NerKor+Cars-OnetoNotes++

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Abstract
In this paper, we present a new version of the Hungarian NYTK-NerKor named entity corpus, which contains about twice as many annotated spans and 7 times as many distinct entity types as the original version. We used an extended version of the OntoNotes 5 annotation scheme including time and numerical expressions. NerKor is the newest and biggest NER corpus for Hungarian containing diverse domains. We applied cross-lingual transfer of NER models trained for other languages based on multilingual contextual language models to preannotate the corpus. We corrected the annotation semi-automatically and manually. Zero-shot preannotation was very effective with about 0.82 F1 score for the best model. We also added a 12000-token subcorpus on cars and other motor vehicles. We trained and release a transformer-based NER tagger for Hungarian using the annotation in the new corpus version, which provides similar performance to an identical model trained on the original version of the corpus.

Keywords: named entity recognition, cross-lingual transfer, annotated corpus, machine-generated annotation, multilingual contextual language models

1. Introduction
In this paper, we present a new version of the Hungarian NYTK-NerKor named entity corpus upgraded to an extended version of the OntoNotes 5 annotation scheme doubling the annotated spans and introducing a 7-fold increase in entity types. We describe the annotation procedure applying cross-lingual transfer followed by semi-automatic and manual correction. This is followed by evaluation of the transfer models and comparison of models trained on the original and the new version of the corpus.

1.1. Resources
Named entity recognition is a fundamental NLP task that plays an important role in tasks like information extraction, document deidentification, conversational models, etc. Following the annotation scheme used in the CoNLL 2002/2003 NER annotation tasks (Tjong Kim Sang, 2002; Tjong Kim Sang and De Meulder, 2003), many legacy named entity corpora contain an annotation distinguishing four entity types: in addition to organizations (ORG), persons (PER), locations (LOC) there is a general entity category covering all the rest (MISC). This was the case for all named entity corpora available for Hungarian, the Szeged NER corpus (Szarvas et al., 2006), the Hungarian Criminal NE corpus, the silver-standard Hungarian hunNERwiki corpus (Simon and Nemeskey, 2012) automatically derived from Wikipedia, and even the most recent NYTK-NerKor corpus (Simon and Vadasz, 2021) published in 2021.

In contrast, some corpora containing named entity annotation, like the English OntoNotes 5 corpus (Weischedel et al., 2013), contain a richer set of entities. The OntoNotes 5 annotation differentiates geopolitical entities (GPE: countries, settlements, etc.) and facilities (FAC: buildings, roads, airports etc.) from geographical locations like mountains or bodies of waters. Within the very generic MISC category, products (PROD), laws, directives and other legal norms (LAW), events (EVENT) and titles of works of art (WORK_OF_ART) are differentiated. In addition, the OntoNotes NER tagset also encompasses time and numerical expressions distinguishing dates and times, cardinal and ordinal numbers, quantities, percentages and amounts of money. In addition, other categories covering non-entities like languages (LANGUAGE) and nationalities, religions and political affiliations (NORP ‘nationality/other/religion/political’) are covered, presumably because English orthography happens to prescribe capitalization for words (in the case of NORP: adjectives) belonging to these categories. See also Table 3 on the tagset used in NerKor+Cars-OnetoNotes++ for further details.
There are more than a dozen named entity resources of English biomedical text covering entities completely different from those annotated in resources for generic text. In most of them, genes and proteins play a major role. Other entity types covered include names of species, diseases, cell lines, anatomic structures and chemical compounds. The most important milestone of biomedical named entity research was the creation of the GENIA corpus covering 47 different entity types. Some resources in languages other than English also use NER tagsets richer than the basic four-class tagset. Although the NoSta-D resource used in the GermEval2014 shared task targeting German NER (Benikova et al., 2014) maintains a four-class distinction, words (especially adjectives) derived from names as well as compounds containing them get special annotation. The same annotation scheme was applied when creating the Danish DaN+ corpus (Plank et al., 2020). In addition, these corpora, similarly to other resources like GENIA, the Spanish and Catalan newspaper text corpus AnCor (Taule et al., 2008) and one of the most richly annotated generically NER corpora, the Czech Named Entity Corpus (CNEC 2) (Sevčíková et al., 2007), feature nested named entities. The ACE task datasets of LDC for English, Chinese and Arabic also have nested entities (and also a relatively fine-grained entity subtype taxonomy) with not only proper names but also NP’s headed by common nouns annotated with entity types and relations also marked. Unfortunately, these resources are not freely available. The same applies to the NNE (Nested Named Entities) dataset (Ringland et al., 2019), which is based on Penn Treebank data. The resources mentioned before involve a (word)-token-level annotation. A fairly recent resource for Hebrew, NEMO (Bareket and Tsarfaty, 2021), (although relatively small at 93,500 tokens) features not only a moderately detailed entity classification (the genuine NE tags of the OntoNotes tagset), but also nested entities and (what is the real novelty) subtoken-(morpheme)-level entity annotation, which again may turn out to be a breakthrough innovation for morphologically complex languages. There are dozens of NER datasets in other languages, which we cannot review here. An overview of the datasets mentioned above is shown in Table 1.

