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# **Cross-lingual and cross-domain Dialog Act Classification**

### **Anonymous EMNLP-IJCNLP submission**

### **Abstract**

The classification of dialog act types is a valuable preprocessing step for downstream applications in dialog systems including dialog managing and automatic speech recognition. However, the availability of training data for dialog act classification is limited, in particular for generally less-resourced languages. In this paper, we investigate methods to transfer models between languages, such that data from well-resourced languages can be used to train models for other languages.

### 1 Introduction

[...]

Below, we use the terms source language to refer to a language for which we have ample training data and target language to denote a language for which we ultimately want to build DAC model from the training data we have available in the source language.

## **Approach**

We use the following different approaches to cross-lingual transfer. They can be categorized roughly into classical cross-lingual strategies that work with language-independent representations of the input data, and models of inductive bias where data from the source language is used to induce a model for a target language. These approaches differ on a number of levels. Most crucially, the former requires a common label space that is shared between languages - or at least that the target language label space is a subset of the source one. On the other hand, it allows for true zero-shot transfer, while approaches of inductive bias require at least some training data to be present for the target language in order to train the target-specific parameters.

### **Cross-lingual embeddings**

As a classical strategy in cross-lingual learning, we investigate the potential of cross-lingual embeddings to perform dialog act classification. Cross-lingual word embeddings define a common vector space for words in multiple languages, such that related concepts are projected in the same region of the vector space across languages. This is a well-established approach to cross-lingual learning [cite].

### **Cross-lingual contextualized** representations

Contextualized word embeddings are behind recent state-of-the-art models across a wide range of NLP tasks. [cite] While not explicitly crosslingual, multilingual models such as Multilingual BERT have recently been shown to achieve competitive results on a number of tasks (Wu and Dredze, 2019).

### Multitask learning

As another way of sharing information between languages, we use hard parameter sharing. In this setting, we define a neural network model with language-specific input and output layers, but shared parameters in between. When training this model with source language data, these shared parameters are updated, thus source-side training informs part of the target-side model. With this approach, some data is required in the target language to tune the target-specific parameters. On the other hand, it has the advantage over classical cross-lingual approaches that the different datasets do not need to share a common label space.

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0	3 Experiments
	3.1 Data
2 3 4	We conduct experiments based on a total of X different languages and datasets.
5	<b>English</b> We use the Switchboard corpus (Godfrey et al., 1992)
7 8 9	<b>Spanish</b> We use the Dihana corpus (Benedi et al., 2006)
)	<b>German</b> We use the Verbmobil corpus (Jekat et al., 1995)
	Chinese
	Thai
5	3.2 Results
7	References
8	
9	José-Miguel Benedı, Eduardo Lleida, Amparo Varona, Marıa-José Castro, Isabel Galiano, Raquel Justo,
)	I López, and Antonio Miguel. 2006. Design and acquisition of a telephone spontaneous speech dialogue corpus in spanish: Dihana. In Fifth International Conference on Language Resources and Evaluation (LREC), pages 1636–1639.
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	pus for research and development. In [Proceedings]
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	Susanne Jekat, Alexandra Klein, Elisabeth Maier, Ilona
	Maleck, Marion Mast, and J Joachim Quantz. 1995.
	Dialogue acts in verbmobil.
	Shijie Wu and Mark Dredze. 2019. Beto, bentz, be-
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