Entity Linking over Nested Named Entities for Russian

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Abstract

In this paper, we describe entity linking annotation over nested named entities in the recently released Russian NEREL dataset for information extraction. The NEREL collection (Loukachevitch et al., 2021) is currently the largest Russian dataset annotated with entities and relations. The paper describes the main design principles behind NEREL’s entity linking annotation, provides its statistics, and reports evaluation results for several entity linking baselines. To date, 38,152 entity mentions in 933 documents are linked to Wikidata. The NEREL dataset is publicly available: https://github.com/nerel-ds/NEREL

Keywords: information extraction, entity linking, nested named entities, Russian language

1. Introduction

Entity linking (EL) is a popular NLP task, where a system needs to link a named entity to a concept in a knowledge base such as Wikidata (Vrandečić and Krötzsch, 2014), DBpedia (Auer et al., 2007), or Freebase (Bollacker et al., 2008). Entity linking is a crucial step in automatic knowledge base construction, it helps disambiguate entity mentions in text documents and enrich them with external information (Sevgili et al., 2020; Oliveira et al., 2021).

Entity linking in the general domain is mainly implemented for named entities. Current studies in named entity extraction comprise creation of datasets with so called nested named entities, when an entity can be annotated within another named entity (Benikova et al., 2014; Ringland et al., 2019). In contrast to corpora with “flat” named entities, nested named entity datasets provide possibilities for fine-grained relations between entities and links to knowledge bases.

For example, Lomonosov Moscow State University (Wikidata ID: Q13164) contains further entities – Moscow (the capital of Russia – Q649) and Mikhail Lomonosov (the founder of the Moscow State University – Q58720).

In the example in Figure 1a, “Famous Diary of Anne Frank” remains in Amsterdam”, the entities Diary of Anne Frank, Anne Frank, and Amsterdam help disambiguate each other. As Figure 1b shows, the word Metro in the sentence “Football team of England will play on Tuesday, writes Metro” refers to a UK newspaper and can be resolved correctly by considering internal entity England.

In this paper, we present entity linking annotation over nested named entities in the recently developed Russian dataset NEREL. The NEREL collection (Loukachevitch et al., 2021) is currently the largest Russian dataset annotated with entities and relations, when compared to the existing Russian datasets (Gordeev et al., 2020; Trotimov, 2014; Mozharova and Loukachevitch, 2016; Gareev et al., 2013).

2. Related Work

Currently, there are several datasets with multiple levels of annotation that allow solving several tasks simultaneously, either independently or within a multi-task learning setup, where information obtained in one task can help solve an-
other task. Table 1 summarizes the characteristics of entity linking datasets. The DWIE corpus \cite{Zaporozjets2021} consists of 802 news articles in English collected from the *Deutsche Welle* news outlet. It combines four annotation sub-tasks: named entity recognition, relation extraction, coreference resolution, and entity linking. DWIE features 311 entity and 65 relation types; named entities are linked to Wikipedia. Another example is SciERC \cite{Luan2021}, which contains abstracts of 1,680 scientific papers on information technology. In total, 3,386 terms are labeled, 1,337 of which are linked to Wikidata entities. How-ever, the first dataset is not freely available, and the second one is rather small. Additionally, neither of these datasets is annotated with nested named entities. Table 1 provides a comparison of the above-mentioned datasets. Recently, \cite{Nesterov2021} have released the Russian-language RuCon dataset related to the clinical domain with annotations of diseases and symptoms linked to the concepts of the UMLS metathesaurus.

### 3. Nested Named Entity Annotation

To date, the NEREL corpus consists of 933 news articles originating mainly from Russian Wikinews, which discuss persons, their relations, and events \cite{Loukachevitch2021}. Figure 1 shows an example of nested named entities

| Dataset                          | Lang | Domain   | Docs | Mentions | Overlap | Levels       |
|---------------------------------|------|----------|------|----------|---------|--------------|
| AIDA-CoNLL \cite{Hoffart2013}   | En   | News     | 1,393| 34,956   | No      | NE/EL        |
| DBpedia Spotlight \cite{Mendes2011} | En   | News     | 10   | 330      | Overlap | EL           |
| TAC-KBP-2010                    | En   | News/Web | 1,013| 1,020    | Overlap | EL           |
| VoxEL* \cite{Rosales-Mendez2018} | De/En/It/Sp/Fr | News | 15   | 204      | No      | EL           |
| VoxEL** \cite{Rosales-Mendez2018} | De/En/It/Sp/Fr | News | 15   | 674      | Overlap | EL           |
| DWIE \cite{Zaporozjets2021}     | En   | News     | 802  | 28,482   | No      | NE/RE/EL/RF  |
| SCIERC \cite{Luan2018}          | En   | Science  | 500  | 8,089    | No      | TE/RE/RF     |
| RuWiki \cite{Sysoev2018}        | Ru   | Wikipedia| 4,024| 60K      | No      | EL           |
| RuSERRC \cite{Bruches2021}      | Ru   | Science  | 1,680| 1,337    | No      | TE/RE/EL     |
| NEREL \cite{ours}              | Ru   | News     | 933  | 38,152   | Nested  | NE/RE/EL     |

