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GrammarTagger: A Multilingual, Minimally-Supervised Grammar Profiler for Language Education

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Abstract

We present GrammarTagger, an open-source grammar profiler which, given an input text, identifies grammatical features useful for language education. The model architecture enables it to learn from a small amount of texts annotated with spans and their labels, which 1) enables easier and more intuitive annotation, 2) supports overlapping spans, and 3) is less prone to error propagation, compared to complex hand-crafted rules defined on constituency/dependency parses. We show that we can bootstrap a grammar profiler model with $F_1 \approx 0.6$ from only a couple hundred sentences both in English and Chinese, which can be further boosted via learning a multilingual model. With GrammarTagger, we also build Octanove Learn, a search engine of language learning materials indexed by their reading difficulty and grammatical features¹.

1 Introduction

Grammar plays an important role in second language (L2) acquisition and education (Long, 1991), and accurately identifying grammatical features in natural language texts has a wide range of applications, such as highlighting grammatical forms (Meurers et al., 2010) and finding authentic materials that match personal interests and proficiency levels (Heilman et al., 2008) for L2 learners and instructors. Grammatical and syntactic features also play an important role in other educational applications, notably readability assessment for L1 (Vajjala and Meurers, 2012) and L2 (Heilman et al., 2007; Xia et al., 2016) acquisition.

There have been previous efforts to build grammar-related resources such as English Gram-



Figure 1: Screenshot of GrammarTagger. GrammarTagger identifies grammatical items in a given text.

mar Profile (Harrison, 2015), A Core Inventory for General English (North et al., 2010), and Global Scale of English (GSE) Teacher Toolkit². However, they are static and require expertise to apply in real-word instructional settings. For example, it is not possible for instructors and learners to choose appropriate learning materials solely based on these resources. In this paper, we address *grammatical profiling*, the task of automatically identifying grammatical features called *grammatical items* (GIs) contained in a given natural language text.

One complication is that what L2 learners and educators perceive as "grammar" (such as the one explained in language textbooks) is different from what computer scientists define as grammar (such as the ones used in constituency and dependency parsing)³. Grammatical items range from simple lexical items such as phrasal verbs to syntactic constructs such as subordinate clauses (Figure 2). To find GIs contained in sentences, Ishii and Tono (2018) wrote regular expressions on sentences auto-

^{*}Work performed during internship at Octanove Labs.

¹The code and pretrained models are publicly available at https://github.com/octanove/ grammartagger. See https://www.youtube.com/ watch?v=8ujYzoezMhI for video demonstration.

²https://www.pearson.com/english/ about/gse/teacher-toolkit.html

³We note that the concept of GIs is related to construction grammar (Goldberg, 2003) and usage-based grammar (Bybee, 2008), although our approach is agnostic of specific definition of GIs.

| Language | GI | Description | Example | |
|----------|----------------|--------------------------------|--|--|
| | PHV.V_PART | PHRASAL VERBS (V+PARTICLE) | Things will likely <mark>turn out</mark> alright. | |
| English | TA.PASTPRG.AFF | TENSE/ASPECT: PAST PROGRESSIVE | We were changing some of our rooms. | |
| | CL.that.OMIT | hope/know/think+CLAUSE | I think the best meal I ever ate was just a hamburger. | |
| | V不V or A不A | (questions) | 我去商店,你去不去? I'm going to the shop, are you going? | |
| Chinese | 越来越 + A + (了) | more and more A | 人与人的联系越来越方便。 Interpersonal communication is getting more and more convenient. | |
| | 可是 | but | 可是她坚持自己的选择。 but she insisted on her choice. | |

Figure 2: Examples of grammatical items (GIs) in English and Chinese.

matically tagged with PoS and lemmas. Grammatical templates (Wang and Andersen, 2016) rely on regular expressions applied to dependency parses. These complex, language-dependent handwritten rules require deep knowledge of computational linguistics to produce, and the algorithms are prone to error propagation from upstream tasks (e.g., PoS tagging and parsing).

