

# Razmecheno: Named Entity Recognition from Digital Archive of Diaries “Prozhito”

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## Abstract

The vast majority of existing datasets for Named Entity Recognition (NER) are built primarily on news, research papers and Wikipedia with a few exceptions, created from historical and literary texts. What is more, English is the main source for data for further labelling. This paper aims to fill in multiple gaps by creating a novel dataset “Razmecheno”, gathered from the diary texts of the project “Prozhito” in Russian. Our dataset is of interest for multiple research lines: literary studies of diary texts, transfer learning from other domains, low-resource or cross-lingual named entity recognition.

Razmecheno comprises 1331 sentences and 14119 tokens, sampled from diaries, written during the Perestroika. The annotation schema consists of five commonly used entity tags: person, characteristics, location, organisation, and facility. The labelling is carried out on the crowdsourcing platform Yandex.Toloka in two stages. First, workers selected sentences, which contain an entity of particular type. Second, they marked up entity spans. As a result 1113 entities were obtained. Empirical evaluation of Razmecheno is carried out with off-the-shelf NER tools and by fine-tuning pre-trained contextualized encoders. We release the annotated dataset for open access.

**Keywords:** named entity recognition, text annotation, datasets

## 1 Introduction

Modern Named Entity Recognition (NER) systems are typically evaluated on datasets such as ACE, OntoNotes and CoNLL 2003, collected from news or Wikipedia. Other common setups to test NER systems include cross-lingual evaluation (Liang et al., 2020) and evaluation in domains, other than

general, such as biomedical domain (Weber et al., 2020; Wang et al., 2019).

Additionally, the vast majority of NER datasets are in English. A few large-scale datasets for other languages are NoSta-D (Benikova et al., 2014) (German), NorNE (Jørgensen et al., 2020) (Norwegian), AQMAR (Mohit et al., 2012) (Arabic), OntoNotes (Hovy et al., 2006) (Arabic, Chinese), FactRuEval (Starostin et al., 2016) (Russian).

We present in this work a new annotated dataset for named entity recognition from diaries, written in Russian, – “Razmecheno”<sup>1</sup>. The texts are provided by the project “Prozhito”<sup>2</sup> which digitizes and publishes personal diaries. Diaries exhibit different surface and style features, such as complex narrative structure, and author-centricity, mostly expressed in simple sentences with predominance of verbs and noun phrases. NER annotation is the first step for summarisation and coreference resolution tasks.

Design choices, made for the corpus construction, are the following. We follow the standard guidelines of named entity annotation and adopt four commonly-used types Person (PER), Location (LOC), Organization (ORG), Facility (FAC). We add one more type, CHAR, which is used for personal characteristic (e.g., nationality, social group, occupation). Texts, used in the corpus, are sampled from the diaries, written in the late 1980s, the time period addressed as Perestroika. We utilized crowdsourcing to label texts.

Our dataset enables assessing performance of the NER models in a new domain or in a cross-domain transferring. We make the following contributions:

<sup>1</sup>“Got annotated”. The short form of the past participle neuter singular of the verb *размечать* (“to annotate”). <https://github.com/hse-cl-masterskaya-prozhito/main>

<sup>2</sup>“Got lived”. The short form of the past participle neuter singular of the verb *прожить* (“to live”). <https://prozhito.org/>

These authors contributed equally to this work.

1. We present a new dataset for Named Entity Recognition of 14119 tokens from 124 diaries from Prozhito. Entity types, used in the dataset, follow standard guidelines. The dataset will be freely available for download under a Creative Commons Share-Alike 4.0 license at <https://github.com/hse-cl-masterskaya-prozhito/main>;
2. We assess the performance of the off-the-shelf NER taggers and fine-tuned BERT-based model on this data.

## 2 Related work

Most of the standard datasets for named entity recognition, as ACE (Walker et al., 2005) and CoNLL (Sang and De Meulder, 2003), consist of general domain news texts in English. For our study, there are two related research lines: NER for the Russian language and NER in Digital Humanities domain.

### 2.1 NER for Russian language

The largest dataset for Russian was introduced by (Loukachevitch et al., 2021). In NEREL, entities of types PER, ORG, LOC, FAC, GPE (Geopolitical entity), and FAMILY were annotated, and the total number of entities accounts to 56K.

(Starostin et al., 2016) presented FactRuEval for NER competition. The dataset included news and analytical texts, and the annotation was made manually for the following types: PER, ORG and LOC. As of now, it is one of the largest datasets for NER in Russian as it includes 4907 sentences and 7630 entities.

Several other datasets for Russian NER, such as *Named Entities 5*, WikiNER, are included into project Corus<sup>3</sup>. Its annotation schema consists of 4 types: PER, LOC, GEOLIT (geopolitical entity), and MEDIA (source of information). Another golden dataset for Russian was collected by (Gareev et al., 2013). The dataset of 250 sentences was annotated for PER and ORG. For the BSNLP-2019 shared task, a manually annotated dataset of 450 sentences was introduced (Piskorski et al., 2019). The annotation includes PER, ORG, LOC, PRO (products), and EVT (events). RuREBus (Ivanin et al., 2020) is an example of NER dataset for a specific domain: it was introduced for a shared task in relation extraction

for business. Business-related documents were annotated manually with the help of active learning algorithm.

Several silver datasets exist for Russian NER. WikiNEuRal (Tedeschi et al., 2021) uses multilingual knowledge base and transformer-based models to create an automatic annotation for PER, LOC, PRG, and MISC. It includes 123,000 sentences and 2,39 million tokens. In Natasha project, a silver annotation corpus for Russian Nerus<sup>4</sup> was introduced. The corpus contains news articles and is annotated with three tags: PER, LOC, and ORG. For Corus project, an automatic corpus WikiNER was created, based on Russian Wikipedia and methodology of WiNER (Ghaddar and Langlais, 2017).

