TamilATIS: Dataset for Task-Oriented Dialog in Tamil

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Abstract

Task-Oriented Dialogue (TOD) systems allow users to accomplish tasks by giving directions to the system using natural language utterances. With the widespread adoption of conversational agents and chat platforms, TOD has become mainstream in NLP research today. However, developing TOD systems require massive amounts of data, and there has been limited work done for TOD in low-resource languages like Tamil. Towards this objective, we introduce TamilATIS - a TOD dataset for Tamil which contains 4874 utterances. We present a detailed account of the entire data collection and data annotation process. We train state-of-the-art NLU models and report their performances. The Joint BERT model with XLM-Roberta as utterance encoder achieved the highest score with an intent accuracy of 96.26% and slot F1 of 94.01%.

1 Introduction

Task-oriented dialog (TOD) systems enable a user to use natural language directions to complete specific tasks. Recently, such systems have been successfully deployed in smart applications such as Amazon’s Echo and Spotify’s Car Thing.

There are several components that are critical to the performance of a TOD system. These components are Natural Language Understanding, Dialogue State Tracking (DST), and Response Selection. In this work, we focus on the NLU component. NLU aims to semantically parse an input utterance and typically has two tasks: intent classification and slot filling (refer Table 1 for example).

Intent classification deals with identifying the underlying motivation or the goal of the user query. This is typically cast as a token classification or span identification task. Slot filling is a challenging task in NLU. The model needs to adapt to unseen domains and identify entities that it has not encountered in training before.

Intent classification and slot filling have been widely researched for the English language. The approaches presented in these works achieve excellent performance due to the availability of large amounts of high-quality and human-annotated datasets. However, such performance has not been achieved for several low-resource languages due to a lack of data. Developing TOD datasets for low-resource languages is essential to the proliferation of NLP technologies in these communities and contributes towards inclusivity and diversity of language resources.

To facilitate this, we present a dataset named TamilATIS, which contains 4874 utterances in Tamil and their corresponding slots and intent annotations. The following are some of the main contributions of this work:

- We present a TOD dataset for Tamil - TamilATIS with 4874 utterances.
- We perform initial experiments with state-of-the-art slot filling and intent detection models to establish the baselines.

The full dataset and the source code of the baseline models are available at https://github.com/ramaneswaran/tamil_atis

| Find | morning | flights | to | Chennai |
|------|---------|---------|----|---------|
| O    | B-period| O       | O  | B-fromcity |

Table 1: Example of user utterance with their corresponding BIO annotation and intent.
2 Related Work

Intent classification and slot filling are two key challenges modelled separately or jointly for Natural Language Understanding (NLU). Joint modelling approaches have attained state-of-the-art performance, and have demonstrated that there exists a significant correlation between the two tasks. Prior works have implemented CNN-CRF (Xu and Sarikaya, 2013), RecNN (Guo et al., 2014), joint RNN-LSTM (Hakkani-Tür et al., 2016), attention-based BiRNN (Liu and Lane, 2016), and slot-gated attention-based model (Goo et al., 2018) and more recently have used BERT (Chen et al., 2019a) and BiLSTM based (Haihong et al., 2019) approaches.

Intent classification and slot filling functions are core modules for NLU in Task-Oriented Dialogue (TOD) systems (Chen et al., 2016; Takanobu et al., 2019; Kummerfeld et al., 2019; Liang et al., 2019; Campagna et al., 2020; Ham et al., 2020). Since these tasks are characterized as sequence classification and token tagging tasks, sentence encoder models have been utilized to solve them. The two extensively utilized large scale datasets in English (high resource language) for this purpose in NLU are: ATIS (Price, 1990), which features audio recordings of individuals booking flight reservations, and SNIPS (Coucke et al., 2018), which is gathered from Snips’ personal voice assistant. Dao et al. (2021) introduced a low-resource language dataset in Vietnamese. Apart from these monolingual English corpora, Schuster et al. (2019) presented a new dataset of 57k annotated utterances in English (43k), including low-resource Spanish (8.6k), and Thai (5k), spanning the topics of weather, alarm, and reminder.