2. The NerKor Corpus

NYTK-NerKor (NerKor) (Simon and Vadász, 2021), with a size of over one million tokens, is much bigger than any of the previous gold standard Hungarian named entity corpora. Moreover, in contrast to its predecessors, which covered only a single domain, NerKor has a broad coverage of domains and topics, and it is thus an important milestone in Hungarian NLP research. Another property that distinguishes it from some earlier Hungarian NER corpora is that it has a permissive licence.

NerKor consists of five 200,000-token subcorpora. The fiction subcorpus contains literary work from the beginning of the 20th century, whose copyright has already expired. These texts deviate from present-day orthography and language use quite significantly. The other part of this subcorpus contains movie subtitles from the Opus OpenSubtitle Corpus. The legal subcorpus consists of sentences taken from EU sources: parts of the 2004 EU constitution, European Economic and Social Committee documents, and portions of JRC-Acquis and DGT-Acquis, all downloaded from the Opus corpus website. A conspicuous feature of these texts is the high prevalence of references to laws, regulations, standards and some difficult-to-categorize EU entities like specific sections of budget. The web subcorpus contains content downloaded from the Hungarian portion of Common Crawl. One source of content in the news subcorpus is the Hungarian edition of Global Voices containing articles translated by non-professional translators. A hallmark of these texts is the prevalence of references to social media sites and content. The rest of this subcorpus comes from the NewsCrawl 2019 corpus created by the team organizing the 2019 WMT machine translation conference. Finally, the wiki subcorpus is a subset of the Hungarian part of the hunNERwiki corpus (Simon and Nemeskey, 2012), which contained a selection of sentences from a dump of Hungarian Wikipedia that contained at least one internal Wikipedia link to a Wikipedia entry that belongs to a named entity type according to DBPedia. The automatically generated silver-standard annotation from HunNERwiki was turned into gold standard annotation during the creation of NerKor.

About one third of the corpus (the fiction subcorpus, Global Voices and a small portion of the Wikipedia content) contains coherent text, the rest is a shuffled collection of unrelated sentences or sentence fragments. In this respect, the corpus differs from earlier Hungarian named entity corpora, which consist predominantly of coherent text. In addition, about half of the corpus contains standard proof-read text that conforms orthographically. Unfortunately, this is the part which consists mostly of shuffled sentences.

Shuffling sentences has been a method applied to...
legacy corpora to avoid copyright problems. Not very long ago, when most NLP models did not try to handle text-level dependencies, shuffling was not too high a price to pay for avoiding legal affairs in order to ensure that corpora can be freely used.

The task of named entity recognition per se, is not in general considered to require a context wider than a sentence. However, Schweter and Akbik (2020) report improvement when incorporating some extrasentential context in their models. Omitting parts of the corpus not containing relevant entities can also be justified by reducing the workload on annotators (we also applied this method when constructing the car subcorpus, see below), although it may significantly affect named entity density and thus possibly also the performance of models trained on the resource. E.g. NE density is 1.7–3.75 times higher in the filtered wiki subcorpus than in other subcorpora of NerKor.

Moreover, considering the effort put into the annotation process, it would be desirable that the corpus could be further annotated for other tasks for which a wider context might be necessary (e.g. co-reference resolution). One third of the NerKor corpus can be used for such purposes: it is indeed a positive aspect of the corpus that some parts of these texts originate from the already coreference-annotated KorKor(pusz) pilot corpus (of 31492 tokens) (Vadász, 2020).

20% of the corpus includes morphological annotation as well, so that traditional machine learning algorithms can also be trained on these portions. In the present adaptation of the corpus, we ignored these morphological annotations.