### 2.2 NER applications to Digital Humanities

Bamman et al. (2019) introduced LitBank, a dataset built on literary texts. The annotation was based on ACE types of named entities, and it includes the following types: PER, ORG, FAC, LOC, GPE (geo-political entity) and VEH (Vehicle). The annotation was made by two of the authors for 100 texts. The experiments with models trained on ACE and on LitBank showed that NER models trained on the news-based datasets decrease significantly in the quality on literary texts. Brooke et al. (2016) trained unsupervised system for named entity recognition on literary texts, which bootstraps a model from term clusters. For evaluation, they annotated 1000 examples from the corpus. Compared to NER systems, the model shows better results on the literary corpus data.

Apart from English LitBank, a dataset for Chinese literary texts was created and described by Xu et al. (2017). The dataset for Chinese literature texts had both rule-based annotation and machine auxiliary tagging, hence, only examples where gold labels and predicted labels differ were annotated manually. The corpus of 726 articles were annotated by five people. Besides standard tags, as PER, LOC, and ORG, the authors used tags THING, TIME, METRIC, and ABSTRACT.

Another approach to annotation was presented by Wohlgenannt et al. (2016). The authors' purpose was to extract social networks of book characters from literary texts. To prepare an evaluation dataset, the authors used paid micro-task crowdsourcing. The crowdsourcing showed high quality results and appeared to be a suitable method for

<sup>3</sup><https://github.com/natasha/corus>

<sup>4</sup><https://github.com/natasha/nerus>

digital humanities tasks.

### 3 Dataset collection

#### 3.1 Annotation schema

Our tag set consists of five types of entities. This tag set was designed empirically for texts of diaries from common tags used in related works (Walker et al., 2005; Bamman et al., 2019).

- **PER**: names/surnames of people, famous people and characters (see Example 1);
- **CHAR**: characteristics of people, such as titles, ranks, professions, nationalities, belonging to the social group (see Example 4);
- **LOC**: locations/places, this tag includes geographical and geopolitical objects such as countries, cities, states, districts, rivers, seas, mountains, islands, roads etc. (see Example 2);
- **ORG**: official organizations, companies, associations, etc. (see Example 3);
- **FAC**: facilities that were built by people, such as schools, museums, airports, etc. (see Example 4);
- **MISC**: other miscellaneous named entities.

We introduce a novel tag CHAR for the following reasons. In diaries, people are often referred with their social status or specialty. Annotation of such mentions allows for further exploration of a social spectrum. See Appendix G.4 for the exact definition of the tag as it has been presented to the assessors. Among the annotated characteristics, plenty of emotional coloured judgements (such as “rebel”, “alcoholic”, “liar”) can be found. While this highlights the subjective nature of this class of entities, it also provides a way to consider the perception of the epoch by various social groups, which we find promising for further studies.

Unlike datasets based on news, when working with diaries, it is important to know not only a person’s name (which is sufficient for news because famous people usually get into them), but also one’s social status. The reason for this is that it gives an opportunity to make assumptions about lifestyle of this person.

These five entity types can be clearly divided into two groups: the first one, PER-CHAR, is related

to people and the second one, ORG-LOC-FAC, is related to places and institutions.

We annotated flat entities, so that the overlap between two entities is not possible. The main principle of the annotation is to mark up the longest possible span for each entity, not to divide them when not required, because our schema does not assume multi-level annotation, when one entity can include another ones. For example, a name and a surname coalesce in single PER entity, rather than being two different ones (see Example 1).

- (1) А ведь Леон просил меня  
 And really **Leon** asked me  
PER  
 отозваться лишь о Жакке Ланге  
 to.talk only about **Jack Lang**  
PER

‘And Leon asked me to talk only about Jack Lang’.

- (2) Орёл самый литературный город в  
**Orel** the.most literary city in  
LOC  
 России  
**Russia**  
LOC

‘Orel is the most literary city in Russia’.

- (3) Позвонил в “Урал”: надо все-таки  
 called in **“Ural”** need after.all  
ORG  
 дать им знать о моем прилете.  
 give them know about my arrival

‘I called the “Ural”: after all, I have to let them know about my arrival’.

- (4) Солдаты живут в вагоне на этой  
**soldiers** live in car on this  
CHAR  
 станции.  
**station**  
FAC

‘Soldiers live in a car at this station’.

In ambiguous cases entity tags were identified based on the context, so the same entity in different

sentences could be tagged as two different types, for instance, *university* could be annotated as ORG or FAC. If an entity was used in a metaphorical sense, it would not be annotated with any tag.

- (5) Будет и на нашей улице праздник  
will and on our street a.festival  
‘Every dog has its own day’.

### 3.2 Preliminary markup

We performed preliminary analysis of the random subsets of the “Prozhito” corpus. The analysis revealed that most of the sentences contain no entities at all. To avoid costly looping over all sentences, we developed a two-stage annotation pipeline. The first stage aims at selecting sentence candidates, which may include entities of interest. This helps to reduce the amount of sentences sent to assessors and exclude sentences with no entities at all. During the second stage, entity spans are labeled in the pre-selected candidates from the first stage.

Two classifiers were trained on a small manually annotated training set — for PER-CHAR and ORG-LOC-FAC groups, respectively. The task of these classifiers is to predict, whether an entity from a group is present in a sentence, or not. These classifiers do not aim at entity recognition, but rather at binary entity detection.

We leverage upon four possible base models as classifiers: ruBERT-tiny<sup>5</sup>, ruBERT<sup>6</sup> (Kuratov and Arkhipov, 2019), ruRoBERTa<sup>7</sup>, XLM-RoBERTa<sup>8</sup>. Table 1 presents with the classification scores. A few marked up sentences (198) were taken as test sample.

Models	Precision	Recall	Micro f1-score
ruBERT-tiny	0.81	0.88	0.84
ruBERT	0.89	0.91	<b>0.90</b>
ruRoBERTa	<b>0.90</b>	0.88	0.89
XLM-RoBERTa	0.80	<b>0.99</b>	0.89

Table 1: Transformer-based binary classifiers scores

As a result, ruRoBERTa was chosen as the base model. In this task, the precision is more impor-

<sup>5</sup><https://huggingface.co/cointegrated/rubert-tiny>

<sup>6</sup><https://huggingface.co/DeepPavlov/rubert-base-cased>

<sup>7</sup><https://huggingface.co/sberbank-ai/ruRoberta-large>

<sup>8</sup><https://huggingface.co/xlm-roberta-base>

tant than the recall, since we mark up only part of the corpus and, therefore, we still miss some information, but at the same time we want to have any entities in the selected sentences with a high probability.

