Universal NER: A Gold-Standard Multilingual Named Entity Recognition Benchmark

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Abstract

We introduce Universal NER (UNER), an open, community-driven project to develop gold-standard NER benchmarks in many languages. The overarching goal of UNER is to provide high-quality, cross-lingually consistent annotations to facilitate and standardize multilingual NER research. UNER v1 contains 19 datasets annotated with named entities in a cross-lingual consistent schema across 13 diverse languages. In this paper, we detail the dataset creation and composition of UNER; we also provide initial modeling baselines on both in-language and cross-lingual learning settings. We will release the data, code, and fitted models to the public.[1]

1 Introduction

High-quality data in many languages is necessary for broadly multilingual natural language processing. In named entity recognition (NER), the majority of annotation efforts are centered on English, and cross-lingual transfer performance remains brittle (e.g., Chen et al., 2023b; Ma et al., 2023). Amongst non-English human-annotated NER datasets, while there have been multiple separate efforts in this front (e.g., Agić and Ljubešić, 2014; Plank, 2019; Adelani et al., 2022), these either have disjoint annotation schemes and labels, cover a single language or small set of related languages, or are not widely accessible (e.g., Strassel and Tracey, 2016). For most of the world's languages, the only readily available NER data is the automatically annotated WikiANN dataset (Pan et al., 2017), though this annotation paradigm introduces data quality issues and limits its usefulness for evaluation (Lignos et al., 2022).

To address this data gap, we propose Universal NER (UNER), an open community effort to

EN	The expedition was led by General Joseph Burgoyne who intended to reach Albany.
DE	Die Expedition wurde angeführt von General Joseph Burgoyne, der Albany erreichen wollte.
RU	Поход возглавлял генерал Джон Бергойн, который намеревался достичь Олбани.
ZH	約翰·伯戈因將軍領導了這次遠征, 他希望能到達奧爾巴尼。

Figure 1: Parallel sentences annotated with person (PER) and location (LOC) named entities in English (EN), German (DE), Russian (RU), and Chinese (ZH).

develop gold-standard named entity recognition benchmarks across many languages. Each dataset in Universal NER is annotated by primarily native speakers on the text of an existing Universal Dependencies treebank (UD; Nivre et al., 2020). Inspired by Universal Dependencies, the overarching philosophy of the UNER project is to provide a shared, universal definition, tagset, and annotation schema for NER that is broadly applicable across languages (Figure 1).

The current version of Universal NER, UNER v1, contains 19 datasets spanning 13 languages (Section 4). To establish performance baselines on UNER, we finetune an XLM-R model on various training configurations (Section 5)and show that while NER transfer performance between European languages is relatively strong, there remains a gap when transferring to different scripts or language typologies.

The goal of the UNER project is to facilitate multilingual research on entity recognition by addressing the need in the multilingual NLP community for standardized, cross-lingual, and manually annotated NER data. With the release of UNER v1, we plan to expand UNER to new languages and datasets, and we welcome all new annotators interested in developing the project.

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[1]https://www.universalner.org, UNER v1 available at https://doi.org/10.7910/DVN/GQ8HDL

2 Dataset Design Principles

Named entity recognition (NER) is the task of identifying text spans in a given context that uniquely refer to specific *named entities*. The task of NER has a long tradition (Grishman, 2019) and facilitates many downstream NLP applications, such as information retrieval (Khalid et al., 2008) and question answering (Mollá et al., 2006). Furthermore, successful NER tagging requires a model to reason about semantic and pragmatic world knowledge, which makes the task an informative evaluation setting for testing NLP model capabilities.

As with Universal Dependencies, the goal of Universal NER is to develop an annotation schema that can work in any language. Traditionally, the UD (Nivre et al., 2016) and UPOS (Petrov et al., 2012) projects have chosen what amounts to the intersection of tags across all language-specific tagsets, keeping the resultant tagset broad and simple. We follow a similar strategy, picking tags that broadly cover the space of proper nouns.

Universal NER's annotation schema emphasizes three coarse-grained entity types: Person (PER), Organization (ORG), and Location (LOC). We provide a short description and an example for each tag.

PER The PERSON tag includes names of people, real or fictional, but not nominals.

"Mr. Robinson$_{PER}$ smiled at the teacher."

ORG The ORGANIZATION tag is used for named collections of people.

"The FDA$_{ORG}$ announced time travel pills tomorrow."

LOC The LOCATION tag covers all types of named locations.

"I will arise and go now, and go to Innisfree$_{LOC}$"

Figure 1 demonstrates how named entities and their corresponding annotations surface across languages. In some cases (such as in the English and German sentences), the surface forms of named entities are shared. However, often these forms vary—as in the Russian and Chinese examples—which makes entity identification and tagging more challenging, particularly in cross-lingual settings.

Annotation Guidelines In preparation for annotation, we developed extensive annotation guidelines,[2] using the NorNE project guidelines (Jørgensen et al., 2020) as a starting point. Along with

[2] http://www.universalner.org/guidelines/

tag descriptions, our guidelines include many examples, as well as instructions for dealing with ambiguity and unclear constructions, such as email addresses, pet names, and typographical errors.

