Findings of the WMT 2021 Shared Tasks in Unsupervised MT and Very Low Resource Supervised MT

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Abstract

We present the findings of the WMT2021 Shared Tasks in Unsupervised MT and Very Low Resource Supervised MT. Within the task, the community studied very low resource translation between German and Upper Sorbian, unsupervised translation between German and Lower Sorbian and low resource translation between Russian and Chuvash, all minority languages with active language communities working on preserving the languages, who are partners in the evaluation. Thanks to this, we were able to obtain most digital data available for these languages and offer them to the task participants. In total, six teams participated in the shared task. The paper discusses the background, presents the tasks and results, and discusses best practices for the future.

1 Introduction

For some languages, machine translation (MT) reached such a high quality that allows a discussion of whether and under what circumstance human parity might have been reached (Popel et al., 2020; Läubli et al., 2020). This is the case, however, for only a small minority of the world’s language. For most of the 7k languages spoken in the world only very limited resources exist. The goal of the WMT Shared Task on Unsupervised and Very Low Resource MT is to promote research on methods for MT that alleviate such data sparsity in a real-world setup.

A task on unsupervised MT was already held at WMT in 2018 (Bojar et al., 2018) and 2019 (Barrault et al., 2019), where the lack of parallel data was simulated on high-resource language pairs: English–German in 2018 and German–Czech in 2019.

Starting from last year, we cooperate with local communities working on preserving their languages. In cooperation with the Sorbian Institute1 and the Witaj Sprachzentrum2, we offered a shared task in translation between German and Upper Sorbian in low-resource and unsupervised tracks (Fraser, 2020). For this year, we kept the low-resource track for Upper Sorbian and added unsupervised translation between German and Lower Sorbian. Upper and Lower Sorbian are minority languages spoken in the east part of Germany in the federal states of Saxony and Brandenburg. Having only 30k and 7k native speakers, processing of the languages is an inherently low-resource problem, without any chance that the size of available resources would ever get close to the size of resources available for languages with millions of speakers. On the other hand, being western Slavic languages, the Sorbian languages can take advantage of existing resources for Czech and Polish.

Additionally, in cooperation with the Chuvash Language Laboratory3, we added another low-resource task, translation between Russian and Chuvash. Chuvash is a minority Turkic language spoken by approximately one million people in the Volga region in the southwest of Russia. There is a larger amount of training data available for Chuvash, but the language is rather isolated in the Turkic language family, so unlike Sorbian, it cannot benefit that much from the existence of closely related languages.

Five teams participated in the German-Upper Sorbian task, six teams in the German-Lower Sorbian task, and two teams in the Russian-Chuvash task.

2 Tasks and Evaluation

This year, there were three tasks for very low resource and unsupervised translation were:

1https://www.serbski-institut.de
2https://www.witaj-sprachzentrum.de/
3https://en.corpus.chv.su/content/about.html
• Very Low Resource Supervised Machine Translation: German ↔ Upper Sorbian.

• Unsupervised Machine Translation: German ↔ Lower Sorbian.

• Low Resource Supervised Machine Translation: Russian ↔ Chuvash.

To make the submissions better comparable with each other, we only allowed using resources released for the task (see Section 3) and resources for related languages commonly used in other WMT tasks. The use of large models pre-trained on large datasets was not allowed. By this decision, we wanted to motivate the participants to find better use of limited language resources.

German↔Upper Sorbian. There is only a very limited amount of parallel data between Upper Sorbian and German. However, because Upper Sorbian is closely related to Czech and Polish, we encouraged the use of all German, Czech and Polish data released for WMT. Other parallel data released from the WMT News Task were also allowed, but the participants were recommended not to use them. Unlike last year, there was no unsupervised task for Upper Sorbian.

German↔Lower Sorbian. For this task, no parallel training data were available, as the only available Lower Sorbian data were monolingual. Lower Sorbian is closely related to other Western Slavic languages, so the same related language data as for the Upper Sorbian task was allowed.