To train both classifiers, a random sample of size 1500 was taken from diaries belonging to the Perestroika period. Texts were independently marked up by assessors for the presence of ORG-LOC-FAC and PER-CHAR. Due to the fact that it was important to achieve a balance of classes in the training sample, and there were more texts with PER-CHAR than ORG-LOC-FAC, the training samples for ORG-LOC-FAC and PER-CHAR turned out to be different – 829 and 1465 records accordingly (see Table 2 for the validation set scores).

All available sentences were marked up by binary classifier and after that were chosen sentences with following conditions:

1. In the sentence there are entities from PER-CHAR and ORG-LOC-FAC groups, respectively;
2. Classifier was the most confident on these sentences.

Entity Type	Precision	Recall	F1-score
ORG-LOC-FAC	0.94	0.92	0.94
PER-CHAR	0.89	0.81	0.82

Table 2: ruRoBERTa scores in the binary classification task

Most confidence here means the average probabilities of each entity groups. Finally, the sentences selected this way were given to the assessors for further marking.

### 3.3 Crowdsourcing annotation

**Annotation setup** For annotation, we used Russian crowdsourcing platform Yandex.Toloka<sup>9</sup>. We prepared two tasks for assessors: determination of PER-CHAR and of ORG-LOC-FAC in “Prozhito” texts. The task was made available only to Russian native speakers. Before annotation, it is necessary to get through the learning pool with hints (20 sentences) and an exam (10 sentences) that show whether assessors understand the meaning of the

<sup>9</sup><https://toloka.yandex.ru/>

given NE tags. The sentences were tokenized with Razdel tokenizer<sup>10</sup>.

The tasks for learning, exam and control were initially annotated by the co-authors with help of annotation tool BRAT<sup>11</sup>.

Each assessor, who succeeded in the learning and exam phases, (mark  $\geq 50\%$  for learning and  $\geq 80\%$  for exam), got access to assessment of sentences in the main pool. Our main pools in both tasks consist of approximately 1500 tasks and 400 control sentences. Tasks were given to assessors on pages, Figure 3 depicts the task interface. Each page consisted of 4 normal tasks and 1 control task. A fee for one page was 0.05\$. The average time of completion of a page was about one minute. Overall, the fee per hour exceeded minimum wage in Russia. The overlap for each sentence given in Toloka is 3 in order to choose the most popular variant of markup as a correct one. Control tasks are necessary for monitoring of an annotation quality. We banned users if they skipped more than 7 task suites in a row or if they had less than 30% correct control responses.

**Assessors agreement analysis** While in most of the cases assessors had no dispute, voting mechanism has been involved in nearly one third of cases provided in the corpus (38% in the ORG-LOC-FAC task, 36% in PER-CHAR tasks, respectively).

In both tasks, the typical assessors' disagreement pattern was two competing annotation hypotheses. In the ORG-LOC-FAC task, that was mostly caused by different labels plausible for certain rare events. The ability to correctly disambiguate such terms relied on rather rare factual knowledge, thus provoking annotation errors (as in *Сижу в гостинице "Одесса"*. ('Staying in the hotel "Odessa"'), the challenging choice is 'hotel "Odessa"' is a FAC or an ORG entity). While the same group of assessors disagreements was found in the PER-CHAR task, there also emerged two more disagreements patterns: (i) identifying the proper span for the characteristics (annotating the whole *полковник в отставке* ('the retired colonel') or only *полковник* ('colonel')) and (ii) inaccurate boundaries' detection for persons initials, which mostly emerged when the assessors missed to highlight the dot in the name shortenings (as with *М. С.* in *М. С. его очень ценил поначалу*. ('M.S. valued him a lot in the beginning')).

<sup>10</sup><https://github.com/natasha/razdel>

<sup>11</sup><https://brat.nlplab.org/>

Rare cases with more than two competing annotations were mostly of random nature (as with birds being annotated as PER), or caused by the appearance of rare words (as with calzones being annotated as Person).

### 3.4 Dataset statistics

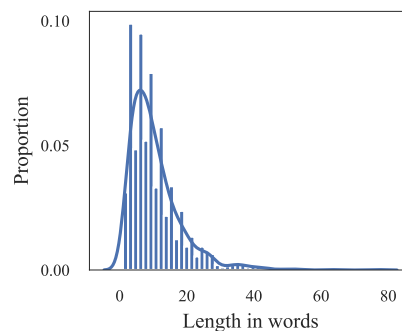


Figure 1: Distribution of sentence lengths

The total number of sentences in the dataset is 1331 and the total number of tokens is 14119. The average sentence length is 10.61 tokens (see Figure 1). 1113 entities were identified at all (1474 mentions). The average length of entity in tokens is 1.32 token.

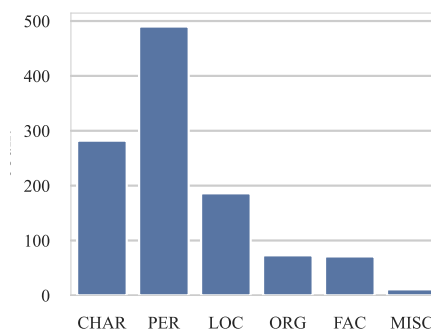


Figure 2: Distribution of entity types

Table 3 and Figure 2 describe dataset statistics.