Instead, we propose grammatical profiling as *span prediction* by borrowing from recent advances in deep NLP methods. Span prediction, widely used for tasks such as reading comprehension (Yu et al., 2018), semantic role labeling (Ouchi et al., 2018), and constituency parsing (Stern et al., 2017; Joshi et al., 2018) has several benefits when applied to grammatical profiling:

- Ease of annotation: annotation does not require linguistic knowledge of any specific tagging or parsing schemes. Annotators only need to mark the start and the end positions of each span and its GI category.
- **Partial annotation**: since predictions are made on a per-span basis, the model can learn from partial annotation. Although our datasets are fully annotated, this opens up a wide range of possibilities for leveraging existing resources such as textbooks as (potentially noisy) training signals.
- Overlapping items: spans can nest and overlap with each other. For example, in the sentence "I am looking forward to...," "I am looking" can be tagged as present progressive, and "looking forward to" can be tagged as a set phrase. It is difficult, if not impossible, to model overlapping spans with other schemes such as sequential labeling.

In this paper, we present GrammarTagger, an open-source grammar profiler based on span prediction (see Figure 1 for a screenshot). We build a grammar profiler model with $F_1 \approx 0.6$ from only a couple hundred sentences both in English and Chinese. We also show that this performance can be further boosted via multitask and multilingual learning.

As a straightforward application of GrammarTagger, we also present Octanove Learn, a search engine that indexes authentic learning materials by their difficulty and GIs. We do not claim to be the first to build such a search engine-the WERTi system (Meurers et al., 2010) analyzes authentic materials such as web pages and highlight grammatical features for learners. They focus on a small set of English GIs (e.g., gerunds, to-infinitives, conditionals) defined using the constraint grammar (Karlsson et al., 2011) on top of PoS tagged text. Ott and Meurers (2011) developed a search engine where users can for texts in terms of their reading difficulties and other linguistic properties. However, little attention has been paid to the grammatical aspects of the materials.

In summary, the contribution of this paper is as follows:

- We present a span-based grammatical profiling model and show that a practical grammatical profiler can be built with a small amount of training data, both in English and Chinese.
- We show that multitask and multilingual modeling could further improve the performance of grammatical profiling with the same capacity.
- We build Octanove Learn, a search engine for language learning materials where users can search for materials by GIs and difficulty.



Figure 3: Overview of the proposed architecture. See Section 2.1 for more details.

2 Span-based Grammar Tagging

2.1 Model

Since GIs are defined as substrings over sentences, span prediction is a natural choice for modeling grammatical profiling, where spans over the input text are classified into distinct GI tags. Our model is heavily inspired by the constituency parsing model proposed in Joshi et al. (2018), where they used pretrained language models and span-based partial annotations for domain adaptation of constituency parsers. However, a major difference is that GIs do not need to form a well-formed parse tree and we do not apply a structure prediction step.

Concretely, we use $S(\mathbf{x}) = \{(i, j, t) | 0 \le i \le j < L, i \in \mathbb{Z}, j \in \mathbb{Z}, t \in T\}$ to denote the set of all spans for a given sentence \mathbf{x} (of length L), where i, j, t are span's start position, end position (inclusive), and its GI tag (which is a member of T, the set of all possible tags). Note that conceptually a span is defined for every possible substring of the given sentence, and an empty tag $t = \emptyset$ is used for spans that do not correspond to any GIs. The goal of grammatical profiling is to predict the set of non-empty spans and their GI tags \tilde{S} for a given sentence.