### Table 1: Properties of NER datasets mentioned in Section 1.1

| corpus               | granul. | non-ent | der/cmpd | nest | cmn N | subtok | language | domain | gold |
|----------------------|---------|---------|----------|------|-------|--------|----------|--------|------|
| CONLL 2002/2003      | -       | -       | -        | -    | -     | -      | en, ne, es | news   | +    |
| Szeged NER           | -       | -       | -        | -    | -     | -      | hu       | business| +    |
| Criminal NER         | -       | -       | -        | -    | -     | -      | hu       | news   | +    |
| hunNERwiki          | -       | -       | -        | -    | -     | -      | hu       | wiki   | -    |
| NYTK-NerKor          | -       | -       | -        | -    | -     | -      | hu       | multi  | +    |
| OntoNotes 5          | +       | +       | -        | -    | -     | -      | en       | multi  | +    |
| Genia                | -       | -       | +        | -    | -     | -      | en       | biomed | +    |
| NoSta-D              | -       | +       | +        | -    | -     | -      | de       | wiki+news | +    |
| DaN+                 | -       | +       | -        | +    | +     | -      | dk       | multi  | +    |
| AnCora               | -       | +       | +        | -    | -     | -      | es, ca   | wiki+news | +    |
| CNEC 2               | ++      | +       | +        | +    | +     | -      | cz       | ?      | +    |
| ACE datasets         | ++      | +       | +        | +    | +     | -      | en, ar, zh, es | news   | +    |
| NNE                  | +++     | +       | +        | +    | +     | -      | en       | news   | +    |
| NEMO                 | +       | +       | +        | +    | +     | -      | he       | news   | +    |

Note, however, that copyright issues do not arise concerning most parts of the corpus containing non-coherent text: the legal, the web or the Wikipedia subcorpus.

3. Annotation Method

Our reannotation workflow for NerKor followed in most aspects the method described in Novák and Novák (2021). We relied on zero-shot application of transformer-based named entity recognition models trained on resources in other languages: English and Czech, algorithmic merging with the original annotation, and semi-automatic and manual correction.

3.1. Zero-shot Preannotation

First we applied two models trained on the English OntoNotes 5 corpus to the Hungarian corpus. The first model was created by the DeepPavlov team (Burtsev et al., 2018) fine-tuning multilingual BERT (Devlin et al., 2019). The other model is based on XLM-RoBERTa (Conneau et al., 2019), a multilingual contextual language model trained on a significantly bigger multilingual corpus than multi-BERT. The latter model is part of the FLAIR tool set (Akbik et al., 2019).

The two models perform different tokenization following the tokenization scheme of the underlying contextual language model: XLM-RoBERTa is based on a SentencePiece tokenizer (Kudo and Richardson, 2018), while the BERT model applies legacy tokenization first, which is followed by WordPiece subword tokenization. Thus the difference between the token sequence in the output of the models and the original input token sequence had to be taken into account when merging the annotation from the models with the original annotation. The merging algorithm considered the spans in the input annotations gold standard in the case of overlapping entity spans, and if the generated annotation contains a compatible entity subtype, the entity type is updated accordingly. E.g. an entity of type location (LOC) in the original annotation is compatible with any of geographical location (LOC), facility (FAC) and geopolitical entity (GPE). Annotation of non-entities, like dates, quantities and nationalities not present in the original annotation was introduced based on the output of the models.

3.2. Error Analysis and Automatic Error Correction

Zero-shot model application resulted in typical errors. E.g., in the case of transfer from English to Hungar-
ian, a typical problem is that for some named entity types, like names of organizations, journals, titles of works of art etc., a definite article is present in Hungarian when the name is incorporated in the sentence structure (but not in parentheticals), while there is no article in English. This made the models include definite articles in the span for these entity types, an error that could be easily eliminated from the output using regular-expression-based patterns. Similar automatic correction patterns were applied to fix certain types of anomalies concerning numerical and quantity expressions.

### 3.3. Benefits and dilemmas arising from cross-lingual mapping

While cross-lingual mapping resulted in some anomalies like inclusion of definite articles, it had other side-effects that we found useful. E.g., since English prepositional phrases of names (which are obviously annotated as named entities) often correspond to adjectives derived from the given name in Hungarian, the output of the models also included entity annotation for these adjectives. In contrast to the German NoSta-D or the Danish DaN+ corpus, words like this remained unannotated in all legacy Hungarian named entity corpora. However, identifying these words as references to named entities is desirable in practical applications like information retrieval or data de-identification. We thus decided to keep this kind of annotation as part of our annotation enrichment effort.