Type	# Entities	% Entities	# Mentions	% Mentions
CHAR	282	25.0%	290	19.7%
FAC	71	6.4%	106	7.2%
LOC	186	16.7%	221	15.0%
ORG	73	6.6%	137	9.3%
PER	490	44.0%	708	48.0%
MISC	11	1.0%	12	0.8%
<b>Total</b>	<b>1113</b>	<b>100.0%</b>	<b>1474</b>	<b>100.0%</b>

Table 3: Dataset entities statistics

Entity Type	Top-10 mentions
CHAR	<i>ребёнок</i> ('child'), <i>женщина</i> ('woman'), <i>президент</i> ('president'), <i>друг</i> ('friend'), <i>поэт</i> ('poet'), <i>папа</i> ('dad'), <i>писатель</i> ('writer'), <i>жена</i> ('wife'), <i>отец</i> ('father'), <i>военный</i> ('military')
FAC	<i>театр</i> ('theatre'), <i>аэропорт</i> ('airport'), <i>дом</i> ('house'), <i>школа</i> ('school'), <i>музей</i> ('museum'), <i>кафе</i> ('cafe'), <i>станция</i> ('station'), <i>библиотека</i> ('library'), <i>посольство</i> ('embassy'), <i>тюрьма</i> ('prison')
LOC	<i>город</i> ('city'), <i>Москва</i> ('Moscow'), <i>Россия</i> ('Russia'), <i>улица</i> ('street'), <i>Ленинград</i> ('Leningrad'), <i>проспект</i> ('avenue'), <i>Кандагар</i> ('Kandagar'), <i>озеро</i> ('lake'), <i>страна</i> ('country'), <i>запад</i> ('west')
ORG	<i>ЦК</i> ('Central Committee'), <i>совет</i> ('council'), <i>парламент</i> ('parliament'), <i>Политбюро</i> ('Politburo'), <i>Правда</i> ('Pravda'), <i>КПСС</i> ('the Communist Party of the Soviet Union'), <i>издательство</i> ('publishing house'), <i>верховный</i> ('supreme'), <i>Мосфильм</i> ('Mosfilm'), <i>союз</i> ('union')
PER	<i>Горбачев</i> ('Gorbachev'), <i>Борис</i> ('Boris'), <i>Ельцин</i> ('Yeltsin'), <i>Володя</i> ('Volodya'), <i>Таня</i> ('Tanya'), <i>Витя</i> ('Vitya'), <i>Рыжков</i> ('Ryzhkov'), <i>Яковлев</i> ('Yakovlev'), <i>Сергей</i> ('Sergey'), <i>Иван</i> ('Ivan')

Table 4: Top-10 mentions for each entity type

PER is the most frequent tag, a little less than a half of all entities are of this type. Persons are often provided via a few tokens. The rest of types does not represent the same variance between mentions and entities. MISC entities are only 1% of all entities.

As expected, popular mentions of entities actually represent concepts and personalities of the Perestroika period (see Table 4). As we can see, there are main politic figures in the list (e.g., Boris Yeltsin, Mikhail Gorbachev, Nikolai Ryzhkov) as well as old soviet political authorities (e.g., Central Committee, the Communist Party of the Soviet Union, Politburo). Some words that were new at that time, such as 'a president' (since Gorbachev became the first president of USSR in 1990) or 'parliament' (the Parliament of USSR was founded in 1989) are among the most frequent words. The mixture of old Soviet terms and new words illustrates this period as a time of transition. Another important trend is the discussion of the Soviet-Afghan war, as Kardagan was one of the centres of soviet troops' dislocation.

Top-10 entities of each type in all diaries for Perestroika period can be found in Appendix H. Texts were marked up by the ruBERT model, trained on texts annotated by assessors.

## 4 Evaluation

We've benchmarked two groups of models on the presented dataset. Off-the-shelf tools were evaluated without any modifications, while transformer-based models were evaluated after a fine-tuning.

### 4.1 Off-the-shelf tools

We use a selection of publicly available, NER systems: DeepPavlov-NER, Natasha-SlovNet, Stanza, and SpaCy.

DeepPavlov-NER is a BERT-based model for NER<sup>12</sup> implemented in DeepPavlov library (Burtsev et al., 2018). Its markup includes 18 tags, including PERSON, ORGANIZATION, FACILITY, and LOCATION.

SlovNet is a neural network based tool for NLP tasks, including NER annotation. SlovNet is a part of Natasha project.<sup>13</sup> SlovNet's annotation includes PER, LOC and ORG.

Stanza is a Stanford state-of-art model<sup>14</sup>. Stanza is based on Bi-LSTM model and CRF-decoder. Stanza for Russian is a 4-entity system, which includes PER, LOC, ORG and MISC.

NER system developed by SpaCy is a transition-based named entity recognition component. We use Natasha-SpaCy<sup>15</sup> model trained on two resources - Nerus<sup>16</sup> and Navec<sup>17</sup>. Natasha-SpaCy model can detect PER, LOC and ORG entities in our dataset.

We have compared results of these models on our dataset.

<sup>12</sup><http://docs.deeppavlov.ai/en/master/features/models/ner.html>

<sup>13</sup><https://github.com/natasha/slovnet#ner>

<sup>14</sup><https://stanfordnlp.github.io/stanza/>

<sup>15</sup><https://github.com/natasha/natasha-spacy>

<sup>16</sup><https://github.com/natasha/nerus>

<sup>17</sup><https://github.com/natasha/navec>

Models	PER	LOC	ORG	Overall
DeepPavlov	0.55	0.0	<b>0.33</b>	0.93
SpaCy	0.64	<b>0.54</b>	0.16	0.95
Stanza	0.69	0.4	0.11	0.94
Natasha	<b>0.77</b>	<b>0.54</b>	0.14	<b>0.96</b>

Table 5: The performance of off-the-shelf tools (accuracy)

As seen from the table 5, *Natasha-SlovNet* showed the best performance on our dataset for PER and LOC, while *SpaCy* was the best on LOC and *DeepPavlov* showed the best results on ORG detection. However, the results of all models are significantly worse than the results on other datasets (Appendix A). Such results prove our hypothesis that off-the-shelf tools do not recognise entities on a diary-based dataset, for they were trained on news data.

Model performance analysis (Figure 5) reveals main entity recognition issues. Most of the models often detect false LOC and PER entities. In this case, *SpaCy* shows the best results. *Natasha-SlovNet* has the greatest recall, especially on LOC and PER. All models often annotated ORG as a non-entity. As our texts come from diaries written in the 1990s, some organisations could not exist anymore, and models do not recognise them.