Our model is a standard span extraction model (Figure 3). It first contextualizes the input token sequence $\mathbf{x} = x_1, ..., x_L$ via BERT (Devlin et al., 2019), then extracts span representation via a function f_{span} as follows:

| Language | # Passages | # Sents | # GIs |
|----------|------------|---------|-------|
| English | 30 | 415 | 3,466 |
| Chinese | | 558 | 1,730 |

Table 1: Dataset statistics

$$\begin{split} \mathbf{h}_1, ..., \mathbf{h}_L &= & \texttt{BERT}(\mathbf{x}), \mathbf{h} \in \mathbb{R}^d \\ \mathbf{h}_{i,j}^s &= & f_{\texttt{span}}((i,j), \{\mathbf{h}_1, ...\}), \mathbf{h}^s \in \mathbb{R}^{d_s} \\ \tilde{p}(t|(i,j)) &= & \texttt{softmax}(\texttt{FFN}(\mathbf{h}_{i,j}^s)) \end{split}$$

where **h** is the contextualized representation obtained by BERT of dimension d, \mathbf{h}^s is the span representation obtained via f_{span} , d_s is its dimension, FFN is a feedforward network, and $\tilde{p}(t|(i, j))$ is the predicted probability of the span (i, j) having GI t. Finally, we optimize the model using the standard cross entropy loss:

$$\mathcal{L}_{span} = -\sum_{(i,j,t)\in S(\mathbf{x})} \log \tilde{p}(t|(i,j)) \qquad (1)$$

We use the concatenation of two endpoints and their difference as the span representation function, i.e., $f_{\text{span}}((i, j), {\mathbf{h}_1, ..., \mathbf{h}_L}) = \mathbf{h}_i \oplus \mathbf{h}_j \oplus (\mathbf{h}_i - \mathbf{h}_j)$ where \oplus is vector concatenation.

2.2 Datasets

We used an in-house, difficulty-controlled English dataset-it consists of 5 passages per CEFR (the Common European Framework of Reference) (Council of Europe, 2001) level written by a native speaker with ESL background. The Chinese dataset consists of level-balanced reading passages taken from HSK (a standard Chinese proficiency test) sample questions⁴. Both datasets were annotated with GIs by native speakers of each language with linguistics background. For English, we used CEFR-J Grammar Profile (Ishii and Tono, 2018), a list of GIs and their per-level statistics developed by the CEFR-J project (Negishi et al., 2013). For Chinese, we used a list of GIs annotated with HSK levels generously provided by Zero to Hero Education⁵. Both lists are published at Open Language Profiles⁶ under a permissive creative commons license. Table 1 shows the statistics of the datasets we used for training and evaluating the model.

⁴http://www.chinesetest.cn/godownload. do

⁵https://www.zerotohero.ca/

⁶https://www.openlanguageprofiles.org/

Note that some GIs correspond to *lack* of some linguistic units—this happens for, e.g., omission of the subordinate clause marker "that" in English and omission of the possessive marker "de" in Chinese. For these GIs, we annotated the subsuming structures, e.g., the main clause (see the third example in Figure 2) or the entire noun phrase, with the corresponding GI.

2.3 Evaluation Metrics

We use the following metrics for model evaluation:

• Labeled precision (P_L) and recall (R_L) defined as follows, and their F_1 measure:

$$P_L = \frac{|S_L \cap \tilde{S}_L|}{|\tilde{S}_L|}, \quad R_L = \frac{|S_L \cap \tilde{S}_L|}{|S_L|},$$

where S_L and \tilde{S}_L are the sets of *labeled* (i.e., (i, j, t)) non-empty spans in the ground truth and the model prediction, respectively.

• Unlabeled precision and recall defined as follows, and their F_1 measure:

$$P_U = \frac{|S_U \cap \tilde{S}_U|}{|\tilde{S}_U|}, \quad R_U = \frac{|S_U \cap \tilde{S}_U|}{|S_U|},$$

where S_U and \tilde{S}_U are the sets of *unlabeled* (i.e., (i, j)) non-empty spans in the ground truth and the model prediction, respectively.

• Macro-averaged precision (*P_M*) and recall (*R_M*) defined as follows, and their *F*₁ measure:

$$P_t = \frac{|S_t \cap \tilde{S}_t|}{|\tilde{S}_t|}, \qquad R_t = \frac{|S_t \cap \tilde{S}_t|}{|S_t|}$$
$$P_M = \frac{1}{|T|} \sum_{t \in T} P_t, \qquad R_M = \frac{1}{|T|} \sum_{t \in T} R_t;$$

where T is the set of all distinct GI tags, S_t and \tilde{S}_t are the sets of spans for tag t in the ground truth and the model prediction, respectively.