In Indian languages, there have been works to synthesize training data by using Google Translate and proposed CNN+LSTM based architecture (Gupta et al., 2020). Malviya et al. (2021) released a Hindi Dialogue Restaurant Search (HDRS) corpus consisting of 1.4k human-to-human typed dialogues collected using the Wizard-of-Oz paradigm and compared various state-of-the-art DST models. Small sized datasets were constructed manually and used with Indic and Code-Switched TOD systems (Jayarao and Srivastava, 2018). (Kanakagiri and Radhakrishnan, 2021) used mBERT based semantic tracking to associate the slot tokens to the respective tokens in the utterance and employed Google Translate API, morphological characteristics and semantics based heuristic slot aligner to publish a dataset for dravidian languages like Kannada and Tamil.

3 Tamil ATIS

The earliest Old Tamil documents are small inscriptions in Adichanallur dating from 905 BC to 696
### Table 2: Comparison of various datasets for TOD in Indian languages.

| Name                | Language | Intent | Slot | Description                                                                 |
|---------------------|----------|--------|------|-----------------------------------------------------------------------------|
| HDRS 2021           | hi       | No     | Yes  | H2H dialogue corpus for restaurant domain in Hindi                          |
| TaskMaster-1 2018   | hi, mr, bn, gj | Yes | No   | Google’s Taskmaster-1 dataset for intent classification automatically translated to 4 Indian languages |
| CoMTIC 2021         | hi, en   | Yes    | No   | Hindi-english code-mixed dataset for intent classification                  |
| Codemix-DSTC2 2018  | hi, bn, gj, ta | Yes | Yes  | DSTC2 dataset manually converted to codemix and slot labels manually annotated |
| Codemix-SNIPS 2020  | hi, en   | Yes    | No   | SNIPS dataset manually converted to hindi-english code-mixed form.          |
| TOD-Dravidian 2021  | kn, ta   | Yes    | Yes  | MTOD dataset automatically translated and slots automatically annotated      |
| Ours                | ta       | Yes    | Yes  | ATIS dataset automatically translated to Tamil and slot labels manually annotated |

#### Figure 2: Translation results from Google Translate API (in blue) and IndicTrans (in red).

Vistara from delhi to mumbai

Air asia flights to delhi

BC. Tamil has the oldest ancient non-Sanskritic Indian literature of any Indian language. Tamil uses agglutinative grammar, which uses suffixes to indicate noun class, number, case, verb tense, and other grammatical categories. Tamil’s standard metalinguistic terminology and scholarly vocabulary is itself Tamil, as opposed to the Sanskrit that is standard for most Aryan languages. Tamil has many forms, in addition to dialects: a classical literary style based on the ancient language (cankattami), a modern literary and formal style (centami), and a current colloquial form (kotuntami) (Sakuntharaj and Mahesan, 2021, 2017, 2016; Thavareesan and Mahesan, 2019, 2020a,b, 2021). These styles blend into one another, creating a stylistic continuity. It is conceivable, for example, to write centami using cankattami vocabulary, or to utilize forms connected with one of the other varieties while speaking kotuntami (Subalalitha, 2019; Srinivasan and Subalalitha, 2019; Narasimhan et al., 2018). Tamil words are made up of a lexical root and one or more affixes. The majority of Tamil affixes are suffixes. Tamil suffixes are either derivational suffixes, which modify the part of speech or meaning of the word, or inflectional suffixes, which designate categories like as person, number, mood, tense, and so on. There is no ultimate limit to the length and scope of agglutination, which might result in large words with several suffixes, requiring many words or a sentence in English (Anita and Subalalitha, 2019b,a; Subalalitha and Poovammal, 2018).

The TamilATIS corpus is collected to promote research and development in the field of task-oriented dialogue systems for the Tamil language. It contains 4874 utterances related to airline-related enquiries.

Table 2 gives an overview of various TOD datasets available for Indian languages. We observe that only two of them, TOD-Dravidian and Codemix-DSTC2 contain Tamil utterances. Our dataset is different from these two. While TOD-Dravidian is annotated using automatic methods, TamilATIS is curated by hand. Codemix-DSTC2 contains Tamil-english code-mixed utterances, unlike ours which does not focus on code-mixing and rather contains utterances in pure Tamil.

Below, we describe the data collection and data annotation processes and give detailed statistics about the TamilATIS dataset.