FAC and CHAR were not on the entity lists of the models, therefore, the models did not recognise these tags. However, we would expect the models to mark CHAR as PER and FAC as LOC or ORG because those tags are related. Indeed, this happens for FAC but not for CHAR. This happens as most of the named entities are proper nouns and start with capitalized letters, unlike CHAR. All models annotated FAC more often as ORG than as non entity.

Another problem is caused by false detection of named entities’ span boundaries. To account for this, we introduced the following approach. We counted all cases when models did not find entities at all, detected false entities or used a wrong tag (combined as ‘false detected’) or models included more or less words from one or both sides. *Natasha* showed the best results, for it detects right boundaries for the most of the spans. The most common error though for all models was not finding an entity. Other mistakes include a shift of boundaries to the left and including more or less

words on the left side, especially for PER recognition. It could be possibly explained that CHAR entity proceeds PER entity (for instance, *профессор Иванов* (‘professor Ivanov’) where ‘professor’ is CHAR). Off-the-shelf models do not include CHAR entity and could annotate them as PER. Problems of narrower boundaries could be caused by excluding quoting markers in automatic annotation.

## 4.2 Fine-tuned models

We fine-tuned multiple Transformer models for NER: *ruBERT*, *ruBERT-tiny*, *ruRoBERTa*, *XLm-RoBERTa*. The performance was evaluated according to F1-scores per named entity and overall micro F1-score.

We used weighted cross-entropy as a loss function. An inverse tag frequency was taken as weights for cross-entropy, which helped us gain better results on unbalanced data. We also sorted the dataset by the length of tokens and then split it in batches, which slightly improved models’ performance. Models were trained in an unfrozen manner. The detailed hyperparameters values used to train the models are provided in the Appendix B. The performance was evaluated according to per-class and overall micro-averaged F1-score.

## 4.3 Results

*Natasha* had the best F1-score among all off-the-shelf tools. Nevertheless, results achieved for our corpus are below *Natasha*’s results on news-based datasets.

Fine-tuned transformers showed better results than off-the-shelf tools. Predictions made by *ruBERT* had the highest overall F1-score, the model’s performance had the best F1-scores for most tags (FAC, LOC, ORG) and top-3 best results for CHAR and PER tags. According to Table 6, we can consider *ruBERT* the best model for our datasets, as it successfully predicts major and minor classes.

The number of epochs was chosen according to the following criteria: the model does not overfit on the train data and shows high results on the development data. To this end, we used early-stopping. For *ruBERT-tiny* even 50 epochs were not sufficient for reaching results comparable to other models’ performances.

According to Figure 5, CHAR and PER entities were mostly wrongly detected as O by *Natasha*, *SpaCy* and *Stanza* assessors. ORG tags were also erroneously detected by these parsers, which

Models	CHAR	FAC	LOC	ORG	PER	Overall
ruBERT-tiny	0.712	0.8	0.748	<b>0.4</b>	0.738	0.731
ruBERT	0.757	<b>1.0</b>	<b>0.793</b>	<b>0.4</b>	<b>0.854</b>	<b>0.813</b>
ruRoBERTa	0.703	0.333	0.729	0.166	0.795	0.739
XLM-RoBERTa	<b>0.817</b>	0.363	0.742	0.333	0.825	0.8

Table 6: Transformer architectures F1-scores

was quite similar to the results of transformer models’ results. LOC tags almost in all cases were detected correctly both by pre-trained parsers’ transformer models, while FAC tags were significantly better found by the former ones.

According to Figure 6, XLM-RoBERTa’s performance could be considered quite successful: CHAR tags, as well as PER and LOC, were almost infallibly predicted. More exactly, PER entity was never predicted as another entity on test data. FAC entity was mixed with ORG tag in XLM-RoBERTa’s predictions, while ORG tag itself is nearly in all cases is considered as O tag by the model.

Figure 6 also presented ruBERT-tiny’s performance: CHAR and ORG entities were erroneously predicted as O more often, if compared to XLM-RoBERTa. Nevertheless, in most cases the model predicts correctly. ruBERT-tiny extracted all FAC and almost all PER tags without major errors.

As for ruBERT’s results, O tags were rarely misclassified as CHAR, while all other tags were predicted entirely correctly or with inconsequential mistakes.

ruRoBERTa’s performance was far from being perfect, as O-entities were heavily confused with other tags, but most predictions of other entities were correct.

As for major tendencies in models’ predictions, we can notice that ORG entity in most cases was detected as O tag which although was not desired, but still can encourage us to reanalyse ORG entities and collect substantially more examples of ORG tag occurrence. FAC entities were either (in most cases) correctly predicted, or mispredicted as ORG. O tags were sometimes detected as PER entity.

Given the evaluation results, one can conclude that while off-the-shelf NER tools sometimes lack desired tags, fine-tuning popular language models allows to support the chosen subset with somewhat reasonable yet far from perfect performance. This highlights the need for better few- and zero-shot sequence tagging tools capable of quickly generalizing onto novel tag-sets.

## 5 Conclusion

This paper introduces Razmecheno, a novel dataset for Named Entity Recognition. The texts in the dataset are sampled from the project “Prozhito”, which comprises personal diaries, written in Russian, from the 17th century up to the end of the 20th century. In particular, texts, marked up in Razmecheno belong to the mid-1980 years, the period in Russia, commonly known as Perestroika. Razmecheno is a middle-scale dataset so that it contains enough data to carry out literal and historical studies.

The annotation schema, used in Razmecheno, is simplistic. It consists of five named entity types, of which four are commonly used in NER datasets, namely, **persons**, **locations**, **organization**, and **facilities**. An only named entity type, introduced in this project, is **characteristics** of the different groups of people. The annotations are flat; overlapped, or nested entities are not allowed at the moment.

As our annotation schema matches a commonly used inventory of named entity types, it is possible to leverage upon pre-trained models and transfer learning techniques. The experimental evaluation of Razmecheno is two-fold. First, we carry out an extensive analysis of how available off-the-shelf NER tools cope with the task. The results reveal, that Natasha outperforms other tools under consideration by a small margin. However, of five named entity types, the off-the-shelf tools used to support only three. Next, we experiment with four state-of-the-art pre-trained Transformers. A monolingual model, ruBERT significantly outperforms other Transformers, followed by a multilingual model XLM-RoBERTa.