We used the labeled F_1 measure as the main evaluation metric for tuning the model parameters.

2.4 Experiments

The feedforward network is a single linear layer, initialized with Xavier initialization (Glorot and Bengio, 2010). We used bert-base-cased for English and bert-base-chinese for Chinese

| Lang | | Prec | Rec | F_1 |
|------|-----------|-------|-------|-------|
| en | Labeled | 0.628 | 0.489 | 0.549 |
| | Unlabeled | 0.694 | 0.540 | 0.606 |
| | Macro | 0.205 | 0.188 | 0.187 |
| zh | Labeled | 0.731 | 0.456 | 0.560 |
| | Unlabeled | 0.748 | 0.466 | 0.573 |
| | Macro | 0.150 | 0.142 | 0.141 |

Table 2: Grammatical profiling performance for English (en) and Chinese (zh)

from the Transformers library (Wolf et al., 2020) as contextualizers. The sentence was tokenized via the tokenizers corresponding to the pretrained model used. This means that Chinese text was effectively tokenized into individual characters. We implemented the model using AllenNLP (Gardner et al., 2018).

Only spans of up to 30 tokens long were considered for prediction, and GI tags that appear only once in the dataset were collapsed to a special UNK tag. We truncated long sentences containing more than 128 tokens.

We used a batch size of 50, and the Adam optimizer (Kingma and Ba, 2015) with a learning rate of 1×10^{-4} , $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 1 \times 10^{-8}$. We trained the model for 100 epochs and chose the best model based the validation labeled F_1 measure. We conducted 10-fold cross validation where we chose one fold for testing, another for validation, and the rest for training, reporting the averaged metrics on the test portion.

Table 2 shows the main result. The model achieves a decent level of grammatical profiling performance in spite of the small training dataset, suggesting that our method is effective for boot-strapping a practical grammar profiler. Note that the macro-averaged precision, recall, and F_1 measure are low, which is due to the heavily skewed distribution of GI tags. A small number of GI tags such as pronouns and tense markers occur frequently while others do not, which makes it difficult to correctly predict infrequent GIs from small training data. Robustly predicting such rarely occurring GIs is future work.

3 Multitask and Multilingual Learning

3.1 Combining with Readability Assessment

Since GIs can be useful features for readability/difficulty assessment, it is natural to ask if gram-

| Model | Labeled | Unlabeled | Macro | Acc. |
|-----------|---------|-----------|-------|-------|
| en-single | 0.549 | 0.606 | 0.187 | 0.561 |
| en-multi | 0.552 | 0.605 | 0.179 | |
| zh-single | 0.560 | 0.573 | 0.141 | 0.557 |
| zh-multi | 0.556 | 0.566 | 0.140 | |

Table 3: Grammatical profiling performance (labeled F_1 , unlabeled F_1 , and macro F_1) combined with readability assessment accuracy

| Lang | Model | Labeled | Unlabeled | Macro |
|------|-------|---------|-----------|-------|
| en | en | 0.549 | 0.606 | 0.187 |
| | en+zh | 0.565 | 0.619 | 0.211 |
| zh | zh | 0.560 | 0.573 | 0.141 |
| | en+zh | 0.566 | 0.588 | 0.147 |

Table 4: Grammatical profiling performance (labeled F_1 , unlabeled F_1 , and macro F_1) in a mono- and multilingual settings

matical profiling and readability assessment can be solved jointly and if these two tasks benefit from each other. As a proof of concept, we built a simple multitask model where the [CLS] embeddings from the final layer of BERT were fed to a linear layer then a softmax layer to predict the difficulty (one of six CEFR levels) of the input. The classification head is trained with standard cross entropy, which we denote \mathcal{L}_{level} . The final loss used for the joint model is:

$$\mathcal{L} = \mathcal{L}_{span} + \alpha \mathcal{L}_{level} \tag{2}$$

We ran minimal grid search to find the optimal value α on the validation set. The result is shown in Table 3.