Russian↔Chuvash. The Chuvash language is not that critically low-resource as the Sorbian languages, but it is still affected by being a minority language. The participants were provided with parallel and monolingual data that we released for the task. Additional data that might be used: Chuvash-Russian part of the JW300 corpus (Agić and Vulić, 2019). In addition, the participants were encouraged to use the Kazakh–Russian corpus and monolingual Kazakh data from WMT19 (Barault et al., 2019) and monolingual Russian data made available for the WMT News tasks.

Evaluation. Following the recent literature on MT evaluation (Mathur et al., 2020; Marie et al., 2021; Kocmi et al., 2021), we evaluate the systems using multiple evaluation measures, both string-based and model-based, and perform statistical testing to decide the ranking of the systems. In particular, we use the BLEU Score (Papineni et al., 2002), chrF score (Popović, 2015) as implemented in SacreBLEU (Post, 2018).

Further, we evaluate the models using BERTScore (Zhang et al., 2020) with XLM-RoBERTa Large (Conneau et al., 2020) as an underlying model for German and Russian

| Dataset | # lines | # chars. |
|---------|---------|----------|
| German↔Upper Sorbian | | |
| WMT20 parallel data | 60k | 11M |
| Parallel data provided by the Witaj Sprachzentrum, collected for the development of its own translator SoTra⁵. | | |
| Additional parallel data | 87k | 17M |
| Additional parallel Witaj Sprachzentrum collected since the last year. | | |
| Sorbian Institute mono | 340k | 39M |
| Upper Sorbian monolingual data provided by the Sorbian Institute. This contains a high quality corpus and some medium quality data which were mixed together. | | |
| Witaj mono | 222k | 19M |
| Upper Sorbian monolingual data provided by the Witaj Sprachzentrum (high quality). | | |
| Web monolingual | 134k | 12M |
| Upper Sorbian monolingual data scraped from the web by CIS, LMU. This should be used with caution, it is probably noisy, it might erroneously contain some data from related languages. | | |

| German↔Lower Sorbian | | |
| Sorbian Institute mono | 145k | 14M |
| The sentences come from the Lower Sorbian reference corpus and were provided by the Sorbian Institute. | | |

| Russian↔Chuvash | | |
| Parallel corpus | 714k | 181M |
| A parallel corpus being collected by the Chuvash Language Laboratory since 2016 with the goal of promoting automatic processing of Chuvash. | | |
| Bilingual dictionary | 74k | 182k |
| Monolingual Chuvash | 5.6M | 749M |
| The dataset contains monolingual sentences from various publicly available sources including Wikipedia, web crawl and fiction. | | |

Table 1: Overview of the data made available for the shared task.

⁵BLEU score signature nrefs:1|case:mixed|eff:no|tok:13a|smooth:exp|version:2.0.0
chrF score signature nrefs:1|case:mixed|eff:yes|nc:6|nr:0|space:no|version:2.0.0

⁶https://github.com/Tiiiger/bert_score
Table 2: Overview of the method used by the task participants. SP stands for SentencePiece, BT for backtranslation.