We expect that the guidelines will be further refined and updated as annotation proceeds. To manage this, we track version numbers and changelogs for different iterations of the guidelines. Each data release will include the corresponding annotation guidelines at the time of release.

3 Dataset Annotation Process

Having described the theoretical basis for the tagset, we now discuss the mechanics of annotation.

Sourcing Data We chose the Universal Dependency corpora as the default base texts for annotation. This jumpstarts the process: there is high coverage of languages, and the data is already collected, cleaned, tokenized, and permissively licensed. Further, by adding an additional annotation layer onto an already rich set of annotations, we not only support verification in our project (Section 4.3) but also enable multilingual research on the full pipeline of core NLP. Since UD is annotated at the word level, we follow a BIO annotation schema (specifically IOB2), where words forming the beginning (inside) part of an X entity (X ∈ {PER, LOC, ORG}) are annotated B-X (I-X, respectively), and all other words are given an O tag. For the sake of continuity, we preserve all tokenization from UD.

While UD is the default data source for UNER, we do not limit the project to UD corpora (particularly for languages not currently included in UD). The only criterion for inclusion in the UNER corpus is that the tagging schema matches the UNER guidelines. We are also open to converting existing NER efforts on UD treebanks to UNER. In this initial release, we include four datasets that are transferred from other manual annotation efforts on UD sources (for DA, HR, ARABIZI, and SR).

Sourcing Annotators For the initial UNER annotation effort, we recruited annotators from the multilingual NLP community through academic networks on social media. Annotators were organized via channels in a Slack workspace. Annotators of the datasets included in UNER thus far are unpaid volunteers. We expect that annotators are native speakers of their annotation language, or are highly proficient, but we did not issue any language tests. For the first release of UNER, the choice of

the 13 dataset languages is solely dependent on the availability of annotators. As the project continues, we expect that additional languages and datasets will be added as annotators in more languages become available to contribute.

Annotation Tool   We collect annotations for the UD treebanks using TALEN (Mayhew and Roth, 2018), a web-based tool for span-level sequence labeling.[3] TALEN includes an optional feature that propagates annotations – if the user annotates "McLovin" in one section of the document, every other instance of "McLovin" in that document is annotated as well. This significantly speeds up annotation but risks over-annotation mistakes. For example, consider the token "US", which may appear with different senses in contexts such as "The US economy..." or "THEY OFFERED TO BUY US LUNCH!"

Secondary Annotators   In addition to collecting a complete set of annotations from a primary annotator for each dataset, we also gather secondary annotations from another annotator on (at least) a subset of the data in order to estimate inter-annotator agreement (Section 4.2). We aim for at least 5% coverage of each data split with these secondary annotations, although most datasets have significantly more (Table 2). When a document has multiple annotators, we include the labels from the annotator with the most entities annotated in that document in the final dataset. This means a dataset may have multiple annotators, but each document has exactly one. We retain annotator identities in the data files.

Annotation Differences and Resolution   When annotators disagreed on annotation decisions or the inter-annotator agreement scores were low, we encouraged them to discuss the disagreements and decide if they were conflicting interpretations of the guidelines or fundamental disagreements. In the former case, annotators came to an agreement on guideline interpretations and updated annotations accordingly. In the latter, the annotations were kept as-is. Not every dataset had this resolution process.

The multilingual nature of this process also highlighted cross-language differences in named entities that affect NER annotation. For instance, most languages in UNER use capitalization as a marker of proper nouns and, therefore, named entities. However, Chinese does not include capitalization in its script, which makes identifying named

entities more difficult and time-consuming than in other languages, potentially leading to more annotation errors. Differences in annotating NER across languages also stem from divergent definitions of proper nouns (PROPN) by language and the effects of translation artifacts; these issues are discussed further in Sections 4.3 and 4.4, respectively.

OTHER Tag   As a helpful check for annotators, we allow the option of annotating a fourth entity type, Other (OTH), which is not included in the final dataset. This had several purposes: to store annotations that behaved like mentions, but didn't conform to the guidelines of the other tags; to measure potential annotation disagreement on ambiguous cases; and to store an additional layer of annotation. Not all annotators used it, and those that did were sometimes inconsistent. In practice, OTH was most often applied to languages, nationalities, and brands. The OTH tag roughly corresponds to the MISC tag used in CoNLL 2003, which has been described as being "ill-defined" (Adelani et al., 2022).

Dataset Transfer   Most of the included datasets are annotated from scratch using the annotation process detailed above, but a few (DA ddt, QAF arabizi, HR and SR set) are transferred from other sources. The Danish ddt annotations are derived from the *News* portion of the DaN+ dataset (Plank et al., 2020); this text corresponds to the Universal Dependencies ddt treebank. The Croatian hr annotations come from the hr500k dataset (Ljubešić et al., 2016), half of which, consisting of newspaper and various web texts, was used for producing the Croatian Universal Dependencies hr_set treebank (Agić and Ljubešić, 2015). The NArabizi arabizi dataset was annotated on UD data using a slightly different NER schema and then automatically converted to the UNER schema. The Serbian sr data come from the SETimes.SR dataset (Batanović et al., 2018), which was used in its fullness to produce the Serbian Universal Dependencies sr_set treebank (Samardžić et al., 2017). The original Croatian and Serbian NER annotations were annotated and curated in multiple iterations by various native speakers. However, the annotations added to the UNER dataset were slightly modified to conform to the UNER annotation guidelines; namely, while nationalities and similar groups are annotated as PER in the original dataset, in the UNER dataset such entities are omitted. Finally, we retain the original annotations from existing NER datasets in the "xner" label column.