Compared to single models, multitasking with readability assessment improved the performance of grammatical profiling for English, while slightly hurting it for Chinese, although the effect is limited for both languages. The additional task may have helped regularize the contextualizer and offered a "priming" effect for grammatical profiling. Note that readability is usually estimated with longer texts such as paragraphs, which may have contributed to the suboptimal results shown here. We leave more detailed analysis and search for better joint/pipeline architectures for future work.

3.2 Multilingual Grammar Profiling

Little attention has been paid to building multilingual models for educational applications, except for e.g., (Vajjala and Rama, 2018). By definition, grammatical profiling is a language dependent task, and past studies dealt only with individual (usually high-resource) languages. However, being based on a language independent architecture, our model opens up a whole new set of possibilities for training multilingual grammar profilers. To investigate its generalization ability in a multilingual setting, we trained an English+Chinese joint model by combining the two training datasets and by using the bert-base-multilingual-cased model as the contextualizer. The set of target GI tags is extended to the union of all the tags in both languages. To the best of our knowledge, ours is the first model that solves grammatical profiling in multiple languages.

Table 4 shows the comparison between monoand multi-lingual settings. The performance of the multilingual model is not just changed—it in fact improves grammatical profiling for English and Chinese, even though the model needs to encode the information from both languages with almost the same capacity. This suggests multilingual modeling is a promising venue for this particular task, being potentially beneficial for low-resource, closely related languages, although detailed investigation of multilingual models is future work.

Interestingly, the improvement in *unlabeled* F_1 measures between the mono- and multi-lingual models is larger than that in labeled measures for Chinese. We posit that, even between vastly different languages such as English and Chinese, *where* grammatically salient constructs occur in sentences might have a lot more in common across languages than *what* these constructs look like.

4 Searching Materials by Grammar

For our demo application we present Octanove Learn⁷ (Figure 4), a search engine which indexes learning materials by the GIs they include and their difficulty, as predicted by GrammarTagger. Here, we define individual materials to each be a document X consisting of a set of sentences x, where the tags associated with a document are the union of the span labels provided by GrammarTagger for all its sentences, and its difficulty is the most common difficulty provided by GrammarTagger among

⁷http://learn.octanove.com/



Figure 4: Screenshot of Octanove Learn. Language learners and educators can search examples of GIs with specific difficulties.

all its sentences. Let G(x) and D(x) be the set of GIs and the difficulty of sentence x returned by GrammarTagger. The set of GIs and the difficulty of document X are defined as:

$$\begin{array}{lll} G(X) & = & \bigcup_{x \in X} G(x) \\ D(X) & = & \operatorname*{argmax}_{d} |\{x \in X \, | D(x) = d\}| \end{array}$$

We can then retrieve the set of documents including a given GI g as $\{X \in \mathcal{X} | g \in G(X)\}$, and documents for a given difficulty d as $\{X \in \mathcal{X} | D(X) = d\}$, where \mathcal{X} is the collection of all documents. It would also be trivial to implement the the ability to search for specific sentences by their GIs and difficulty in a similar fashion.

We imagine the primary application of this technology to be indexing existing data so that it can be searched by language learners and/or educators looking for examples of GIs at specific difficulties. However, we also include interactive profiling functionality which can be used to identify GIs in arbitrary input sentences, both to demonstrate the functionality of GrammarTagger and because it could be helpful to learners attempting to identify GIs in sentences they are having difficulty understanding.

5 Conclusion

We presented GrammarTagger, a grammar profiler that identifies grammatical items from text based on simple and flexible span prediction. The experiments showed that the model achieved the grammatical profiling performance of $F_1 \approx 0.6$ from only a couple hundred sentences both in English and Chinese. We also show that this performance can be further boosted via multitask and multilingual learning.

We are planning on extending GrammarTagger to other languages than English and Chinese. Also, as we've shown partially, multitask and multilingual learning are a promising venue for building a more robust and better grammatical profiling model and we leave the investigation as future work.

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