| Team               | Architecture | Pre-training | Pre-training data | German / Russian mono. | BT iter. | BT filtering | Data tricks | Segmentation | Ensembling | Toolkit          |
|--------------------|--------------|--------------|-------------------|------------------------|----------|--------------|-------------|--------------|------------|-----------------|
| **German ↔ Upper Sorbian** |              |              |                   |                        |          |              |             |             |            |                 |
| NoahNMT Big        | de-cs        | 15M          | 100M              | No                     | None     | Tagged BT, BPE Dropout, Lang. tags | BPE         | Yes          | Inhouse     |                 |
| NRC-CNRC Base      | de-cs        | 16.5M        | 5M                | 2                      | Moore and Lewis (2010) | BPE         | Yes          |             |            | Sockeye        |
| IICT-Yverdon Base  | de-cs, de-hsb | 3M          | 1M                | 1                      | Length   | SP           | BPE Dropout | No           | MASS         |                 |
| CFILT Base         | de-hsb       | 2×.7M        | .7M               | 60                     | None     | BPE Dropout  | BPE         | No           | MASS         |                 |
| LMU Munich Big     | de-cs, de-hsb | 25M         | 15M               | 4                      | Length   | Tagged BT    | BPE         | Yes          | Fairsseq     |                 |
| **German ↔ Lower Sorbian** |              |              |                   |                        |          |              |             |             |            |                 |
| NRC-CNRC Base      | de-cs, de-hsb | 16.5M        | 147k to 5.2M      | 2                      | Moore and Lewis (2010) | BPE Dropout | BPE         | Yes          | Sockeye     |                 |
| IICT-Yverdon Base  | de-hsb       | 150k         | 1M                | 1                      | Length   | SP           | BPE Dropout | No           | MASS         |                 |
| CFILT Base         | de-hsb       | 3×.7M        | .7M               | 60                     | None     | BPE Dropout  | BPE         | No           | MASS         |                 |
| CL_RUG XLM         | de-cs, de-hsb | 8.5M         | 10.6M             | 2                      | None     | BPE Dropout  | BPE         | No           | MASS         |                 |
| LMU Munich Big     | de-cs, de-hsb | 45M         | 15M               | 8                      | Length   | BPE Dropout  | BPE         | Yes          | Fairsseq     |                 |
| **Russian ↔ Chuvash** |              |              |                   |                        |          |              |             |             |            |                 |
| NoahNMT Big        | en-ru        | 17M          | 110M              | 3                      | None     | Domain adap. | BPE         | Yes          | Inhouse     |                 |
| LMU Munich Big     | ru-kk        | 11M          | 18M               | 2                      | Length   | Tagged BT    | BPE         | Yes          | Fairsseq     |                 |

and mBERT (Devlin et al., 2019) for Chuvash. We conduct the significance test using bootstrap resampling (Koehn, 2004) at a significance level of 0.95.

The final ranking is determined by the number of points each system gets. The systems get one point for each system that is significantly worse in each of the metrics. This means that if a system is significantly better than 1 system in the BLEU score, 2 systems in the chrF score, and 3 systems in the BERTScore, it gets 6 points in total.

3 Data

**Upper Sorbian.** The data for this task was provided by the Sorbian Institute (monolingual data) and The Witaj Sprachzentrum (Witaj Language Center) (both parallel and monolingual data).

The development and test data for Upper Sorbian are the same as the last year. There was a different blind test set than the last year.

**Lower Sorbian.** As far as we know, there is no parallel data for Lower Sorbian except for the development and test data provided for this task.

**Chuvash.** The validation data are sampled from the training set. The development test data and blind test data were also sampled from the parallel corpus and manually filtered by a native speaker.

In addition to the described data, the use of other parallel and monolingual data available for WMT News Tasks was allowed (see Section 2).

4 Submitted systems

Six teams participated in the shared task, five teams in Upper Sorbian-German, slightly different five in Lower Sorbian-German, and two in the Russian-Chuvash direction. An overview of the systems is in Table 2, a brief description of the systems follows. For detailed information, we refer the reader to the respective system description papers.

**NoahNMT (Zhang et al., 2021b).** NoahNMT submitted their systems into the supervised tasks. The NoahNMT submission is a standard Transformer model equipped with our recent technique of dual transfer (Zhang et al., 2021a). Compared to other systems, these submissions used a significantly larger amount of monolingual data.

**NRC-CNRC (Knowles and Larkin, 2021).** The Upper Sorbian-German system is an ensemble of eight systems with 25k BPE vocabulary, incorporating transfer learning (from cs–de) with continued training, monolingual data filtering, back-translation (Sennrich et al., 2016), BPE-dropout (Provilkov et al., 2020), and multilingual models.
Table 3: The main results of the task. Points awarded in the particular metrics are in gray.

