Low-resource Bilingual Dialect Lexicon Induction with Large Language Models

Abstract

Bilingual word lexicons map words in one language to their synonyms in another language. Numerous papers have explored bilingual lexicon induction (BLI) in high-resource scenarios, framing a typical pipeline that consists of two steps: (i) unsupervised bitext mining and (ii) unsupervised word alignment. At the core of those steps are pre-trained large language models (LLMs). In this paper we present the analysis of the BLI pipeline for German and two of its dialects, Bavarian and Alemannic. This setup poses a number of unique challenges, attributed to the scarceness of resources, relatedness of the languages and lack of standardization in the orthography of dialects. We analyze the BLI outputs with respect to word frequency and the pairwise edit distance. Finally, we release an evaluation dataset consisting of manual annotations for 1K bilingual word pairs labeled according to their semantic similarity.

1 Introduction

Learning in low-resource settings is one of the key research directions for modern natural language processing (NLP; Hedderich et al., 2021). The omnipresent pre-trained language models support high-resource languages by using increasingly large amounts of raw and labeled data. However, data scarcity hinders the training and evaluation of NLP models for less-resourced languages. At the same time, the participation of native speakers of different languages in the world of digital technologies increases the demand for supporting more language varieties. This encourages studies to explore suitable transfer learning and cross-lingual techniques.

Local varieties (dubbed as dialects) may fall under the umbrella of low-resource languages. Processing dialects faces unique challenges that should be addressed from a new perspective. Large volumes of writing in dialects such as newspapers or fiction are rarely produced and access to conversational data in social media is limited and difficult to reliably collect. Besides, dialects are non-standardized, they lack unified spelling rules and exhibit a high degree of variation (Millour and Fort, 2019). Finally, dialects may additionally show a significant rate of code-mixing to standard languages (Muysken et al., 2000).

The mainstream of cross-lingual transfer research towards low-resource languages, e.g., (Muller et al., 2021; Riabi et al., 2021), builds upon cross-lingual representations, namely static embeddings (Lample et al., 2018) or multilingual pre-trained language models (Devlin et al., 2019; Conneau et al., 2020). As shown by Muller et al. (2021) various factors can influence the performance, including the degree of relatedness to a pre-training language and the script. As there is no winning technique for all languages, it is important to understand how cross-lingual representations act for each particular language or a language family and whether the results in processing standard languages are transferable to its dialects.

In this paper, we focus on the ability of cross-lingual models to make semantic similarity judgments in German and two of its dialects, namely Bavarian (ISO 639-3:bar) spoken in South Germany, Austria, South Tyrol, and Alemannic (ISO 639-3:gsw) spoken in Switzerland, Swabia, Tyrol, Liechtenstein, Alsace, and Italian regions. Using the available raw data in Wikipedia (Section 3) we induce two bilingual lexicons, mapping words from Bavarian / Alemannic to German. To do so, we first mine bitext sentences (Section 4 and exploit machine translation aligners (Section 5). The output lexicon exhibits an evident tendency for a

German word to be aligned to multiple dialect synonyms due to spelling variations. Finally, we manually evaluate the output of each step: we evaluate the semantic similarity in (i) 1k bitext sentences according to the Likert scale and (ii) 1k bilingual word pairs according to the binary scale. Our results demonstrate the discrepancy between natural writing and linguistic dictionaries.

To sum up, the main contributions of this paper are the following. (i) We conduct a thorough analysis of cross-lingual models' behavior in two tasks of bitext mining and word alignment for the German language and two of its dialects. (ii) We release manually evaluated samples of bitext and bilingual lexicons for further uptake. (iii) We publish the code to reproduce bitext extraction and word alignment in open access.

2 Related work

NLP for German dialects. Previous efforts in processing German dialects mainly concentrate on speech processing. BAStat comprises the recordings of spoken conversational speech from main areas of spoken German (Schiel, 2010). Dogan-Schönberger et al. (2021) build a parallel corpus of spoken Alemannic dialect, in which a sentence in German is matched with spoken and written translations into eight dialects. ArchiMob is a general domain spoken corpus equipped with transcriptions and part-of-speech labeling (Scherrer et al., 2019). In the domain of written text processing, machine translation techniques have been applied to re-write sentences from dialect to standard German (Honnet et al., 2018; Plüss et al., 2020; Lambrecht et al., 2022). Other works tackle sentiment classification (Grubenmann et al., 2018), part-of-speech tagging (Hollenstein and Aepli, 2014) and dialect identification tasks (von Däniken et al., 2020). Burghardt et al. (2016) have collected a bilingual Bavarian-German lexicon using the knowledge of Facebook users, while Schmidt et al. (2020) hire expert native speakers to build a bilingual Alemannic-German lexicon. Language resources used to collect raw dialect data are Wikipedia, social media (Grubenmann et al., 2018), regional newspapers, and fiction (Hollenstein and Aepli, 2014).