This decision, however, also raises dilemmas not complicating one’s life if one refrains from annotating derived adjectives. While in the original OntoNotes corpus, adjectives labeled as NORP, such as *Chinese* can be easily distinguished from cases where elements with similar meanings appear as possessive or prepositional constructions like *off/of/from China* (a GPE or ORG annotation is used in these cases), their Hungarian equivalent is often neutralized, and this may lead to ambiguities that are difficult to resolve. In some cases the equivalents differ, like for *English vs. off/of England*: *angol* vs. *angliai*, and it is relatively clear in such cases that the former should be labeled as NORP and the latter as GPE. However, in most analog cases there is no lexical difference, e.g. *Chinese* and *off/of/from China* both neutralize to *kínai*. In these cases, the guideline for manual disambiguation or annotation was to use the *angol* vs. *angliai* duality as an analogy, but it is easy to make mistakes when making these annotation decisions.

When extending annotation to non-name entities, such as time expressions and quantities, the exact range of terms to be annotated is also relatively difficult to define coherently and to consistently adhere to. In addition, the emergence of new entity types leads to a proliferation of elements increasing the need to annotate nested entities, which we have so far refrained from.

After automatic correction of entity spans and types, we manually merged the outputs of the two models by checking the differences of the two annotations. In the annotation generated by the OntoNotes models, quantities form a separate class: these are composed of a number and a unit of measure. However, expressions of time durations, such as *két napra* ‘for two days’, *hároméves* ‘three-year-long/three-year-old’ were annotated by the models as dates. We have checked these expressions manually and transformed them either to spans of type *time duration* or *age*.

### 3.4. NameTag 2

We also applied a third model to the corpus. We used the Czech model of the NameTag 2 neural named entity tagger (Straková et al., 2019) trained on the Czech Named Entity Corpus CNEC 2 (Sevcíková et al., 2007). This model is based on a fine-grained hierarchy of entity classes having many subclasses within the broader categories like a distinction of companies vs. governmental/political institutions vs. academic/educational/cultural/sports institutions and conferences/contests (the latter are also considered a subclass of organizations). NameTag 2 is capable of returning nested annotations (with a maximal depth of two overlapping entities). The model can be accessed via a web service. Although this fine-grained model seemed attractive, at least in the zero-shot cross-lingual setting, the annotation generated by this model turned out to be much less accurate than those generated by OntoNotes-based models. This may not only be due to the higher number of distinct classes and the more complicated algorithm but also the limited size of the CNEC 2 training data (consisting of about 200 thousand tokens vs. the 1.5 million tokens in OntoNotes 5).

Since there is no definite article in Czech, we expected this model to have a problem with definite articles for the entity types the English models struggled with, but it turned out to have this problem only in the case of sentence-initial capitalized definite articles (probably due to a constraint on capitalization that might be included in the algorithm). A more prevalent problem with this model was that it often assigned different classes to different occurrences of the same entity (and usually this was an error rather than real ambiguity) and often left the same entity unannotated. Identification of the span of the entities was also less accurate than what the English-based models generated.

### 3.5. A lemmatized named entity list and automated correction patterns

In spite of its weaker performance, annotation generated by the Czech model proved to be useful. We lemmatized the entity annotations generated by all models (only the head, i.e. the last token of names were lemmatized) and created a list of all the lemmatized named entities occurring in the corpus grouped by named entity types, resulting in a gazetteer-like resource. This
list contained all alternative analyses for each entity along with their corpus frequencies. Reviewing these lists, we have found that the Czech model frequently fails to assign the correct classification, thus we did not adopt the taxonomy of CNEC.