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[3]https://github.com/mayhewsw/talen-react

Lang.	Dataset	Sentences				Entities				Tokens			
		Train	Dev	Test	All	Train	Dev	Test	All	Train	Dev	Test	All
DA	ddt	4,383	564	565	5,512	3,022	379	446	3,847	80,378	10,332	10,023	100,733
EN	ewt	12,543	2,001	2,077	16,621	7,022	966	1,088	9,076	204,579	25,149	25,097	254,825
HR	set	6,914	960	1,136	9,010	8,261	1,218	1,403	10,882	152,857	22,292	24,260	199,409
PT	bosque	7,018	1,172	1,167	9,357	8,101	1,401	1,215	10,717	171,776	28,447	27,604	227,827
QAF	arabizi	1003	139	145	1287	1320	204	194	1718	15,522	2,124	2,118	19,764
SK	snk	8,483	1,060	1,061	10,604	2,707	636	915	4,258	80,628	12,733	12,736	106,097
SR	set	3,328	536	520	4,384	5,020	742	847	6,609	74,259	11,993	11,421	97,673
SV	talbanken	4,303	504	1,219	6,026	967	23	196	1,186	66,646	9,797	20,377	96,820
ZH	gsd	3,997	500	500	4,997	6,136	754	767	7,657	98,616	12,663	12,012	123,291
	gsdsimp	3,997	500	500	4,997	6,118	753	763	7,634	98,616	12,663	12,012	123,291
DE	pud	–	–	1,000	1,000	–	–	1,039	1,039	–	–	21,331	21,331
EN	pud	–	–	1,000	1,000	–	–	1,038	1,038	–	–	21,176	21,176
PT	pud	–	–	1,000	1,000	–	–	1,099	1,099	–	–	23,407	23,407
RU	pud	–	–	1,000	1,000	–	–	1,036	1,036	–	–	19,355	19,355
SV	pud	–	–	1,000	1,000	–	–	1,029	1,029	–	–	19,076	19,076
ZH	pud	–	–	1,000	1,000	–	–	1,137	1,137	–	–	21,415	21,415
CEB	gja	–	–	188	188	–	–	49	49	–	–	1,295	1,295
TL	trg	–	–	128	128	–	–	92	92	–	–	734	734
	ugnayan	–	–	94	94	–	–	61	61	–	–	1,097	1,097

Table 1: Universal NER has broad coverage of named entities in several languages and domains, adding annotations to the development, testing, and training sets from Universal Dependencies (Nivre et al., 2020).

4 Universal NER: Statistics and Analysis

This section presents an overview of the Universal NER (UNER) dataset. UNER v1 adds a NER annotation layer to 19 datasets (primarily treebanks from UD). It covers 13 geneologically and typologically diverse languages: Cebuano, Danish, German, English, Croatian, Narabizi, Portuguese, Russian, Slovak, Serbian, Swedish, Tagalog, and Chinese[4]. Overall, UNER v1 contains ten full datasets with training, development, and test splits over nine languages, three evaluation sets for lower-resource languages (TL and CEB), and a parallel evaluation benchmark spanning six languages.

4.1 Dataset Statistics

In Table 1, we report the number of sentences, tokens, and annotated entities for each dataset in UNER. The datasets in UNER cover a wide range of data quantities: some provide a limited amount of evaluation data for a commonly low-resourced language, whereas others annotate thousands of training and evaluation sentences.

The datasets in UNER also cover a diverse range of domains, spanning web sources such as social media to more traditional provenances like news text. Table 5 in the appendix presents the complete set of sources for the data and the distribution of NER tags in each dataset, along with references to

each original treebank paper. The variety in data sources leads to varied distributions of tags across datasets (Figure 2).

4.2 Inter-Annotator Agreement

We calculate inter-annotator agreement (IAA, Table 2) for each dataset in UNER that was annotated with the above process and for which we have secondary annotations. Table 2 reports agreement as per-label F_1 score, using one annotator as "reference," and the other as "prediction."

ORG vs LOC Confusion The agreement on ORG and LOC is generally lower than that on PER. The annotation guidelines allow certain named entities to take either the ORG or LOC tag based on context. In some cases, the context is underspecified, leading to ambiguity. For example, a restaurant is a LOC when you go there to eat, but it is an ORG when it hires a new chef. A city is a LOC when you move there, but it is an ORG when it levies taxes. Officially, it is the
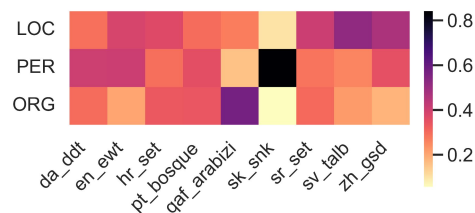

Figure 2: Distribution of tags in different UNER training sets. zh_gsdsimp has the same distribution as zh_gsd.