Table 1: Datasets with manual entity linking annotation. Levels of annotation include: TE – term recognition, NE – named entity annotation, RE – relation extraction, EL – entity linking, RF – coreference annotation. VoxEL* – a strict version of the VoxEL dataset without overlapping entities, VoxEL** – a relaxed version of VoxEL with overlapping entities.
The entity types can be grouped in the following way:

Second, in addition to annotating traditional named entities that are mainly expressed by nouns and noun phrases, we also annotated adjectives such as British or Russian derived from named entities. An adjective can be essential for establishing a relation in a sentence or in the whole text due to absence or long distance to the corresponding noun (Benikova et al., 2014). Moreover, an adjective often conveys a reference to the same entity in a knowledge base as the noun, from which the adjective is derived.

Third, we annotated entities beyond the traditional named entity typeset in the general domain: crimes, penalties, diseases, professions, and professional titles are annotated independently of their capitalization. This was done due to the significance of corresponding relations in person-related texts. Such entities also provide additional links to the knowledge graph.

Currently, there are 29 entity types in the NEREL dataset. The entity types can be grouped in the following way:

- basic entity types (PERSON, ORGANIZATION, LOCATION, FACILITY, geopolitical entities subdivided into several subgroups);
- numerical entities (NUMBER, ORDINAL, DATE, TIME, PERCENT, MONEY, AGE);
- NORP entities (NATIONALITY, RELIGION, IDEOLOGY) and LANGUAGE;
- law-related entities (LAW, CRIME, PENALTY);
- work-related entities (PROFESSION, WORK_OF_ART, PRODUCT, AWARD) and DISEASE;
- EVENT.

In the first phase of the entity linking annotation, we focused on 16 entity types. We excluded seven numerical types, as well as EVENT, IDEOLOGY, and DISEASE entities; statistics of the remained subset in the NEREL dataset is presented in Table 2. As can be seen from the Table, all but one (LANGUAGE) entity type have at least 100 annotated examples.

4. Entity Linking Annotation Guidelines

Since we establish links to Wikidata for both named entities and instances of general concepts such as CRIME, PENALTY, or LANGUAGE, our entity linking can be viewed as a subtype of general named entity linking (Ling et al., 2015). Entity linking annotators rely fully on existing annotations of named entities. If an annotator encounters an alleged problem with named entity annotations, they report the problem to a moderator and get permission to fix it. If an entity is absent in Wikidata, then it should be linked to NULL, but its internal entities may still have corresponding links. For example, the entity Mayor of Novosibirsk is absent in Wikidata, but Mayor’ and Novosibirsk entities have links to Q30185 and Q883 Wikidata items, respectively. NEREL annotations exist for such entities, too.

With other entities in a text. Therefore, we decided to annotate nested named entities in the NEREL dataset.

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### Table 2: Statistics of the named entity (NE stats) and entity linking (EL stats) annotation steps in 933 NEREL documents.

Note that EL statistics correspond to ‘cleaned’ documents, where only one mention per entity is retained. The last three columns report the accuracy of the automatic linkage suggestions against manual annotation: 1) combination of the original Wikinews annotation and the linker’s output with entity type verification (L+T+W, this variant was presented to the annotators), 2) top-1 linker candidate (L), and 3) original Wikinews annotation (W). In all automatic annotation variants, an empty suggestion was treated as NULL.