In the opposite direction, the submission is an ensemble of 7 systems. The Lower Sorbian-German and German-Lower Sorbian systems are ensembles of 2 and 4 systems, respectively, with 20k BPE vocabulary, incorporating transfer learning from hsb–de and de-hsb systems along with iterative backtranslation.

**IICT-Yverdon (Atrio et al., 2021).** The system used the Transformer architecture with back-translation of large German corpora and parent-language initialization using Czech-German data. The final submission is an ensemble of different models with some changes in their training setups to maximize the diversity among the models.

**CFILT.** The submitted systems cover four language pairs: German↔Upper Sorbian German↔Lower Sorbian. For de↔hsb, the system was pre-trained using the MASS objective (Song et al., 2019) and finetuned using iterative back-translation. Final finetuning is performed using the provided parallel data for the translation objective. For de↔dsb, no parallel data is provided in the task. The final de↔hsb model is used for initialization of the de↔dsb model, which is further trained using iterative back-translation, using the same vocabulary as used in the de↔hsb model.

**CL_RUG (Edman et al., 2021).** CL_RUG’s submission uses the MASS model, focusing pre-training on 2 languages at a time, from least to most related to Lower Sorbian. The largest improvement comes from a novel method for initializing the Lower Sorbian word embeddings from Upper Sorbian, using a bilingual dictionary created in an unsupervised fashion.

**LMU Munich (Libovický and Fraser, 2021).** The LMU submissions for all tasks are Transformer models first pre-trained on related languages and then finetuned on the low-resource languages. For the Sorbian languages, the systems are pre-trained on German–Czech translation. The system is fine-tuned using the authentic German–Upper Sorbian data, which is the starting point for four iterations of tagged back-translation. The unsupervised German–Lower Sorbian translation is trained by iterative back-translation using the monolingual data only. The Upper Sorbian–German system is used to generate the first translation of Lower Sorbian. The Russian–Chuvash systems were pretrained on Russian–Kazakh translation and finetuned using the provided parallel data.

5 Results

The results are presented in Table 3. The most successful teams were NRC-CNRC, which was the best or on par with the best systems in all Sorbian
tasks, and NoahNMT which were the best in the Chuvash tasks, on par with the best systems in German-Upper Sorbian translation and the second in the Upper Sorbian-German direction.

In German-Upper Sorbian translation, the best two systems, NRC-CNRC and NoahNMT reach very similar results although they use significantly different sizes of monolingual data for backtranslation. NRC-CNRC manage to compensate for the smaller data size by accumulating minor tricks including monolingual data selection (Moore and Lewis, 2010), tagged backtranslation (Caswell et al., 2019), BPE dropout (Provilkov et al., 2020), and language tags in multilingual training. LMU, which used data of a similar size to NRC-CNRC but did not use most of the further tricks, ranked below these two.

In Upper Sorbian-German translation, all teams used German-Czech parallel data for pre-training, except for CFILT who only used monolingual data for pre-training and scored 0 points in both directions.

In the unsupervised German-Lower Sorbian task, CL_RUG ranked on par with NRC-CNRC in translation into German (despite not using ensembling), but at third place in the opposite direction. This suggests that CL_RUG’s innovative vocabulary transfer method works better on the encoder side than on the decoder side.

In the Russian-Chuvash translation, NoahNMT outperformed LMU Munich by using larger datasets and a more advanced transfer learning technique.

6 Conclusions

In WMT 2021 shard task on Unsupervised and Very Low Resource MT, we created realistic benchmarks for low-resource minority language which reflect the needs of the language communities trying to preserve their languages. In the task, we provided the participants with comprehensive resources for translation between German and Upper and Lower Sorbian and for translation between Russian and Chuvash. We hope that this will increase the interest of the community in these languages.

The six teams that participated in the task used state-of-the-art MT techniques to develop high-quality systems. The main technical takeaways from the results are that pre-training on parallel data in related languages is important and that carefully applying known tricks can to a large extent compensate for using smaller datasets.

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