Nevertheless, using the automatically generated named entity list, we were able to identify elements frequently misclassified in the OntoNotes model, and entities that should be assigned to distinct classes, such as journals and social media sites. These were assigned the MISC annotation in the original NerKor annotation when they denoted the newspaper or the social media site itself, and ORG if they denoted the corresponding company, publisher, or editorial board, i.e. in NerKor, the annotation generally follows the tag-for-meaning principle. The OntoNotes models, however, assigned an ORG annotation to all of these entities, which is not an optimal solution as the two entities are not identical. We assigned new entity types (MEDIA and SME-DIA) to these MISC types, inspired by the solution used in the CNEC corpus. We identified other entity subtypes, like awards and projects/programs in a similar fashion. Elements to be reclassified were marked manually in the list, and we automatically generated regular-expression-based correction scripts from these that automatically corrected the annotation of all inflected forms of the listed entities in the corpus. Using these patterns, we bulk-corrected the annotation.

### 3.6. Manual error correction

In the whole corpus, we have performed manual error correction starting from three points. First, we have reviewed and corrected anomalies in the lemmatized named entity list, as described in the previous section, applying mainly automatic patterns, but also checking manually. Second, we have resolved contradictions of the annotations in the original corpus and those generated by the transfer models (and also the differences of the annotations generated by the transfer models) by manually correcting each case. Third, we have noticed that the generated annotation for references to legislation in the law subcorpus (e.g. [1260/2001/EK rendelet] [1. cikke (1) bekezdésének a) pontjában] ‘in point (a) of Article 1(1) of Regulation (EC) No 1260/2001.’), was often fragmented and produced various annotation patterns. We normalized these in the form that the name of the law was considered a single entity, and the exact location/document part within the legal reference was another one following it. We also corrected any errors found around any corrections and if a recurrent error type was discovered, we also looked them up and corrected these in the corpus. Systematic correction of the whole corpus is in progress, we have finished about 25%, including the test set.

### 3.7. Metonymic language use

In the original NerKor corpus, metonymic uses of names were assigned the tag corresponding to the meaning of the actual occurrence of the entity (tag-for-meaning annotation). This was the case not only for the journal/publisher annotation, but also when for example country names are used as agents in the text. In these cases, they were annotated as organization instead of location. This type of metonymy is completely productive for every geopolitical entity, and we think that annotating all of them uniformly as geopolitical entities can handle this frequent type of metonymic language use.

We have annotated country names as simple organizations only if they referred to national teams (a case of so-called ‘nickname metonymy’), similarly to the annotation of other sport teams. The use of countries as agents, in our opinion, significantly differs from the phenomena of using the same name for a company and its product or other less productive (nickname metonymic) patterns, like using a street name (Wall Street) to denote an organization (the New York Stock Exchange) or a city name (Brussels) to denote a much more extensive geopolitical entity (the EU). In these cases the distinction is clearly justified, since they are different quite loosely related entities.

In the original corpus, predicative occurrences of names, like her name was X, were annotated as MISC. In these cases, the first step was to add a label to the MISC tag that indicates the real class of the name, such as MISC-PER for a person’s name. For practical purposes, however, these cases can also be considered as references to the given person/organization, so we feel it is appropriate to consider them simply as a person/organization mention.

In Table 2 presenting the tag distribution of the corpus and for the evaluation we applied the latter strategy, but in the published version of the corpus we did not simplify these tags, so that the information coded in the original annotation can also be retrieved. The case of author-work metonymy (e.g. Chomsky olvas ‘he is reading Chomsky’) was handled similarly in the original NerKor annotation. However, while it is evident that it is not the author that is read, but his work, for practical purposes these can be considered mentions of the author.

As we have already mentioned, we introduced new types for the annotation of media, social media, project and award entities (subtypes of the umbrella MISC category). There are, however, further borderline entities that fall into the vague region of the organization-media-‘work-of-art’-product continuum. The annota-

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15The guidelines to the annotations of LDC ACE resources discuss in detail metonymies of GPE’s, and while some metonymy types resembling ORG, LOC or PER entities are identified, many other uses involve more than one aspect of these complex entities. Poibeau (2006) also shows that the distinction of PER vs. ORG metonymies of geopolitical entities is problematic even for humans.

16GPE subtypes (state, province, city, etc.) would be needed to distinguish cases of the latter type from simple city mentions.
tal class, we chose vehicles within the product class. As the experimental class, we chose vehicles within the product class. For training, we selected articles from the archive of the hvg.hu news site using motor-vehicle-related keywords. Then, we chose sentences from this collection that contained car makes and models that were present in the menu structure of a car dealer’s website. This method resulted in a 12000-token corpus, which we annotated using the Flair OntoNotes model. We then manually corrected the annotation and replaced product tags by car tags for car names. We added this special subcorpus as a training/dev/test set for motor vehicles.