| NE type          | NE stats | EL stats | Automatic EL |
|------------------|----------|----------|--------------|
|                  | #NE      | #Nested  | #Unique incl. | L+T+W | L   | W   |
| AWARD            | 767      | 405      | 600           | 186   | 0.51 | 0.49 | 0.39 |
| CITY             | 2,293    | 21       | 1,450         | 11    | 0.71 | 0.65 | 0.32 |
| COUNTRY          | 4,444    | 13       | 1,991         | 5     | 0.75 | 0.72 | 0.25 |
| DISTRICT         | 203      | 24       | 156           | 10    | 0.66 | 0.58 | 0.31 |
| FACILITY         | 742      | 285      | 556           | 172   | 0.49 | 0.45 | 0.45 |
| LANGUAGE         | 85       | 0        | 70            | 0     | 0.77 | 0.63 | 0.09 |
| LAW              | 713      | 441      | 584           | 311   | 0.29 | 0.28 | 0.56 |
| LOCATION         | 534      | 121      | 403           | 71    | 0.45 | 0.40 | 0.32 |
| NATIONALITY      | 754      | 56       | 532           | 6     | 0.32 | 0.27 | 0.03 |
| ORGANIZATION     | 7,066    | 2,312    | 4,666         | 975   | 0.61 | 0.58 | 0.34 |
| PERSON           | 9,687    | 103      | 4,459         | 908   | 0.57 | 0.54 | 0.43 |
| PRODUCT          | 492      | 39       | 344           | 27    | 0.83 | 0.80 | 0.25 |
| PROFESSION       | 8,758    | 2,873    | 5,922         | 1,732 | 0.54 | 0.48 | 0.30 |
| RELIGION         | 175      | 3        | 107           | 4     | 0.53 | 0.48 | 0.13 |
| STATE_OR_PROVINCE| 750      | 1        | 473           | 1     | 0.81 | 0.76 | 0.34 |
| WORK_OF_ART      | 689      | 135      | 544           | 143   | 0.55 | 0.51 | 0.42 |
| **Total**        | 38,152   | 6,832    | 22,857        | 4,562 | 0.59 | 0.54 | 0.34 |

*Moskovskii* derived from *Moscow* is linked to the same item as the initial name: *Moscow* (Q649). Linking of adjectives increases coverage of the annotation. Adjectives derived from nations and nationalities are especially difficult for manual annotation and automatic linking because of their ambiguity. For example, the adjective *russkii* (*Russian*) in different contexts can mean the Russian Federation (Q159, NER type COUNTRY), Russian citizens (Q49542, NER type NATIONALITY) or Russian language (Q7737, NER type LANGUAGE).

We linked PROFESSION entities to profession items in Wikidata, not to a person who is currently holding this post. For example, Mayor of Moscow mention is linked to the Mayor of Moscow Wikidata item Q1837906, not to Sergey Sobyanin (Q319497), the current Moscow mayor. This is because specific persons can change their posts in the appointment and resignation contexts.

### 5. Annotation Process Details

We use Wikidata as our target knowledge base (KB). Wikidata is a large open multilingual KB that is being actively developed by the community. To date, there are about 7.5M Wikidata items with Russian labels.

#### 5.1. Preliminary Automatic Annotation

We used the BRAT annotation tool (Stenetorp et al., 2012), in particular – its normalization feature for entity linking. As a preparation step, we removed markup of the entities that are not intended for linking to Wikidata, as well as relations, from the BRAT standoff annotation files. In addition, we removed all but one mention per entity in the document based on *alternative_name* and *abbreviation* relations annotated in NEREL. Removing multiple mentions of the same entity within a document decreased the number of named entities to be linked to Wikidata by 40% (from 38,152 to 22,857 in 933 documents). We applied an entity linker that was originally developed for the annotation of a question answering dataset. The linker builds a search index over a collection of Russian labels and aliases that correspond to around 4M Wikidata entities using ElasticSearch. The linker converts an input string into a series of phrase and fuzzy search queries, aggregates the search results, and returns a ranked list of candidate entities. The final ranking is performed based on a combination of ElasticSearch matching scores and page view statistics of the corresponding Wikipedia articles. Adding the latter parameter turned out to be very efficient to downrank noisy candidates. The linker implementation details can be found in Korablinov and Braslavski (2020). In the original Wikinews articles, some entity mentions are linked to corresponding Wikipedia pages. For about 15% (3,454) of entities to be linked, we could provide alternate names, e.g. *October 2009* → Q243251 that are not very helpful in the context of our task.