There are a few directions for Razmecheno development. We plan to annotate the collected sentences for other information extraction tasks, including co-reference resolution, relation extraction, and entity linking. Providing NER is the first step to present the diary’s plot in a concise form. This can be beneficial for studying the narratives and events present in diaries. This way, Razmecheno could serve as a test-bed for end-to-end information extraction models. Experiments in domain adaptation and cross-lingual transfer from other languages are another research line. Finally, we have set up the whole environment to annotate texts from “Prozhito”, so that diaries from other periods can be marked up with a little effort.



## Acknowledgments

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## Appendix A Models performance on different datasets

Models	factru			ne5			bsnlp			razmecheno		
	PER	LOC	ORG	PER	LOC	ORG	PER	LOC	ORG	PER	LOC	ORG
DeepPavlov	0.91	0.886	0.742	0.942	0.919	0.881	0.866	0.767	0.624	0.55	0	0.33
SpaCy	0.901	0.886	0.765	0.967	0.928	0.918	0.919	0.823	0.693	0.64	0.54	0.16
Stanza	0.943	0.865	0.687	0.923	0.753	0.734	0.938	0.838	0.724	0.69	0.4	0.11
Natasha	<b>0.959</b>	<b>0.915</b>	<b>0.825</b>	<b>0.984</b>	<b>0.973</b>	<b>0.951</b>	<b>0.944</b>	0.834	0.718	0.77	0.54	0.14
ruBERT-tiny	0.619	0.395	0.558	0.619	0.414	0.564	0.318	0.333	0.180	0.738	0.748	<b>0.4</b>
ruBERT	0.548	0.358	0.461	0.883	0.777	0.856	0.483	0.451	0.423	<b>0.854</b>	<b>0.793</b>	<b>0.4</b>
ruRoBERTa	0.468	0.261	0.406	0.768	0.593	0.687	0.192	0	0	0.795	0.729	0.166
XLM-RoBERTa	0.879	0.763	0.78	0.963	0.936	0.944	0.762	<b>0.899</b>	<b>0.726</b>	0.825	0.742	0.333

Table 7: See Section 2.1 for the review of these corpora in the Nerus suite. The data on the performance for off-the-shelf were taken from Natasha project<sup>18</sup>

## Appendix B Transformers hyper-parameters

Models	Number of epochs	Learning rate	Weight decay
ruBERT-tiny	50	1e-5	3e-5
ruBERT	10	1e-4	2e-5
ruRoBERTa	5	1e-5	2e-5
XLM-RoBERTa	10	3e-5	1e-4

Table 8: Transformer architectures' hyperparameters

## Appendix C Crowd-sourcing task interface

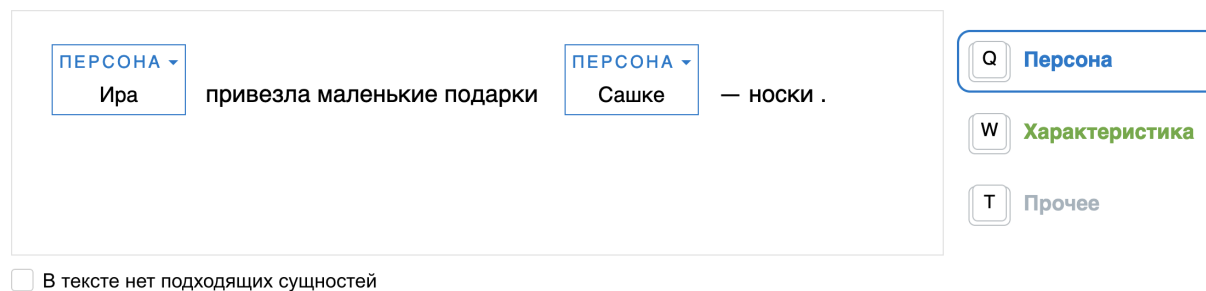


Figure 3: Annotation of a phrase given in Yandex.Toloka: *Ира привезла маленькие подарки Сашке — носки.* ('Ira brought socks as small presents for Sasha.')

Available annotations (hotkeys to annotate the selection are depicted on the right) are: *Персона* ('Person', PER, blue), *Характеристика* ('Characteristics', CHAR, green), *Прочее* ('Misc', MISC, grey), *В тексте нет подходящих сущностей* ('No entities present', checkbox).

<sup>18</sup><https://github.com/natasha/slovnet#ner>

## Appendix D Off-the-Shelf models' span recognition

To evaluate how precise off-the-shelf models are in span recognition, we divide all cases of recognition in 11 groups:

- **left more:** the right border of a span was detected correctly but on the left border a model included more words than in our annotation;
- **right more:** more words were included into a span on the right side;
- **left less:** the right border was correctly detected but on the left side one or more words were missing;
- **right less:** the left border was detected but on the right side less words were included;
- **more:** on both sides a model annotated more words than in the data;
- **less:** on the both sides a model detected a smaller span;
- **equal:** a model detected a span correctly;
- **left right:** the borders of a span were shifted from left to right, i.e., on the left side less words were included and on the right side a model detected some extra words;
- **right left:** the borders of a span were shifted from right to left;
- **not found:** models did not find a span or annotated it with a wrong tag;
- **false detected:** models found spans that were not in the manual annotation.

Figure 4 shows the absolute number of cases of each type described above.

