathan K. Kummerfeld, Kevin Leach, Michael A. Laurenzano, Lingjia Tang, and Jason Mars. 2019b. An evaluation dataset for intent classification and out-of-scope prediction. 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 1311–1316, Association for Computational Linguistics, Hong Kong, China.
Larson, Stefan, Anthony Zheng, Anish Mahendran, Rishi Tekriwal, Adrian Cheung, Eric Guldan, Kevin Leach, and Jonathan K. Kummerfeld. 2020b. Iterative feature mining for constraint-based data collection to increase data diversity and model robustness. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8097–8106, Association for Computational Linguistics, Online.

Lee, Sungjin, Hannes Schulz, Adam Atkinson, Jianfeng Gao, Kaheer Suleman, Layla El Asri, Mahmoud Adada, Minlie Huang, Shikhar Sharma, Wendy Tay, and Xiujuan Li. 2019. Multi-domain task-completion dialog challenge. In Dialog System Technology Challenges 8.

Li, Fei and H. V. Jagadish. 2014. Constructing an interactive natural language interface for relational databases. *Proc. VLDB Endow.*, 8(1):73–84.

Li, Haoran, Abhinav Arora, Shubhui Chen, Anchit Gupta, Sonal Gupta, and Yashar Mehdad. 2021. MTOP: A comprehensive multilingual task-oriented semantic parsing benchmark. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2950–2962, Association for Computational Linguistics, Online.

Li, Xin and Dan Roth. 2002. Learning question classifiers. In COLING 2002: The 19th International Conference on Computational Linguistics.

Lin, Xi Victoria, Chenglong Wang, Luke Zettlemoyer, and Michael D. Ernst. 2018. NL2Bash: A corpus and semantic parser for natural language interface to the linux operating system. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), European Language Resources Association (ELRA), Miyazaki, Japan.

Liu, J., P. Pasupat, S. Cyphers, and J. Glass. 2013. Asgard: A portable architecture for multilingual dialogue systems. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 8386–8390.

Liu, Jiao, Yanling Li, and Min Lin. 2019. Review of intent detection methods in the human-machine dialogue system. *Journal of Physics: Conference Series*, 1267:012059.

Liu, Jie, Ryuichi Takanobu, Jiaxin Wen, Dazhen Wan, Hongguang Li, WeiranNie, Cheng Li, Wei Peng, and Minlie Huang. 2021. Robustness testing of language understanding in task-oriented dialog. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2467–2480, Association for Computational Linguistics, Online.

Liu, Yijin, Fandong Meng, Jinchao Zhang, Jie Zhou, Yufeng Chen, and Jinan Xu. 2019. CM-net: A novel collaborative memory network for spoken language understanding. 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 1051–1060, Association for Computational Linguistics, Hong Kong, China.

Louvain, Samuel and Bernardo Magnini. 2020. Recent neural methods on slot filling and intent classification for task-oriented dialogue systems: A survey. In Proceedings of the 28th International Conference on Computational Linguistics, pages 480–496, International Committee on Computational Linguistics, Barcelona, Spain (Online).

McTear, Michael. 2020. Conversational ai: Dialogue systems, conversational agents, and chatbots. *Synthesis Lectures on Human Language Technologies*, 13(3):1–251.

Mehri, S., M. Eric, and D. Hakkani-Tür. 2020. Dialoglue: A natural language understanding benchmark for task-oriented dialogue. *arXiv preprint arXiv:2009.13570*.

Mesnil, Grégoire, Yann Dauphin, Kaisheng Yao, Yoshua Bengio, Li Deng, Dilek Hakkani-Tur, Xiaodong He, Larry Heck, Gokhan Tur, Dong Yu, and Geoffrey Zweig. 2015. Using recurrent neural networks for slot filling in spoken language understanding. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 23(3):530–539.

Mesnil, Grégoire, Xiaodong He, Li Deng, and Yoshua Bengio. 2013. Investigation of recurrent-neural-network architectures and learning methods for spoken language understanding. In *Interspeech 2013*.

Negri, Matteo, Yashar Mehdad, Alessandro Marchetti, Danilo Giampiccolo, and Luisa Bentivogli. 2012. Chinese whispers: Cooperative paraphrase acquisition. In Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC’12), pages 2659–2665, European Language Resources Association (ELRA), Istanbul, Turkey.

Ni, Jinjie, Tom Young, Vlad Pandelea, Fuzhao Xue, V. Adiga, and E. Cambria. 2021. Recent advances in deep learning-based dialogue systems. *arXiv preprint arXiv:2105.04387*.

Niu, Jingcheng and Gerald Penn. 2019. Rationally reappraising ATIS-based dialogue systems. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5503–5507, Association for Computational Linguistics, Florence, Italy.