https://www.wikidata.org/wiki/User:Mr._Ibrahem/Language_statistics_for_items

https://github.com/vladislavneon/koba-tools/

https://www.elastic.co/

Among them, there are many links to year or month entities, e.g. *October 2009* → Q243251 that are not very helpful in the context of our task.
Wikidata IDs inferred from the original Wikipedia links. For the rest of the mentions, we took up to three Wikidata entity candidates with non-zero Wikipedia page views returned by the linker. We also associated each entity type with a generic Wikidata concept, e.g. CITY – city/town (Q7930989), AWARD – award (Q618779), etc. We kept only candidates that are connected with the corresponding superconcepts by a path of the instance of (P31) or subclass of (P279) properties. The best candidate, if any, was provided as a suggestion for subsequent manual annotation, while the remaining candidates formed a ‘local’ BRAT knowledge base. Annotators were presented with documents with highlighted entities. The majority of entities are provided with candidate Wikidata linkages along with their IDs, labels, and descriptions. Annotators were also able to follow a hyperlink to a Wikidata entity page. To correct an existing linkage or produce a new one, annotators could search the local collection of Wikidata entities using a built-in BRAT search interface based on substring matching. Alternatively, they were instructed to use the Wikidata search box or search Wikipedia through a major search engine like Google or Yandex. In the latter case, a Wikidata ID can be easily obtained by following the Wikidata item link from the navigation panel of a Wikipedia page. This way appeared to be the easiest and most natural for annotators. If no corresponding Wikidata item was found, the annotators provided the entity mention with a special NULL value. On average, annotators spent 1 hour processing 100 entity mentions.

### 5.2. Annotation Results and Evaluation of Automatic Pre-Annotation

| Outer NE type | Inner NE type | #Links | # w/o NULLs | # with NULLs |
|---------------|---------------|--------|-------------|--------------|
|               |               |        |             |              |

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Table 3: The most frequent nested pairs and their links to Wikidata

However, in some cases, it can discard correct linkages. For example, a mention of *Heracles* was correctly linked to *Q122248* but was rejected by the type check since the entity belongs to *demigod* (*Q466470*), not *human* (*Q5*) that was set as a parent class for PERSON.
| Entity Type          | SapBERT Acc.(top-1) | SapBERT Acc.(top-5) | mGENRE Acc.(+NULLs) |
|---------------------|---------------------|---------------------|---------------------|
| AWARD               | 0.598               | 0.750               | 0.660               |
| CITY                | 0.281               | 0.670               | 0.859               |
| COUNTRY             | 0.286               | 0.622               | 0.911               |
| DISTRICT            | 0.500               | 0.833               | 0.524               |
| FACILITY            | 0.505               | 0.667               | 0.822               |
| LANGUAGE            | 0.227               | 0.727               | 0.667               |
| LAW                 | 0.625               | 0.750               | 0.786               |
| LOCATION            | 0.368               | 0.632               | 0.705               |
| NATIONALITY         | 0.197               | 0.364               | 0.231               |
| ORGANIZATION        | 0.547               | 0.682               | 0.754               |
| PERSON              | 0.552               | 0.656               | 0.634               |
| PRODUCT             | 0.483               | 0.586               | 0.900               |
| PROFESSION          | 0.285               | 0.468               | 0.294               |
| RELIGION            | 0.500               | 0.688               | 0.870               |
| STATE OR PROVINCE   | 0.417               | 0.800               | 0.946               |
| WORK OF ART         | 0.442               | 0.687               | 0.688               |
| Macro-Accuracy      | 0.426               | 0.661               | 0.703               |
| Micro-Accuracy      | 0.431               | 0.673               | 0.637               |

Table 4: Baseline results of entity linking derived from SapBERT and mGENRE models

After the Wikidata linking was finished, we restored initial NE/relation annotations and propagated Wikidata linkages to other mentions of the same entities in the corresponding BRAT standoff files. Finally, we provide the distribution of NE types in linked nested named entities. Overall, the dataset contains 10,710 pairs of nested named entities, in 5,394 pairs, both entities (outer and inner) are linked to Wikidata. The majority of the remaining pairs (4,454) have NULL-links for the outer entity only; 707 pairs have both entities with NULL-links. In Table 3, we provide statistics on linkages to Wikidata for the most frequent pairs of nested entities. It can be seen that geopolitical entities are mainly presented in Wikidata; they are nested inside entities of various types: AWARD, LAW, ORGANIZATIONS, PROFESSION, etc. Internal entities of the PERSON type are mainly well-known; they have corresponding Wikidata items.

In addition, we analyzed connections between nested entities and found that only 61% of nested named entity pairs are actually connected in Wikidata in a single hop (the remaining 39% of pairs have no connection). The most frequent types of such connections are: COUNTRY (P17), APPLIES TO JURISDICTION (P1001), SUBCLASS OF (P279), PART OF (P361), NAMED AFTER (P138), LOCATED IN ... (P131), INSTANCE OF (P31), HEADQUARTERS LOCATION (P159), ORGANIZATION DIRECTED BY THE OFFICE OR POSITION (P2389) and FOUNDED BY (P112). Thus, these nested relations describe different aspects of relation between an outer entity and Locations/Persons/Organizations that are mentioned as an inner entity.