#### 3.1 Data Collection

We derive the Tamil ATIS dataset by automatically translating a modified version of the ATIS dataset (Hemphill et al., 1990) to Tamil and then manually annotating the slot labels. The ATIS dataset is a standard benchmark dataset for intent classification and slot filling. It consists of audio recordings and manual transcripts of humans enquiring about
flight-related information on an automated airline travel inquiry system.

We experiment with two methods for translation: IndicTrans (Ramesh et al., 2021) and Google Translate API. We randomly sampled 50 utterances from the ATIS dataset and translated them using IndicTrans and the Google Translate API and manually inspected the translation quality. We noticed that translated utterances obtained from Google Translate were of much higher quality. Figure 2 shows some examples where IndicTrans did not give correct translations. For eg. in the first example, IndicTrans is not able to identify Vistara as an airline and combines it with Delhi, and in the second example, airline information is lost in translation. However, in both these cases, Google translate was able to provide proper translations.

3.2 Annotation Setup

For annotation, we follow earlier work on TOD (Malviya et al., 2021) where each utterance is annotated by one annotator. Since we derive utterances from ATIS, we already have a list of slot labels expected in each utterance and the annotator has to correctly map the slot label to the correct value in the utterance.

To aid with the annotation, we designed an interface that provides the annotators with an easy-to-use platform for annotation. Each annotator was assigned random batches of utterances and they worked independently in their own schedule.

3.3 Annotators

For the annotation process, we had 3 annotators. Two of the annotators are bachelor’s student and one of them is a master’s student. All three of the annotators have native language proficiency in Tamil. The details of the annotators are summarized in Table 3.

3.4 Annotation Process

Before the start of the annotation process, we briefed the annotators about TOD and trained them to identify intent and slots in an utterance from the TamilATIS dataset using examples covering all the different intent and slot labels. We conducted the annotation in two phases the dry run and a final annotation.

**Dry run.** We conducted a dry run on a subset of 200 utterances. We ensure that we uniformly sample the utterances from the dataset to ensure we have all the intents and slot labels in this subset. We then asked each of the three annotators to independently annotate each utterance. After this annotation, we computed the Cohen’s $\kappa$ for each pair of annotators. Table 4 shows the $\kappa$ scores obtained. The high $\kappa$ scores indicate that the annotators got a good grasp of the annotation process.

**Final annotation.** After the dry run, we started the final annotation process. In this stage, we also asked the annotators to reject an utterance if the translation was not correct. A total of 78 utterances were rejected in this phase.

3.5 Corpus Statistics

The corpus statistics for the TamilATIS dataset are given in Table 5. The minimum and maximum utterance lengths are 7 and 252 respectively, while the minimum and the maximum number of tokens in the utterance are 2 and 29. However, these are edge cases and the average utterance length and number of tokens are 76 and 8 respectively.

| Annotator Identity | Educational Background | Native Proficiency |
|--------------------|------------------------|-------------------|
| 1                  | Bachelors              | ✓                 |
| 2                  | Bachelors              | ✓                 |
| 3                  | Masters                | ✓                 |

Table 3: Annotators and their details

| Annotators | $\kappa$ |
|------------|----------|
| $\alpha_1$ $\alpha_2$ | 0.94 |
| $\alpha_1$ $\alpha_3$ | 0.95 |
| $\alpha_2$ $\alpha_3$ | 0.97 |

Table 4: Cohen’s $\kappa$ agreement obtained during the annotation dry run. $\alpha_1$, $\alpha_2$ and $\alpha_3$ are the three annotators
can observe in Figure 4 and 3 that the length and number of tokens in the utterances are consistent across the train, validation and test split.

## 4 Experimental Settings

We benchmark the TamilATIS dataset on eight state-of-the-art NLU models. In this section, we describe the models used and present the baseline results obtained. The problem of intent detection and slot filling can be cast as a generation task or a classification task, and in our baseline models, we include both of these types of architectures.

- **Seq2seq:** (Liu and Lane, 2016) propose an attention-based encoder-decoder model for joint intent detection and slot filling. Due to the explicit alignment requirement in the slot-filling task, the authors use an attention mechanism to incorporate alignment information into the encoder-decoder framework.

- **Slot-Gated:** (Goo et al., 2018) propose a slot-gated joint model that explicitly models the relationship between the slot and the intent attention vectors.