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[4]Languages sorted by their ISO 639-1/639-2 codes (International Organization for Standardization, 2002, 1998)

Lang.	Dataset	Train				Dev				Test			
		LOC	ORG	PER	% Docs	LOC	ORG	PER	% Docs	LOC	ORG	PER	% Docs
DA	ddt	.875	.778	.959	100%	.917	.765	.934	100%	.882	.805	.975	100%
EN	ewt	.696	.533	.925	20%	.786	.640	.949	20%	.825	.869	.969	20%
PT	bosque	.928	.902	.974	11%	.850	.885	.980	25%	.955	.914	.975	23%
SK	snk	.840	.743	.900	100%	.801	.597	.770	100%	.837	.621	.823	100%
SV	talbanken	.857	.670	.913	100%	.800	.461	.888	100%	.937	.812	.871	100%
ZH	gsd	.800	.724	.917	14%	.795	.661	.956	100%	.860	.711	.944	23%
DE	pud	–	–	–	–	–	–	–	–	.709	.840	.812	6%
EN	pud	–	–	–	–	–	–	–	–	1.00	.936	.966	6%
PT	pud	–	–	–	–	–	–	–	–	.903	.920	.985	14%
RU	pud	–	–	–	–	–	–	–	–	.719	.531	.891	100%
SV	pud	–	–	–	–	–	–	–	–	.865	.735	.944	100%
ZH	pud	–	–	–	–	–	–	–	–	.752	.776	.971	20%
CEB	gja	–	–	–	–	–	–	–	–	.769	1.00	.914	71%
TL	trg	–	–	–	–	–	–	–	–	.833	–	.957	100%
	ugnayan	–	–	–	–	–	–	–	–	.913	–	–	100%

Table 2: Inter-annotator agreement scores for the datasets annotated natively for the Universal NER project. We don't report IAA for the datasets adapted from other sources, or from `zh_gsdsimp`, which has nearly identical annotations to `zh_gsd`. **% Docs** refers to the percentage of documents annotated by multiple annotators.

city government that levies taxes, but common usage allows, for example, "Springfield_ORG charges a brutal income tax." CoNLL 2003 English also has this ambiguity, with many documents where city names, representing sports teams, are annotated as ORG. We find this ambiguity is particularly common in the en_ewt train and validation splits, primarily in documents in the *reviews* domain, which are short and very informal (e.g. "we love pamelas").

4.3 Agreement with the PROPN POS Tag

The proper noun (PROPN) part-of-speech tag used in UD represents the subset of nouns that are used as the name of a specific person, place, or object (Nivre et al., 2020). We hypothesize that named entities as defined in UNER act roughly as a subset of these PROPN words or phrases, although not a strict subset due to divergent definitions. To test this, we calculate the precision of the UNER annotations against the UD PROPN tags (Table 3, F_1 scores reported in Table 4). Overall, precision is relatively high, with a mean precision of 0.761 across datasets. Lower precision is often due to multi-word names containing non-PROPN words (e.g., "Catherine the Great"). The differences in precision can also be due to language-specific PROPN annotation guidelines: for example, while the English PUD treebank tags the United States entity as "United_PROPN States_PROPN", Russian PUD tags it as "Соединенных_ADJ Штатов_NOUN".

Lang.	Dataset	Train	Dev	Test
DA	ddt	.709	.729	.722
EN	ewt	.890	.895	.892
HR	set	.683	.651	.671
PT	bosque	.864	.881	.844
QAF	arabizi	.952	.960	.985
SK	snk	.803	.783	.688
SR	set	.687	.631	.680
SV	talbanken	.766	.756	.842
ZH	gsd	.605	.624	.616
ZH	gsdsimp	.601	.604	.617
DE	pud	–	–	.712
EN	pud	–	–	.872
PT	pud	–	–	.749
RU	pud	–	–	.708
SV	pud	–	–	.810
ZH	pud	–	–	.634
CEB	gja	–	–	.980
TL	trg	–	–	.958
TL	ugnayan	–	–	.654

Table 3: Comparing the overlap (Precision) between UNER annotations and UD PROPN tags.

4.4 Cross-lingual Agreement in UNER

UNER contains sentence-aligned evaluation sets for six languages (German, English, Portuguese, Russian, Swedish, and Chinese) that are annotated on top of the Parallel Universal Dependencies treebanks (PUD; Zeman et al., 2017). Figure 3 summarizes the similarity of the NER annotations across these target languages in PUD.