5. Features of the corpus

Size and label distribution of the original NerKor corpus and the newly created version is shown in Table 2. The number of distinguished entity types increased 7-fold while the number of entities marked almost doubled from the original. The annotation also features many types not present in the OntoNotes tag set either, e.g. DUR (time duration), AGE, MEDIA (journals, tv stations and news portals) and SMEDIA (social media), PROJ (projects and programs), AWARD and ID. The tags used for entity types in the corpus are described in Table 3.

| PERa | 15266 | PERb | 15234 | LOC | 2226 | FAC | 831 | PROJ | 254 |
|------|-------|------|-------|-----|------|-----|-----|------|-----|
| GPEb | 13872 | DATE | 11224 | QUANTITY | 1918 | TIME | 661 |
| MISC | 5751 | ORGb | 9512 | CAR | 1423 | EVENT | 627 |
| NYTK-NerKor | | | | | | | | | |
| tokens | 1027218 | entities | 46348 |

Table 2: Size and label distribution of the original and new corpus versions

6. Possible future enhancements

While corpora containing nested entities have existed for some languages and domains, most resources contained only unnested annotation for the lack of competitive nested taggers. Recently, the development of models that can also handle nested entities has gained momentum, and some open source neural nested entity taggers have emerged (Wang et al., 2020; Shibuya and Hovy, 2020) [Shen et al., 2021]. However, these models have sub-SOTA performance on flat NER datasets (we also found Nametag 2 to generate much less accurate annotation than the OntoNotes 5-based models), nevertheless updating the dataset to have nested entities is a possible future enhancement of the corpus. In many cases it would be easier to make annotation decisions if we allowed nested entities, and such an annotation would also be more motivated for information retrieval applications.

7. Models and performance

We evaluated the zero-shot performance of the transfer-based models: the OntoNotes5-based Flair and DeepPavlov models and the Czech NameTag2 tagger on the test set of the corpus. We also performed the evaluation with the tagset normalized to the tags present in the original model (ignoring distinctions the model was not trained to make). We also trained a neural tagger model based on the Hungarian huBERT contextual language model (Nemeskey, 2021) on the training set of the corpus using the HuggingFace Transformers library (Wolf et al., 2020) with an improved Viterbi-like decoding that eliminates invalid tag sequences from the output (Nemeskey, 2020). The performance of these models is shown in Table 4. We report P, R and F1 scores as percentage.

Models using language transfer performed quite well, but among the English models trained on the same corpus, the XLM-RoBERTa-based Flair model performed significantly (about 10% F-measure) better. The Flair model using a “stronger” language model obtained higher precision and recall values across the board for all named entity types, than the weaker model. The performance of these models increased (by 5-6% F-measure) when the automatic regular-expression-based correction of definite articles was applied to their output. The zero-shot performance of the Flair model on entity types in common with those in the final version (i.e. ignoring the newly introduced MEDIA, SMEDIA, PROJ, etc. tags) is quite convincing. This performance made our re-annotation effort feasible.

The apparently quite weak performance of the Czech model is partly explained by the fact that it works with a much more fine-grained tagset, thus in order to mea-
Table 3: Description of tags/entity types used in the corpus. Types in bold are not present in the OntoNotes 5 tagset.

| non-entities | DATE | dates and intervals (granularity over 24 hours) |
|--------------|------|-----------------------------------------------|
|              | CARDINAL | cardinal numbers |
|              | NORP | nationalities, religion, political affiliation (adjectives) |
|              | ORDINAL | ordinal numbers |
|              | LAW | references to laws, directives and other norms |
|              | QUANTITY | quantities: cardinal number + unit of measure |
|              | DUR | time durations (time quantites, unanchored to the timeline) |
|              | PERCENT | percentages and ratios (in OntoNotes: only percentages) |
|              | TIME | time and short intervals (granularity below 24 hours) |
|              | LANGUAGE | names of languages |
|              | AGE | age of persons and things (time durations with spec. semantics) |
|              | MONEY | sums of money: cardinal number + monetary unit |

| organizations | ORG | organizations: companies, parties, institutions, teams etc. |
|              | PER | people, fictive persons, families, animals |

| places | GPE | geopolitical entities: states, settlements, provinces, counties etc. |
|        | LOC | geological locations: mountains, deserts, bodies of water etc. |
|        | FAC | facilities: roads, streets, buildings etc. |

| other entities | WORK_OF_ART | titles of creative works |
|               | PROD | products (except motor vehicles) |
|               | MEDIA | journals, tv channels, news sites |
|               | CAR | motor vehicles |
|               | SMEDIA | social media |
|               | EVENT | named events (except projects) |
|               | PROJ | projects and programmes |
|               | AWARD | awards |
|               | MISC-ORG | organization-like types of residual entities |
|               | MISC | residual entities |