Pang, Bo and Lillian Lee. 2005. Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. In Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL’05), pages 115–124, Association for Computational Linguistics, Ann Arbor, Michigan.
Peng, Baolin, Chunyuan Li, Zhu Zhang, Chenguang Zhu, Jinchao Li, and Jianfeng Gao. 2021. RADDLE: An evaluation benchmark and analysis platform for robust task-oriented dialog systems. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 4418–4429, Association for Computational Linguistics, Online.

Qin, Libo, Tianbao Xie, Wanxiang Che, and Ting Liu. 2021. A survey on spoken language understanding: Recent advances and new frontiers. In Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI).

Qin, Libo, Xiao Xu, Wanxiang Che, and Ting Liu. 2020. AGIF: An adaptive graph-interactive framework for joint multiple intent detection and slot filling. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1807–1816, Association for Computational Linguistics, Online.

Rastogi, Abhinav, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 8689–8696.

Razumovskaia, Evgeniia, Goran Glavaš, Olga Majewska, Anna Korhonen, and Ivan Vulić. 2021. Crossing the conversational chasm: A primer on multilingual task-oriented dialogue systems. arXiv preprint arXiv:2104.08570.

Ribeiro, Marco Tulio, Tongshuang Wu, Carlos Guéstrin, and Sameer Singh. 2020. Beyond accuracy: Behavioral testing of NLP models with CheckList. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4902–4912, Association for Computational Linguistics, Online.

Rubino, Melanie, Nicolas Guenon des Mesnards, Uday Shah, Nanjiang Jiang, Weiqi Sun, and Konstantine Arkoudas. 2022. Cross-top: Zero-shot cross-schema task-oriented parsing. arXiv preprint arXiv:2206.05352.

Schuster, Sebastian, Sonal Gupta, Rushin Shah, and Mike Lewis. 2019. Cross-lingual transfer learning for multilingual task-oriented dialog. 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 3795–3805, Association for Computational Linguistics, Minneapolis, Minnesota.

Serban, Iulian Vlad, 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.

Shah, Pararth, Dilek Hakkani-Tür, Gokhan Tür, Abhinav Rastogi, Ankur Bapna, Neha Nayak, and Larry Heck. 2018. Building a conversational agent overnight with dialogue self-play. arXiv preprint arXiv:1801.04871.

Socher, Richard, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1631–1642, Association for Computational Linguistics, Seattle, Washington, USA.

Solawetz, Jacob and Stefan Larsson. 2021. LSOIE: A large-scale dataset for supervised open information extraction. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2595–2600, Association for Computational Linguistics, Online.

Sowinski, Marcin and Artur Janicki. 2020. Leyzer: A dataset for multilingual virtual assistants. In Text, Speech, and Dialogue - 23rd International Conference, TSD 2020, Brno, Czech Republic, September 8-11, 2020, Proceedings, volume 12284 of Lecture Notes in Computer Science, pages 477–486, Springer.

Susanto, Raymond Hendy and Wei Lu. 2017. Neural architectures for multilingual semantic parsing. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 38–44, Association for Computational Linguistics, Vancouver, Canada.

Tan, Ming, Yang Yu, Haoyu Wang, Dakuo Wang, Saloni Potdar, Shiyu Chang, and Mo Yu. 2019. Out-of-domain detection for low-resource text classification tasks. 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 3566–3572, Association for Computational Linguistics, Hong Kong, China.

Tang, Lappoon R. and Raymond J. Mooney. 2000. Automated construction of database interfaces: Integrating statistical and relational learning for semantic parsing. In 2000 Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora, pages 133–141, Association for Computational Linguistics, Hong Kong, China.

Templin, Mildred C. 1957. Certain Language Skills in Children: Their Development and Interrelationships. University of Minnesota Press.

Tomashenko, Natalia, Antoine Caubriè, Yannick Estèве, Antoine Laurent, and Emmanuel Morin. 2019. Recent advances in end-to-end spoken language understanding. In 7th International Conference on Statistical Language and Speech Processing, pages 44–55, Springer International Publishing.
Tur, Gokhan, Anoop Deoras, and Dilek Hakkani-Tür. 2014. Detecting out-of-domain utterances addressed to a virtual personal assistant. In *Proceedings of Interspeech*, ISCA - International Speech Communication Association.

Upadhyay, Shyam, Manaal Faruqui, Gokhan Tur, Dilek Hakkani-Tur, and Larry Heck. 2018. (almost) zero-shot cross-lingual spoken language understanding. In *Proceedings of the IEEE ICASSP*.

Vertanen, Keith. 2017. Towards improving predictive aac using crowdsourced dialogues and partner context. In *ASSETS ’17: Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility*.

Wang, Yang, Quanming Yao, James T. Kwok, and Lionel M. Ni. 2020. Generalizing from a few examples: A survey on few-shot learning. *ACM Comput. Surv.*, 53(3).