We checked that in many cases the absence of a relation between a longer and internal entities in Wikidata can be due to short descriptions of Wikidata items. For example, Mariinsky Theatre Concert hall item (Q4231897) is not linked to the Mariinsky Theatre item (Q207028). Also, we noted that two nested entities from NEREL dataset can be connected by up to six different types of properties in Wikidata (e.g., the Q42274: Google Earth and the Q95: Google).

6. Entity Linking Baselines

As baselines for entity linking, we evaluated two models: (i) a sequence-to-sequence system for the Multilingual Entity Linking (mGENRE) (De Cao et al., 2021) and (ii) a model based on the SapBERT (Liu et al., 2021) that implements self-alignment of representation space during pre-training. The models appear to be state-of-the-art, and can be applied to texts in Russian as they have capabilities to process texts in several languages. Note, that both models were used in the zero-shot evaluation mode without fine-tuning them on the NEREL data. However, we use the NEREL train set to optimise a threshold for NULL linkage prediction.

The mGENRE model uses Wikidata as the KB while exploiting Wikipedia hyperlinks as the source of supervision during training. Given a mention, mGENRE predicts the name of the entity in an autoregressive fashion (token-by-token). To evaluate the model, we transformed the mentions of entities from the NEREL dataset into the mGENRE input format (with “[START]” and “[END]” tags around each mention), keeping a few tokens from the context of each mention, keeping a few tokens from the context of each mention. The mGENRE model was used for inference without any fine-tuning on the NEREL data, which can explain quite moderate performance of the baseline (Table 4). As mentioned above, in the NEREL dataset, links between entities and Wikidata can have a NULL tag, meaning that there is no corresponding entity in the Wikidata. However, mGENRE outputs a list of candidate entities along with a certainty score for each mention. To deal with NULL linkages, we applied the following approach: fitting a certainty-based threshold for decision about the NULL-
linkage. Therefore, the mGENRE either will return a Wikidata entity, or the null linkage. The threshold is fitted on the train part of the NEREL dataset and applied to the test subset. The train, dev, and test sets contain 746, 94, and 93 documents, respectively. The last column of the Table 4 shows results of the mGENRE model that correspond to the optimal threshold value (0.51).

Table 4 also contains the results of another baseline based on the SapBERT model \(^{3}\). This model was originally proposed for biomedical entity linking exploiting concepts from the Unified Medical Language System (UMLS) as the source of supervision. Therefore, we trained the model on 'wikititles+muse' pairs of labels to enrich with general-domain knowledge. The training was done according to the SapBERT authors’ recommendations.\(^ {4}\) Note, that SapBERT returns vector representations for entity mentions which can be compared to vectors of target Wikidata entities using a similarity. Here, again a threshold for the similarity value can be applied to predict null linkages. This threshold was fitted on the NEREL train set to keep the same proportion of nulls. One can see significant difference between top-1 and top-5 accuracy of SapBERT, which means that top-5 candidates contain correct links, but the ranking is not perfect (probably, due to the lack of context). Using the same motivation, we explored tow options for the target entity sets: (i) with the whole list of Wikidata entities and their labels (more than 6 million QIDs) and (ii) with a cleaned version, which has around 2.9 million QIDs. The former (bigger version) led to much worse results (0.3 accuracy), presumably, due to noisy entity labels. Therefore, in the Table 4 for SapBERT we provide results of linking to the latter (shorter) list of Wikidata entities.

7. Conclusion

In this paper, we described entity linking annotation within the NEREL dataset, the largest Russian dataset for information extraction. Entity linking annotation to Wikidata items is provided for 933 documents, 16 entity types, and 38,152 entity mentions. The annotation contains a significant share of nested named entities (more than 17%), supporting a broader coverage of linking. Currently, NEREL is the only dataset for Russian annotated with links to Wikidata entities. It is also the only Russian dataset with three levels of annotation. NEREL can be used for developing and testing entity linking models applied to nested named entities and also for creating end-to-end models accounting for nested entities.

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\(^{6}\)The list can be found here: [github.com/cambridgeltl/sapbert/tree/main/training_data]

\(^{7}\)Here, by ‘cleaning’ we mean keeping only Russian labels and dropping from a label any text inside parentheses, which can provide a noisy signal to the entity linking model (e.g. the label ‘Andacollo(Chile)’ was substituted with the label ‘Andacollo’); labels without Russian characters were dropped.

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