	DeepPavlov						Natasha					
	CHAR	PER	LOC	ORG	LOC	FAC	CHAR	PER	LOC	ORG	LOC	FAC
left_more	0	0	0	0	0	0	0	0.75	0	0	0	0
right_more	0	0	0	0	0	0	0	0	0	0	0	0
left_less	0	13.56	0	0	0	0	0	0	0	0	0	0
right_less	0	0.85	0	0	0	0	0	0.75	0	0	0	0
more	0	0	0	0	0	0	0	0	0	0	0	0
less	0	0.85	0	0	0	0	0	0	0	0.75	0	0
equal	0	45.76	0	0.85	0	0	0	48.87	13.53	0.75	0	0
left_right	0	0	0	0	0	0	0	0	0	0.75	0	0
right_left	0	0	0	0	0	0	0	0	0	0	0	0
not_found	32.2	1.69	1.69	0.85	0	1.69	26.32	5.26	1.5	0	0	0.75
false_detected	0	0	0	0	0	0	0	0	0	0	0	0

	SpaCy						Stanza					
	CHAR	PER	LOC	ORG	LOC	FAC	CHAR	PER	LOC	ORG	LOC	FAC
left_more	0	1.5	0	0	0	0	0	2.33	0	0	0	0
right_more	0	0	0	0	0	0	0	0	0	0	0	0
left_less	0	4.51	0	0	0	0	0	0.78	0	0	0	0
right_less	0	1.5	0	0	0	0	0	1.55	0	0	0	0
more	0	0	0	0	0	0	0	0	0	0	0	0
less	0	0	0	0.75	0	0	0	0	0	0	0	0
equal	0	39.85	13.53	0.75	0	0	0	43.41	12.4	0.78	0	0
left_right	0	0	0	0.75	0	0	0	0	0	0	0	0
right_left	0	0	0	0	0	0	0	0	0	0	0	0
not_found	27.07	7.52	1.5	0	0	0.75	27.13	6.98	3.1	0.78	0	0.78
false_detected	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4: Off-the-shelf tools' mistakes in span recognition for each entity

## Appendix E Off-the-shelf tools confusion matrix

		DeepPavlov				Natasha				SpaCy				Stanza						
CHAR	0	1.2	0	0	CHAR	0	1.15	0	0.05	CHAR	0	1.18	0	0.03	CHAR	0	0.03	1.13	0	0.05
FAC	0	0.08	0	0	FAC	0	0.03	0.05	0	FAC	0	0.03	0.05	0	FAC	0.05	0	0.03	0	0
LOC	0	0.44	0	0.1	LOC	0.49	0.05	0	0	LOC	0.49	0.05	0	0	LOC	0.44	0	0.1	0	0
O	0.1	92.4	0	2.61	O	0.79	92.5	0.49	1.33	O	0.79	92.4	0.44	1.46	O	1.08	1.13	91.3	0.33	1.28
ORG	0	0.1	0.03	0	ORG	0	0.08	0.05	0	ORG	0	0.08	0.05	0	ORG	0	0	0.1	0.03	0
PER	0	0.77	0	2.1	PER	0	0.2	0	2.66	PER	0.03	0.97	0	1.87	PER	0.08	0.15	0.44	0	2.2
		LOC	O	ORG	PER			LOC	O	ORG	PER			LOC	O	ORG	PER			

Figure 5: Confusion matrix for off-the-shelf tools per token in relative weights

## Appendix F Transformers confusion matrix

		ruBERT						ruBERT-tiny							
CHAR		1.1	0	0	0.13	0	0	CHAR		1.2	0	0	0.37	0	0.01
FAC		0	0.06	0	0	0	0	FAC		0	0.07	0	0	0	0
LOC		0	0	0.49	0.02	0	0	LOC		0	0	0.69	0.04	0	0.03
O		0.52	0	0.24	93	0.04	0.99	O		0.52	0.01	0.39	91	0.03	1.9
ORG		0	0	0	0.15	0.02	0	ORG		0	0	0	0.15	0.01	0
PER		0	0	0	0.02	0	3.4	PER		0	0	0	0.09	0	3.8
		CHAR	FAC	LOC	O	ORG	PER			CHAR	FAC	LOC	O	ORG	PER

		ruRoBERTa						XLM-R							
CHAR		1.2	0	0	0.08	0	0	CHAR		1.3	0	0	0.11	0	0
FAC		0	0.1	0	0	0	0	FAC		0	0.048	0	0	0.048	0
LOC		0	0	0.62	0.06	0	0	LOC		0	0	0.58	0.048	0	0
O		0.97	0.21	0.43	90	0.21	2.2	O		0.34	0.13	0.29	91	0.032	1.5
ORG		0	0	0	0.14	0.02	0	ORG		0	0	0	0.11	0.016	0
PER		0	0	0	0.02	0	4	PER		0	0	0	0	0	4.1
		CHAR	FAC	LOC	O	ORG	PER			CHAR	FAC	LOC	O	ORG	PER

Figure 6: Confusion matrix of ruBERT, ruBERT-tiny, ruRoBERTa and XLM-RoBERTa models' results on the test dataset

## Appendix G Crowd-sourcing tasks guidelines

### G.1 Binary annotation for LOC, ORG, and FAC

Please note that this task is only for Russian native speakers.

Notice if the sentence contains references to places or organizations.

Here are examples of sentences that mention places or organizations:

1. *Whatever you say, **Orel** is the most literary city in **Russia**.*
2. *A dark dream: we are going to some agricultural work along an embankment highway in a low place, a flood meadow (like the intersection of the **Kyiv** highway with **the Ugra River**)*
3. *I called "**Ural**": I had to let them know about my arrival*
4. *At eight in the morning they called us to **the headquarters** and put on the bus*
5. *A ferry on **the Danube** and **Czechoslovakia** are seen from the parapet*
6. *From the very beginning I did not like the name, but I remembered a twenty-five-year-old meeting in our **House of Culture** with a group of poets.*
7. *Soldiers live in a carriage at **this station**.*

Here are examples of sentences where there is no mention of entities:

1. *Which of the **Muscovites** is a great writer?*
2. *Unpleasant letters caught my eye in the morning.*
3. *Everything should be harmonious and beautiful.*

### G.2 Binary annotation for PER and CHAR

Please note that this task is only for Russian native speakers.

Note whether the sentence mentions people or not.

Here are examples of sentences that include mentions of people.

1. *Which of **the Muscovites** is a great writer? Well, **Pushkin**, of course.*
2. *What time did **the parents** call **the boys**?*
3. ***Asya** laughed like crazy.*
4. ***Father Alexander** came to our house from a neighboring church.*
5. ***Comrade J. V. Stalin** never trusted **that Englishman**.*
6. ***We** entered the Viennese shrine - the church of **St. Stephan** - with the flow of city guests.*

Here are examples of sentences where there is no mention of entities:

1. *In Chernobyl, we stood in line for two hours for dinner for two hours.*
2. *Unpleasant letters caught my eye in the morning.*
3. *Everything should be harmonious and beautiful.*

### G.3 Span annotation for LOC, ORG, and FAC

Please note that this task is only for Russian native speakers.