We find that the overall distribution of tags is similar for the Western European languages (left
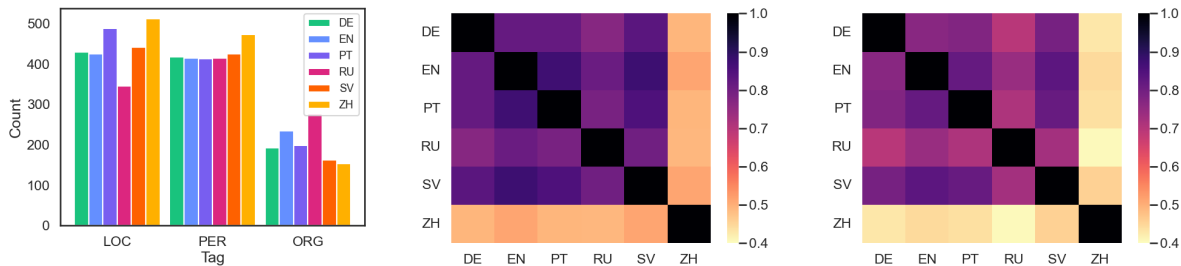
Figure 3: Cross-lingual comparison of NER Annotations on top of PUD treebanks. **Left**: Global distribution of tags for each PUD language. **Center**: Sentence-level agreement between languages for the number of entities. **Right**: Sentence-level agreement between languages for the identity of entities.

panel): the English, German, and Swedish annotations contain very similar counts of LOC and PER entities, with slightly more variance in ORG tags. Portuguese has a similar distribution with slightly more LOC entities. However, the Russian and Chinese annotations contain differing distributions from both these languages and each other.

A similar trend occurs in the sentence-level pairwise agreement on entity counts and identities between languages (center). There is relatively high agreement on the number of entities between European languages, with Russian differing slightly more from English, German, Portuguese, and Swedish. However, the Chinese benchmark agrees less frequently: the Chinese annotations match other languages on the number of entities in 50.4% of sentences; the other languages have an average agreement of 71.7–75.6%. Pairwise agreement on the specific entities in a given sentence shows similar behavior, albeit with lower agreement overall (right).

Many of these annotation differences likely stem from the translation process. While the data is aligned at the sentence level, linguistic variation and translator decisions may cause an entity to be added to or removed from the sentence, or the concept may be expressed in a manner that no longer qualifies as a named entity under the annotation guidelines.[5] While we cannot directly measure inter-annotator agreement across languages because of the above differences, some variation also undoubtedly stems from annotation differences and errors, just as these cause disagreement between annotators on the same benchmark.

In the case of Chinese and English, we manually audited the annotation discrepancies. The differences in the LOC and ORG tags mainly stem from the confusion outlined in Section 4.2. Additionally, we observed more than 30 instances that could be explained by language-specific morphological inflection rules. Specifically, country names are used directly to modify the following nouns in Chinese as opposed to English using the adjectival form.[6] Finally, the increase in PER entities can be best explained by the style of Chinese writing, which tends to transliterate non-Chinese names into Chinese and append the Latin name in parentheses; in these cases, each instance of the name would be tagged as a separate PER entity.[7]

5 Baselines for UNER

This section establishes initial baselines on the datasets in UNER v1 and provides in-language and cross-lingual results with XLM-R$_{\text{Large}}$.

5.1 Experiment Setup

We finetune XLM-R$_{\text{Large}}$ (560M parameters) (Conneau et al., 2020) on the UNER datasets in which train and dev sets are available,[8] using a single NVIDIA GeForce RTX 3090 GPU. We also evaluate the performance of XLM-R$_{\text{Large}}$ jointly finetuned on all training sets (all) listed above. We use a learning rate of 3e-5 and batch size of 16, except for bosque, where we used a batch size of

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[5]Consider the phrases: "奧巴馬對在北卡羅來納大學運動場上的群眾説道。" and "he told the crowd gathered on a sports field at the University of North Carolina." In Chinese, *Obama* (奧巴馬) is referred to by name, whereas the English version uses a pronoun.

[6]I.e., "韓國公司" 'South Korean company'. The Chinese word "韓國" means the country 'South Korea', and in this case, directly modifies the noun "公司" 'company'. This word was consequently labeled as LOC, whereas its English counterpart is O.

[7]An example is "聖羅斯季斯拉夫 (St. Rastislav)", in which the English name is parenthesized and kept in the Chinese sentence, causing both names to be annotated.

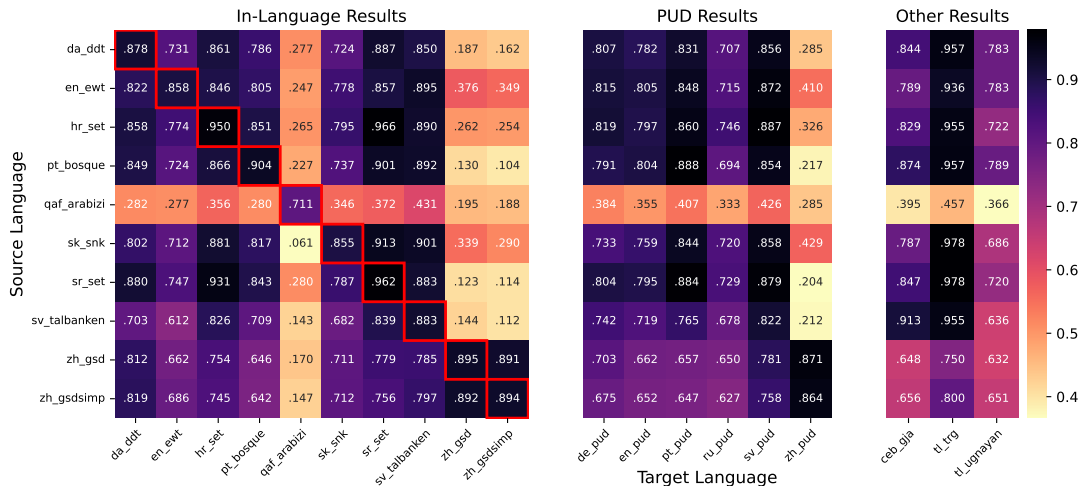[8]ddt, ewt, set, bosque, arabizi, snk, set, talbanken, gsd, gsdsimp