- **Capsule NLU:** (Zhang et al., 2019) propose hierarchical capsule nets to model the semantic hierarchy present among words, slots, and the intent of the utterance. They use context-aware word representations and dynamic routing to perform intent detection and slot-filling.

- **SF-ID:** (E et al., 2019) propose a bi-directional interrelated model for joint intent detection and slot filling. An SF-ID network is used to establish connections between the two tasks to help them promote each other mutually.

- **Stack-Propagation:** (Qin et al., 2019) propose a stack-propagation framework to incorporate the intent information during slot tagging. This allows the model to capture the intent of semantic knowledge. Moreover, to avoid error propagation in the model, token-level intent detection is performed.

- **SlotRefine:** (Wu et al., 2020) cast the task of joint intent detection and slot filling as a tag generation task and propose a non-autoregressive model for it. They use a two-pass mechanism to explicitly predict the slot boundary.

- **GL-GIN:** (Qin et al., 2021) propose a non-autoregressive model for joint intent detection and slot filling. It employs graph interaction networks to model slot dependency to model the interaction between intents and all the slots in the utterance.

- **JointBERT:** (Chen et al., 2019b) propose a joint model for intent detection and slot filling using the BERT model. The intent detection task is modelled as sequence classification while the slot filling task is modelled as token classification and the losses from the two models are jointly optimized.

## 5 Result and Analysis

In this section, we report the results obtained by the baseline models. We evaluate the NLU performance for slot filling using the F1(Micro) score and intent prediction using accuracy. The score obtained by each of the baselines is shown in Table 6.

Since the focus of these experiments is to just establish baselines and provide a starting point for further exploration, we restrict ourselves from in-depth error analysis.
The baselines can be broadly classified into two approaches, generative approaches and classification-based approaches. The lowest scoring model is Seq2seq, which uses a simple encoder-decoder architecture to generate intent and slot details. This approach scores a decent accuracy of 83.11 for intent detection but a low F1 score of 56.99 for slot filling. Other generative approaches like Stack-Propagation, SlotRefine and GL-GIN achieve much better performances. These approaches have components in their architecture (like Stack-propagation framework, graph interaction layers etc) that help them explicitly model the relationship between the slots and intent leading to superior performance.

Classification based approaches like SF-ID, Capsule NLU and Slot-Gated achieve performance similar to the three generative architectures mentioned before. All of these approaches we discussed use sophisticated techniques to better model the interaction between intent and slot information and yield noticeable improvements over a simple architecture like Seq2Seq.

However, the best score is obtained by JointBERT. It obtains an intent accuracy of 96.26% and slot F1 score of 94.01%. This is an absolute improvement of 1.96% and 1.91% in intent accuracy and slot F1 over the second-best performing model (SlotRefine). JointBERT shows the effectiveness of transformer architectures pre-trained on large datasets when applied to downstream tasks like intent detection and slot filling.

We further investigate the JointBERT architecture by using different multilingual models as utterance encoders. Table 7 gives an overview of the score obtained by using different utterance encoders. XLM-Roberta and mBERT perform similarly, with XLM-Roberta getting slightly scores. IndicBERT and Muril, two transformer models pre-trained on Indian languages however fail to produce scores as good as mBERT and XLM-Roberta. The superior performance of these two encoders could be attributed to the robust architecture and training strategy of XLM-Roberta and the large amount of data used to pretrain XLM-Roberta and mBERT.

## 6 Conclusion

In this paper, we presented TamilATIS, a TOD dataset in Tamil with 4874 utterances. We benchmarked the dataset with eight state-of-the-art NLU models and reported their intent accuracy and slot F1. Both generative and classification-based approaches perform similarly and achieve high intent accuracy and slot F1 score. We also highlighted the importance of modelling the relation between intent detection and slot labelling to yield performance improvement. The Joint BERT model with XLM-Roberta as utterance encoder achieved the highest score with an intent accuracy of 96.26% and slot F1 of 94.01%.

In future work, we plan to extend this dataset to other low-resource Dravidian languages like Malayalam, Kannada and Telugu. This would contribute towards the proliferation of TOD technology in the communities that speak these languages and also promote the development of multi-lingual TOD models for Dravidian languages. Having multi-domain utterances is another important research direction.

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