calamanCy: A Tagalog Natural Language Processing Toolkit

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Abstract

We introduce calamanCy, an open-source toolkit for constructing natural language processing (NLP) pipelines for Tagalog. It is built on top of spaCy, enabling easy experimentation and integration with other frameworks. calamanCy addresses the development gap by providing a consistent API for building NLP applications and offering efficient multitask models with out-of-the-box support for dependency parsing, part-of-speech (POS) tagging, and named entity recognition (NER). calamanCy aims to accelerate the progress of Tagalog NLP by consolidating disjointed resources in a unified framework. The calamanCy Github repository can be found at https://github.com/ljvmiranda921/calamanCy.

1 Introduction

Tagalog is a low-resource language belonging to the Austronesian family, with over 76 million speakers in the Philippines (Lewis, 2009). Despite its speaker population, limited resources are available for the language (Cruz and Cheng, 2021). For example, there are few monolingual language models (LMs) in Tagalog (Cruz and Cheng, 2021; Jiang et al., 2021), and the language is not well-represented in the training pool of most multilingual LMs (Conneau et al., 2019; Devlin et al., 2019). Language resources are also scarce. Tagalog treebanks within the Universal Dependencies framework are tiny (Samson, 2018; Aquino and de Leon, 2020), while domain-specific corpora are only a handful (Enriquez and Estuar, 2023; Livelo and Cheng, 2018). Thus, consolidating these disjointed resources in a coherent framework is still an open problem. The lack of such framework hampers model development, experimental workflows, and the overall advancement of Tagalog NLP.

To address this problem, we introduce calamanCy,[1] an open-source toolkit for Tagalog NLP. It is built on top of spaCy (Honnibal et al., 2020) and offers end-to-end pipelines for NLP tasks such as dependency parsing, parts-of-speech (POS) tagging, and named entity recognition (NER). calamanCy also provides models of different sizes to fit any performance or accuracy requirements. Finally, our work has two main contributions: (1) an open-source toolkit via calamanCy, and (2) out-of-the-box support for Tagalog NLP tasks using efficient multitask pipelines with reasonable benchmarks.

2 Related Work

Open-source toolkits for NLP There has been a growing body of work in the development of NLP toolkits in recent years. For languages, these software include DaCy for Danish (Enevoldsen et al., 2021) and HuSpaCy for Hungarian (Orosz et al., 2022). For domain-specific data, there is medspaCy for clinical text (Eyre et al., 2021) and scispaCy for scientific text (Neumann et al., 2019). These tools were based on spaCy (Honnibal et al., 2020), an industrial-strength open-source software for natural language processing. Using spaCy as a foundation to build NLP toolkits is an optimal choice given its popularity and integration with other frameworks such as HuggingFace (Wolf et al., 2019). However, no tool exists for Tagalog until now. In this paper, we will showcase how calamanCy provides similar capabilities as DaCy and HuSpaCy using Tagalog resources.

Evaluations on Tagalog NLP Tasks Structured evaluations for core NLP tasks, such as dependency parsing, POS tagging, and NER, are sparse. However, we have access to a reasonable amount of data to conduct comprehensive benchmarks. For example, TLUnified (Cruz and Cheng, 2021) is a pretraining corpus that combines news reports (Cruz et al., 2020), a preprocessed version of Com-

[1] The name "calamanCy" came from *kalamansi*, a citrus fruit native to the Philippines.

Entity	Description	Examples
Person (PER)	Person entities limited to humans. It may be a single individual or group.	Juan de la Cruz, Jose Rizal, Quijano de Manila
Organization (ORG)	Organization entities limited to corporations, agencies, and other groups of people defined by an organizational structure.	Meralco, DPWH, United Nations
Location (LOC)	Location entities are geographical regions, areas, and landmasses. Geo-political entities are also included within this group.	Pilipinas, Manila, CALABARZON, Ilog Pasig

Table 1: Entity types used for annotating `calamanCy-gold` (derived from the TLUnified corpus of Cruz and Cheng, 2021). Annotation guidelines can be found at https://github.com/ljvmiranda921/calamanCy/tree/master/datasets/tl_calamancy_gold_corpus/guidelines

monCrawl (Suarez et al., 2019), and several other datasets. However, it was evaluated on domain-specific applications that may not easily transfer to more general tasks. For dependency parsing and POS tagging, we have Universal Dependencies treebanks such as TRG (Samson, 2018) and Ugnayan (Aquino and de Leon, 2020). This paper will fill the evaluation gap by providing structured benchmarks on core NLP tasks.