Figure 4: Heatmap of micro F_1 scores on test sets with different fine-tuned models. The y-axis indicates the dataset that the model is fine-tuned on, and the x-axis indicates the datasets that the models are evaluated on. **Left**: Model performance on datasets that contains the train, dev and test splits. The highlighted diagonal cells are the in-dataset results. **Center**: Model performance on the PUD datasets. **Right**: Model performance on all other datasets.

8, and batch size of 4 in the cases of `talbanken` and `all`. All the code we used is adapted from the Huggingface `transformers` package (Wolf et al., 2020).

5.2 Results and Discussion

Figure 4 reports the micro F_1 scores on all test sets when XLM-R$_{\text{Large}}$ is finetuned on different languages. The in-language performance shown on the diagonal on the left of Figure 4 is almost always the highest among all test sets, with a few exceptions such as Simplified Chinese vs Traditional Chinese (ZH) and Croatian (HR) vs Serbian (SR). This most likely stems from the fact that both pairs are closely related languages.

We also observe that in most cases (i.e., between European languages), cross-lingual transfer performs well, achieving over .600 F_1. However, transfer results in strikingly low performance on all three Chinese datasets {gsd, gsdsimp, pud}, as well as on the Maghrebi-Arabic-French (QAF) dataset {arabizi}. The results on the Chinese datasets align with observations from previous work (Chen et al., 2023a; Wu et al., 2020a; Bao et al., 2019) that other languages do not transfer well to Chinese. Narabizi is a North-African Arabic dialect written in Latin script that often involves code-switching with French. The lack of similarities between this language and all other languages in our dataset might have resulted in poor transfer performance. Furthermore, Narabizi — along with Cebuano — are not included in the pretraining lan-

guages for XLM-R, which likely also affects their performance in this setting.

Table 6 (in the Appendix) shows the tag-level performance breakdown. For all languages, F_1 on ORG is always the lowest, and LOC is almost always the second lowest. This likely stems from the similarity between ORG and LOC entities discussed in Section 4.2, whereas the names of people are usually less ambiguous, resulting in the highest F_1 on PER for most datasets. Overall, the trained models finetuned on the UNER datasets exhibit promising results, and we leave further improvements on multi- and cross-lingual NER with these datasets to future work.

Finally, the performance of the model finetuned on `all` is included in Figure 5. Most `all` F_1 scores are similar to the F_1 scores from individual training sets or lead to a moderate decrease in performance; however, in some cross-lingual cases the joint training improves performance, such as on `zh_pud` which improved from .410 using a model finetuned on `en_ewt` to .860. Finetuning on a diverse multilingual dataset helps preserve and even improve the performance on benchmarks in diverse languages.

6 Related Work

Adding a NER layer to UD Some single-language efforts have added a manually annotated NER layer to emerging or existing UD data. Agić and Ljubešić (2014) annotated the SETimes.HR dataset with linguistic and NER information, be-
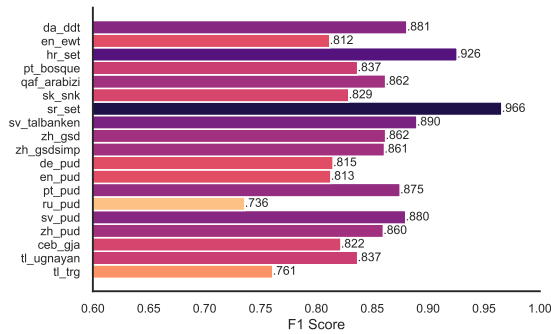
Figure 5: F$_1$ scores of each UNER test set after finetuning XLM-R$_{Large}$ on `all` training sets.

coming the `set_hr` UD dataset later (Agić and Ljubešić, 2015). Plank (2019) added a layer of NER to the dev and test portions of the Danish UD treebank (DDT) for cross-lingual evaluation; Plank et al. (2020) fully annotated it with nested NER entities. Hvingelby et al. (2020) annotated the same Danish UD data with a flat annotation scheme.

Other languages have seen efforts in a similar spirit. Jørgensen et al. (2020) added a named entity annotation layer on top of the Norwegian Dependency Treebank, Luoma et al. (2020) built the Turku NER corpus, and Plank (2021) added a layer on top of English EWT. Recently, Muischnek and Müürisep (2023) introduced the largest publicly available Estonian NER dataset. Complementing these efforts, Riabi et al. (2023) added several annotation layers, including NER, to the NArabizi treebank (Seddah et al., 2020), a North-African Arabic dialect dataset written in Latin script with a high-level of language variability and code-switching.