Table 4: Performance of models on the test set, CZ: Czech model NameTag2, DP: DeepPavlov OntoNotes/m-BERT, FL: Flair-OntoNotes-Large/XLM-RoBERTa, NKC: NerKor+Cars/huBERT, test: precision of the test set before manual correction.

| version | original | Det fixed | only labels in common | com. labels, Det fixed |
|---------|----------|-----------|-----------------------|------------------------|
| model   | P        | R         | F1        | P        | R         | F1        | P        | R         | F1        | P        | R         | F1        |
| CZ      | 15.82    | 11.39     | 13.25     | 15.89    | 11.44     | 13.30     | 64.57    | 52.92     | 58.16     | 64.63    | 52.97     | 58.22     |
| DP      | 66.32    | 60.41     | 63.23     | 71.66    | 65.27     | 68.31     | 68.79    | 63.42     | 65.99     | 74.63    | 68.81     | 71.60     |
| FL      | 74.81    | 70.73     | 72.71     | 80.59    | 76.19     | 78.33     | 77.68    | 74.34     | 75.97     | 83.90    | 80.29     | 82.06     |
| NKC     | 91.07    | 88.12     | 89.57     | 91.64    | 89.18     | 90.39     | 91.92    | 87.65     | 89.73     | 91.92    | 87.65     | 89.73     |

7.1. Comparison with performance on the original NerKor annotation

We also compared the performance of the best tagger model with that of the same algorithm trained on the original NerKor annotation to see how the division of some entity classes (especially MISC) into several sub-classes impacts performance. For the sake of comparability, we partitioned entity types into non-entities, which are not part of the original NerKor annotation (numerical and time expressions, language names, NORP adjectives and law references), and named entities. The results are shown in Table 5: non-entities at the top half (ordered by decreasing frequency in the test set), entities at the bottom half, with aggregate scores on named entities at the bottom row.

The huBERT-based model with the Viterbi-based decoding performed similarly on named entities to a similar model (emBERT) (Simon et al., 2022) trained on the original version of the corpus.

The F-score on locations is lower than in the case of the model trained on the original corpus partly due to missed adjectival GPE entities (not present in the origi-
Table 5: Performance of the best model trained on NerKor+Cars on each entity type compared to performance a similar model on the original NerKor annotation. Tags ordered within the categories with descending frequency in the test set top to bottom.

| NerKor F1 | NerKor+Cars F1 |
|-----------|----------------|
| DATE      | 88.85          |
| CARDINAL  | 83.78          |
| NORP      | 87.12          |
| ORDINAL   | 94.67          |
| LAW       | 82.12          |
| QUANTITY  | 91.11          |
| DUR       | 74.67          |
| PERCENT   | 84.21          |
| TIME      | 66.67          |
| LANGUAGE  | 83.33          |
| AGE       | 100.00         |
| MONEY     | 87.50          |
| ORG       | 88.45          |
| PER       | 95.32          |
| LOC       | 92.28          |
| MISC      | 81.85          |
| WORK_OF_ART | 90.27   |
| PROD      | 79.37          |
| MEDIA     | 91.53          |
| CAR       | 92.86          |
| SMEDIA    | 73.33          |
| EVENT     | 72.73          |
| MISC-ORG  | 47.06          |
| PROJ      | 66.67          |
| AWARD     | 100.00         |
| MISC      | 66.67          |
| 91.02     | 89.57/92.05    |

8. Conclusion

In this paper, we have presented our research concerning the automatic enhancement of the annotation of the large NYTK-NerKor named entity corpus containing Hungarian texts of various genres. We have almost doubled the number of annotated elements in the corpus and made the number of distinguished classes 7 times bigger. For this, we applied cross-lingual transfer, which proved to be efficient according to our evaluation, but the performance of various transfer models showed significant differences. We have corrected the annotation using semi-automatic methods. Most confusion is within subtypes of locations.

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