3 Implementation

The best way to use calamanCy is through its trained pipelines. After installing the library, users can access the models via:

```
import calamancy as cl
nlp = cl.load("tl_calamancy_md-0.1.0")
```

Here, the variable `nlp` is a spaCy processsing pipeline.[2] It contains trained components for POS tagging, dependency parsing, and NER. calamanCy offers three pipelines of varying capacity: two word vector-based models (`md`, `lg`), and one transformer-based model (`trf`). We will discuss how these pipelines were developed in the following section.

3.1 Pipeline development

Data annotation To construct the NER corpus, we curated a portion of TLUnified (Cruz and Cheng, 2021) to only contain Tagalog news articles. Including the author, we recruited two more annotators who have at least a Bachelors degree and whose native language is Tagalog. The three annotators labeled over the course of four months given three entity types as seen in Table 1. The entity types were chosen to resemble ConLL (Sang, 2002; Sang and Meulder, 2003), a standard NER benchmark. We measured inter-annotator agreement (IAA) by taking the pairwise Cohen's κ without the un-annotated tokens then averaged them for all three pairs. This process resulted to a Cohen's κ score of 0.78. To avoid confusing with the original TLUnified corpora, we will refer to this annotated NER dataset as `calamanCy-gold`. The final dataset statistics can be found in Table 2.

Dataset	Examples	PER	ORG	LOC
Training	6252	6418	3121	3296
Development	782	793	392	409
Test	782	818	423	438

Table 2: Dataset statistics for `calamanCy-gold`.

Model training We considered three design dimensions when training the calamanCy pipelines: (1) presence of pretraining, (2) the word representation, and (3) the representation size. *Pretraining* involves learning vectors from raw text to better inform model initialization. This process is done using a variant of the cloze task (Devlin et al., 2019). Here, the pretraining objective asks the model to predict some number of leading and training UTF-8 bytes for the words. *Word representations* may either involve training static word embeddings using floret,[3] an efficient version of fastText (Bojanowski et al., 2016), or using context-sensitive vectors from a transformer (Vaswani et al., 2017). Finally, *representation size* is an engineering dimension determined via a performance-accuracy tradeoff.

The general process involves pretraining a fil-

[2] https://spacy.io/usage/processing-pipelines

[3] https://github.com/explosion/floret

tered version of TLUnified (removing overlaps with `calamanCy-gold`), constructing static word embeddings if necessary, and training the downstream components. We trained the NER component using data from `calamanCy-gold`, while the dependency parser and POS tagger were trained using the Ugnayan treebank. In the end, we came up with three language pipelines of varying sizes:[4]

- `tl_calamancy_md`: Medium-sized Tagalog pipeline optimized for CPU. Pretrained using raw texts from TLUnified. Includes a static word embedding table (floret) containing 50k unique vectors (200 dimensions).
- `tl_calamancy_lg`: Large-sized Tagalog pipeline optimized for CPU. Same training setup as the medium-sized model. Compared to the medium-sized model, this pipeline contains 200k unique vectors (200 dimensions).
- `tl_calamancy_trf`: Transformer-based Tagalog pipeline. No pretraining. Instead of a static word embedding table, it uses context-sensitive vectors from the roberta-tagalog-base transformer (Cruz and Cheng, 2021).

The full training configuration for v0.1.0 of the calamanCy pipelines can be found on Github: https://github.com/ljvmiranda921/calamanCy/tree/master/models/v0.1.0.

4 Evaluation

5 Discussions

6 Conclusion

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[4] The naming convention resembles spaCy's model names: `{language code}_{source}_{size}`

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