Multilingual NER resources Several benchmark datasets for NER offer coverage for a variety of representative languages. Aside from well-known benchmarks such as CoNLL 2002/2003 (Tjong Kim Sang, 2002; Tjong Kim Sang and De Meulder, 2003), other datasets were built to address a unique need, such as focusing on low-resource languages like LORELEI (Strassel and Tracey, 2016) or incorporating particularly challenging annotations, as seen in MultiCoNER (Malmasi et al., 2022a,b). MasakhaNER (Adelani et al., 2022) harnessed the *Masakhane* community to produce gold-standard annotations for ten African languages.

Other datasets for multilingual and non-English NER use a silver-standard annotation process (Nothman et al., 2013; Pan et al., 2017; Tedeschi et al., 2021). Nonetheless, CoNLL 2002/2003 re-

mains one of the main benchmarks in multilingual NER. A recent work, also called UNER (Alves et al., 2020), attempts to produce silver-standard corpora by propagating English annotations across parallel corpora but with no baseline evaluations. Lastly, another contemporary work called Universal NER (Zhou et al., 2023) bears no relation to our effort as it contains no annotation component.

Modeling for multilingual NER Several works have explored the task of NER outside of English. The earliest build language-independent methods (Cucerzan and Yarowsky, 1999; Lample et al., 2016, *inter alia*). Cross-lingual techniques have also emerged to transfer information between languages, especially from high- to low-resource languages (Ruder et al., 2019) or combining model and data transfer across languages (Wu et al., 2020b). Currently, the standard paradigm for multilingual NER involves finetuning or prompting multilingual language models (e.g., Wu and Dredze, 2020; Muennighoff et al., 2023). UNER supports these modeling efforts by providing gold-standard annotations across various languages.

Community-driven annotation projects The field of NLP has been shaped by community-driven annotation projects. One prime example is the Universal Dependencies (UD) project (Nivre et al., 2020), precipitated by the earlier introduction of the universal POS tagset (McDonald et al., 2013). Extensions and sister projects to UD have emerged (e.g., Savary et al., 2023; Kahane et al., 2021), to which UNER is now added. Another notable endeavor is UniMorph (Kirov et al., 2018; McCarthy et al., 2020), which covers 182 languages (Batsuren et al., 2022, 2021). The Masakhane Project has also produced several high-quality community efforts (Adelani et al., 2021, 2022; Dione et al., 2023b,a).

The UNER project follows the same community-driven approach by asking volunteers to contribute annotations for their respective languages.

7 Conclusion

We introduce Universal NER (UNER), a gold-standard data initiative covering 13 languages for named entity recognition (NER). The datasets included in UNER v1 cover a wide variety of domains and language families, and we establish initial performance metrics for these benchmarks. UNER opens several opportunities for research

in NER outside of English and for cross-lingual transfer; in particular, this project provides human-annotated and standardized evaluations for multilingual NER.

After releasing the current version of the UNER project, we plan to expand language coverage and diversity of this effort by both recruiting additional annotators and integrating existing NER datasets when possible. This will also allow us to obtain more robust agreement measures and verify the quality of existing annotations in UNER. In the longer term, our aims for Universal NER include rigorous quality checking of annotation results for robustness and further integration of finetuned models and data analysis tools into the project.

Limitations

Dataset Domains and Languages The data included in UNER v1 covers a range of domains and languages, depending on the available annotators and datasets in UD (Appendix Table 5). The variance in domains and languages will generally affect the efficacy of cross-lingual learning and evaluation. However, we also provide a standardized, parallel evaluation set for a subset of the languages in UNER. Furthermore, we invite researchers who would like to see additional languages in UNER to join the annotation effort.

Springboarding from Universal Dependencies Our preliminary criterion for languages and data to be included in the current version of UNER is that it should be already in the Universal Dependencies (UD) (de Marneffe et al., 2021). This is to ensure the quality of the underlying data and to facilitate research in conjunction with existing UD treebanks, which include part-of-speech tags, tokenization, lemmas, and glosses. However, future iterations of the UNER initiative are open to all languages, especially low-resource ones, regardless of whether they are present in UD.

Number of Annotators The UNER project relies on crowd-sourcing and community participation for annotation efforts. Thus, the languages included have varying numbers of annotators who have accepted the invitation to contribute. Nonetheless, as reported in Table 2, each language has at least **two** annotators for a subset of its documents and thus a corresponding measure of inter-annotator agreement.

Ethics Statement

Our annotated data is built on top of Universal Dependencies, an already established data resource. Thus, we do not foresee any serious or harmful issues arising from its content. Interested volunteer annotators who were invited to the project have also been informed of the guidelines as discussed in Section 3 for annotating NER-ready datasets before starting with the process.

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A Contributions

Stephen Mayhew conception, kickoff, all initial organization, recruitment, and annotation, development of annotation tool, manuscript writing.

Terra Blevins annotation, organization, PUD analysis scripts, core manuscript writing.

Shuheng Liu annotation, all baseline experiments and analysis.

Marek Šuppa annotation, PROPN analysis, paper writing, GPU resources.

Hila Gonen advising, organization of and feedback on manuscript.