Wang, Zhen. 2022. Modern question answering datasets and benchmarks: A survey. *arXiv preprint arXiv:2206.15030*.

Weld, Henry, Xiaoxi Huang, Siqi Long, Josiah Poon, and Soyeon Caren Han. 2022. A survey of joint intent detection and slot filling models in natural language understanding. *ACM Comput. Surv.*, Just Accepted.

Wen, Tsung-Hsien, Pei-Hao Su, Pawel Budzianowski, Ifigo Casanueva, and Ivan Vulić. 2019. Data collection and end-to-end learning for conversational AI. 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): Tutorial Abstracts*, Association for Computational Linguistics, Hong Kong, China.

Wen, Tsung-Hsien, David Vandyke, Nikola Mrkšić, Milica Gašić, Lina M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, pages 438–449, Association for Computational Linguistics, Valencia, Spain.

Wiegreffe, Sarah and Ana Marasović. 2021. Teach me to explain: A review of datasets for explainable nlp. *arXiv preprint arXiv:2102.12060*.

Wong, Yuk Wah and Raymond Mooney. 2006. Learning for semantic parsing with statistical machine translation. In *Proceedings of the Human Language Technology Conference of the NAACL, Main Conference*, pages 439–446, Association for Computational Linguistics, New York City, USA.

Wu, Chien-Sheng, Steven C.H. Hoi, Richard Socher, and Caiming Xiong. 2020a. TOD-BERT: Pre-trained natural language understanding for task-oriented dialogue. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 917–929, Association for Computational Linguistics, Online.

Wu, Di, Liang Ding, Fan Lu, and Jian Xie. 2020b. SlotRefine: A fast non-autoregressive model for joint intent detection and slot filling. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1932–1937, Association for Computational Linguistics, Online.

Xiong, Wei, Yaojia Li, and Sander Dieleman. 2020. Deep voice translation: One to many speech translation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5052–5063, Association for Computational Linguistics, Online.

Yaghmazadeh, Navid, Yuepeng Wang, Isil Dillig, and Thomas Dillig. 2017. Sqlizer: Query synthesis from natural language. *Proc. ACM Program. Lang.*, 1(OOPSLA).

Yaghoub-Zadeh-Fard, M., B. Benatallah, F. Casati, M. C. Barukh, and S. Zamanirad. 2020. User utterance acquisition for training task-oriented bots: A review of challenges, techniques and opportunities. *IEEE Internet Computing*, 24(3):30–38.

Yao, Kaisheng, Baolin Peng, Yu Zhang, Dong Yu, Geoffrey Zweig, and Yangyang Shi. 2014. Spoken language understanding using long short-term memory neural networks. In *2014 IEEE Spoken Language Technology Workshop (SLT)*, pages 189–194.

Yao, Kaisheng, Geoffrey Zweig, Mei-Yuh Hwang, Yangyang Shi, and Dong Yu. 2013. Recurrent neural networks for language understanding. *Interspeech*.

Ye, Fanghua, Jie Wang, and Duen Horng Chau. 2021. MultiWOZ 2.4: A multi-domain task-oriented dialogue dataset with essential annotation corrections to improve state tracking evaluation. *arXiv preprint arXiv:2104.00773*.

Yin, Wenpeng. 2020. Meta-learning for few-shot natural language processing: A survey. *arXiv preprint arXiv:2007.09604*.

Yu, Tao, Rui Zhang, Kai Yang, Michihiro Yasunaga, 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, Association for Computational Linguistics, Brussels, Belgium.
Zang, Xiaoxue, Abhinav Rastogi, Srinivas Sunkara, Raghav Gupta, Jianguo Zhang, and Jindong Chen. 2020. MultiWOZ 2.2: A dialogue dataset with additional annotation corrections and state tracking baselines. In Proceedings of the 2nd Workshop on Natural Language Processing for Conversational AI, pages 109–117, Association for Computational Linguistics, Online.

Zelle, John M. and Raymond J. Mooney. 1996. Learning to parse database queries using inductive logic programming. In Proceedings of the Thirteenth National Conference on Artificial Intelligence - Volume 2, AAAI'96, page 1050–1055, AAAI Press.

Zhang, Wei-Nan, Zhigang Chen, Wanxiang Che, Guoping Hu, and Ting Liu. 2017. The first evaluation of Chinese human-computer dialogue technology. arXiv preprint arXiv:1709.10217.

Zheng, Yinhe, Guanyi Chen, and Minlie Huang. 2020. Out-of-domain detection for natural language understanding in dialog systems. IEEE/ACM Trans. Audio, Speech and Lang. Proc., 28:1198–1209.

Zhong, Victor, Caiming Xiong, and Richard Socher. 2017. Seq2sql: Generating structured queries from natural language using reinforcement learning. arXiv preprint arXiv:1709.00103.