Find mentions of entities in the text and highlight them in different colors: highlight a place in **blue**, an organisation in **green** and a facility in **red**. If you can't decide on a color to mark an entity, highlight them in **gray**.

Annotation schema

- **Place** includes the names of countries, cities, states, etc. (when they designate a place), as well as natural features: mountains, bodies of water, etc.
- **Organization** is an official association, such as names of firms, companies, etc.
- **Facility** is an institution built by humans: schools, museums, offices, airports, railway stations, etc.
- **Other** is used if there is some named entity in the text (Place or Organization), but you cannot determine which one.

**Advice.** Select all the entities that you found in the text (see Example 1, there are two entities in it).

**Advice.** If several consecutive words form one entity, extend the selection to all these words (see Example 6, where the House of Culture is one entity).

Entity examples

Location: **Orel**, **Russia**, **Kyiv highway**, **Ugra river**

Organization: **“Ural”**, **headquarters**

Institution: **Lyceum 1535**, **Tretyakov Gallery**, **Kyiv Railway Station**

Markup Examples

1. Whatever you say, **Orel** is the most literary city in Russia.
2. A dark dream: we are going to some agricultural work along an embankment highway in a low place, a flood meadow (like the intersection of the **Kyiv highway** with **the Ugra River**).
3. I called **“Ural”**: I had to let them know about my arrival.
4. At eight in the morning they called us to **the headquarters** and put on the bus.
5. A ferry on **the Danube** and **Czechoslovakia** are seen from the parapet.
6. From the very beginning I did not like the name, but I remembered a twenty-five-year-old meeting in our **House of Culture** with a group of poets.
7. Soldiers live in a carriage at **this station**.

### G.4 Span annotation for PER and CHAR

Please note that this task is only for Russian native speakers.

Mark references to people in the text and highlight it in different colors: highlight a person in **blue** and a characteristic in **green**. If you can't decide on a color to tag a person, highlight them in **gray**.

Annotation schema

- **Person** is a name (as well as a surname, pseudonym, etc.) of a person or group of people, including fake and famous ones.
- **Characteristic** is a characteristic of a person (**rank, profession, nationality, belonging to a social group**)

- Other is used if there is some named entity (Person or Characteristic) in the text, but you cannot determine which one.

**Advice.** Select all the entities that you found in the text (see Example 4, there are two entities in it).

**Advice.** If several consecutive words form one entity, extend the selection to all these words (see Example 5, where J. V. Stalin is one entity).

#### Entity examples

Persons: [Asya](#), [Pushkin](#), [J. V. Stalin](#) (J.V. Stalin is one person, so you should extend one selection to all three words.)

Characteristics: [schoolchildren](#), [girls](#), [women](#), [priests](#), [Americans](#)

#### Markup Examples

1. [Asya](#) laughed like crazy. (Asya is a person's name)
2. Which of [the Muscovites](#) is a great writer? Well, [Pushkin](#), of course. (Pushkin is the name of a person, Muscovite is a characteristic)
3. What time did [the parents](#) call [the boys](#)? (the parents is a characteristic, the boys is a social group)
4. [Father Alexander](#) came to our house from a neighboring church (the word father here is a profession (his characteristic), Alexander is the name of a person)
5. Comrade [J. V. Stalin](#) never trusted [that Englishman](#). (Comrade is definitely something like Characteristics, but it seems that it does not fall under the description of Characteristics; J.V. Stalin is the name of a person; Englishman is a nationality))



## Appendix H Top-10 entities of each type in the Prozhito diaries

Entity Type	Top-10 mentions
CHAR	<i>ребёнок</i> ('child'), <i>жена</i> ('wife'), <i>секретарь</i> ('secretary'), <i>женщина</i> ('women'), <i>мама</i> ('mom'), <i>отец</i> ('father'), <i>командир</i> ('commander'), <i>писатель</i> ('writer'), <i>президент</i> ('president'), <i>начальник</i> ('chief')
FAC	<i>театр</i> ('theatre'), <i>музей</i> ('museum'), <i>школа</i> ('school'), <i>институт</i> ('institute'), <i>церковь</i> ('church'), <i>университет</i> ('university'), <i>училище</i> ('college'), <i>госпиталь</i> ('hospital'), <i>кафе</i> ('cafe'), <i>монастырь</i> ('monastery')
LOC	<i>Москва</i> ('Moscow'), <i>Россия</i> ('Russia'), <i>Ленинград</i> ('Leningrad'), <i>Кандагар</i> ('Kandagar'), <i>город</i> ('city'), <i>Кабул</i> ('Kabul'), <i>Афганистан</i> ('Afghanistan'), <i>советский</i> ('soviet'), <i>страна</i> ('a country'), <i>СССР</i> ('USSR')
ORG	<i>ЦК</i> ('Central Committee'), <i>Политбюро</i> ('Politburo'), <i>партия</i> ('party'), <i>КПСС</i> ('the Communist Party of the Soviet Union'), <i>МИД</i> ('Foreign Ministry'), <i>КГБ</i> ('Committee for State Security'), <i>член</i> ('member'), <i>союз</i> ('union'), <i>СП</i> ('Union of writers'), <i>правительство</i> ('government')
PER	<i>Горбачев</i> ('Gorbachev'), <i>М. С.</i> ('M. S., Gorbachev's initials'), <i>Ельцин</i> ('Yeltsin'), <i>Веничек</i> ('Venichek'), <i>Любимов</i> ('Lubimov'), <i>Ерофеев</i> ('Yerofeyev'), <i>Яковлев</i> ('Yakovlev'), <i>Сталин</i> ('Stalin'), <i>Галя</i> ('Galya'), <i>Володя</i> ('Volodya')

Table 9: Top-10 mentions for each entity type on the whole Prozhito diaries during the Perestroika period