Joseph Marvin Imperial facilitated annotations for Tagalog and Cebuano, additions to manuscript for TL/CEB results, limitations, ethics, and conclusion sections.

Börje F. Karlsson annotation, manuscript writing and editing, advising.

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LJ Miranda annotation, related work section, comments, edits.

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Yuval Pinter advising, organization of and writing of manuscript.

B Additional Dataset Details

In this section, we provide additional statistics and analysis of the datasets included in UNER v1. Table 5 documents the domains included in each dataset along with their distributions of NER tags, and Table 4 presents the F1 overlap score between named entities in UNER and PROPN tags in the underlying UD treebanks. We also report the full numerical results of our baseline experiments in Table 6.

Lang.	Dataset	Train	Dev	Test
DA	ddt	.824	.835	.836
EN	ewt	.813	.815	.817
HR	set	.810	.785	.799
PT	bosque	.844	.859	.856
QAF	arabizi	.942	.962	.971
SK	snk	.848	.783	.771
SR	set	.811	.769	.807
SV	talbanken	.830	.805	.839
ZH	gsd	.700	.696	.720
ZH	gsdsimp	.695	.695	.719
DE	pud	–	–	.785
EN	pud	–	–	.826
PT	pud	–	–	.805
RU	pud	–	–	.779
SV	pud	–	–	.877
ZH	pud	–	–	.708
CEB	gja	–	–	.926
TL	trg	–	–	.696
TL	ugnayan	–	–	.723

Table 4: Comparing PROPN overlap (F1 scores).

C Dataset Licensing

The Universal Dependencies datasets are licensed under Creative Commons Attribution-ShareAlike (CC BY-SA)[9]. This license requires that "if you remix, transform, or build upon the material, you must distribute your contributions under the same license as the original." Thus, we distribute all of our datasets under the same license.

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Data Source	Lang.	Dataset	Domains	Entity Dist. (%)		
				LOC	ORG	PER
Johannsen et al. (2015)	DA	ddt	fiction, news, nonfiction, spoken	28.0	30.8	41.2
Silveira et al. (2014)	EN	ewt	blog, email, reviews, social, web	37.8	21.8	40.4
Agić and Ljubešić (2015)	HR	set	news, web, wiki	37.4	33.0	29.6
Rademaker et al. (2017)	PT	bosque	news	29.5	33.9	36.6
Seddah et al. (2020)	QAF	arabizi	blog, web, social	57.5	27	15.4
Zeman (2017)	SK	snk	fiction, news, nonfiction	21.2	6.2	72.6
Samardžić et al. (2017)	SR	set	news	41.4	30.2	28.4
McDonald et al. (2013)	SV	talbanken	news, nonfiction	54.0	20.0	25.0
Shen et al. (2016)	ZH	gsd	wiki	48.1	17.9	34.0
Qi and Yasuoka (2019)		gsdsimp	wiki	48.0	18.0	34.0
	DE	pud	news, wiki	41.3	18.5	40.2
	EN	pud	news, wiki	39.5	21.9	38.6
Zeman et al. (2017)	PT	pud	news, wiki	44.4	18.0	37.6
	RU	pud	news, wiki	33.4	26.6	40.0
	SV	pud	news, wiki	43.0	15.7	41.3
	ZH	pud	news, wiki	44.9	13.5	41.6
Aranes (2022)	CEB	gja	grammar examples	12.3	2.0	85.7
Samson and Cöltekin (2020)	TL	trg	grammar examples	10.9	0.0	89.1
Aquino et al. (2020)		ugnayan	fiction, nonfiction	47.5	0.0	52.5

Table 5: Domains and distribution of entity types for datasets in UNER. Domains are categorized for the underlying UD datasets at `https://universaldependencies.org/`.

Source		Target		F_1			
Lang.	Dataset	Lang.	Dataset	LOC	ORG	PER	Overall
DA	ddt	DA	ddt	.879	.826	.924	.878
EN	ewt	EN	ewt	.871	.709	.950	.858
HR	set	HR	set	.977	.891	.970	.950
SK	snk	SK	snk	.846	.635	.882	.855
PT	bosque	PT	bosque	.882	.861	.966	.904
QAF	arabizi	QAF	arabizi	.780	.520	.717	.711
SR	set	SR	set	.981	.913	.983	.962
SV	talbanken	SV	talbanken	.904	.742	.928	.883
ZH	gsd	ZH	gsd	.906	.819	.922	.896
ZH	gsdsimp	ZH	gsdsimp	.906	.802	.925	.894
		DE	pud	.816	.603	.893	.814
		EN	pud	.785	.593	.922	.805
EN	ewt	PT	pud	.845	.698	.914	.848
		RU	pud	.681	.451	.875	.715
		SV	pud	.887	.655	.928	.872
		ZH	pud	.465	.308	.389	.410
		CEB	gja	.556	.000	.842	.789
EN	ewt	TL	trg	1.00	–	.923	.936
		TL	ugnayan	.857	–	.000	.783

Table 6: The full results of our baseline experiments from finetuning XLM-R$_{Large}$ on UNER. All scores are reported in micro-F_1. ORG F_1 scores are not reported for the two TL datasets since there are no ORG entities labeled.