Bitext mining. Sentence representations are core to mining bitext (dubbed as *parallel* or *comparable* datasets) in an unsupervised fashion (Hangya et al., 2018). Pires et al. (2019) show that `[CLS]`-pooling with multi-lingual encoders performs reasonably well for the task. Most recent studies proposed learning sentence embeddings from encoder-decoder models with a machine translation objective (Artetxe and Schwenk, 2019), by extending a monolingual sentence model to cross-lingual encoding with knowledge distillation (Reimers and Gurevych, 2020), or from dual encoders with a translation ranking loss (Feng et al., 2022). Bitext datasets collected from Wikipedia (Schwenk et al., 2021a) and the Common Crawl corpus (Schwenk et al., 2021b) serve to train machine translation models (Briakou et al., 2022) and to improve cross-lingual methods for structured prediction (El-Kishky et al., 2021). Chimoto and Bassett (2022) show that cross-lingual sentence models scale across unseen languages. We adopt the recent state-of-the-approach of (Reimers and Gurevych, 2020), which scores sentences embeddings, obtained from cross-lingual embedders, with cosine similarity measure in order to retrieve most similar sentence pairs.

Bilingual lexicon induction (BLI). Works in bilingual lexicon induction can be cast into two groups. *Mapping-based approaches* project monolingual word embeddings into a shared cross-lingual space with a varying degree of supervision (Lample et al., 2018; Artetxe et al., 2018; Joulin et al., 2018). *Corpora-based* methods combine bitext mining with word alignment (Shi et al., 2021). Intrinsic evaluation compares induced bilingual lexicons to gold standard dictionaries (Rapp et al., 2020). Extrinsic evaluation is conducted through cross-lingual downstream tasks (Glavaš et al., 2019). Finally, several factor affect the quality of induced bilingual lexicons: edit distance, contextual and topical similarity between words in source and target languages (Scherrer, 2007; Irvine and Callison-Burch, 2017).

In this project, we apply best practices for *bitext mining* and *bilingual lexicon induction* and demonstrate their strengths and weaknesses in the low-resource settings of *German dialects*.

3 Data

Wikipedia offers articles written in more than 300 languages[1]. It is recognized that some parts of Wikipedia are human-translated (Schwenk et al.,

[1] `en.wikipedia.org/wiki/List_of_Wikipedias`, as of 01 Nov 2022

Language	# sent.	# tokens	#types
Bavarian	230k	3.7mln	350k
Alemannic	500k	9.5mln	600k
German	56mln	106.4mln	1.12mln

Table 1: Data statistics for Bavarian and Alemannic dialect Wikipedia. Alemannic Wikipedia is bigger than Bavarian.

2021a); examples are shown in (Table 2). The sentences for our bitext mining and bilingual lexicon induction experiments were extracted from Wikipedia articles in Bavarian [2], Alemannic[3], and German[4]. The Bavarian and Alemannic Wikipedias contain articles marked with nuanced variations in local dialects depending on the region of use. Of the eight dialects of the Bavarian Wikipedia, the most popular is *Westmittelbairisch* (Westmiddlebavarian), with nearly 3k pages. The Alemannic Wikipedia covers 32 dialect varieties, of which *Schwizerdütsch* (Swiss German) is the largest, containing 19k pages. In this work, we do not distinguish between these varieties and treat each Wikipedia as a single corpus.

We used the Wikipedia2corpus[5] tool to extract raw sentences. The texts were split into sentences and tokenized with the SoMaJo sentence splitter and tokenizer[6] (Proisl and Uhrig, 2016). The sentences were filtered by the 5-to-25 token range. Incomplete sentences were removed according to simple heuristics, such as the number of opening and closing brackets or the presence of a bullet point. Sentences containing non-German characters (e.g. letters from Greek, Cyrillic, and Hebrew alphabets) were filtered out. Table 1 reports the total number of sentences, the number of tokens, and types per language in the resulting Wikipedia datasets. They illustrate the low-resource status of the Germanic dialects compared to the standard.

4 Bitext mining

Method. We start from the assumption parallel sentences are most often found on parallel pages. We collect inter-lingual links between pages in dialect Wikipedia and German Wikipedia. Overall, we found 11k parallel pages for Bavarian and 32k parallel pages for Alemannic out of 43k and 35k, correspondingly. Given two parallel pages split into sentences, we embed each sentence with a language model. For each dialect sentence, we retrieve the nearest neighbors using the cosine similarity. Table 2 provides examples of the found parallel sentences and the corresponding cosine similarity values. We aim to select the best-performing embedding model and the optimal cutoff value.

Models. We leverage the SentenceTransformer toolkit[7] (Reimers and Gurevych, 2020) for bitext mining. The experiments are with the following mono- and multi-lingual encoders and sentence models released as a part of HuggingFace library[8] (Wolf et al., 2020):

- **MBERT** (Devlin et al., 2019) was pre-trained on Wikipedia data. **MBERT** supports Bavarian and German.
- **GBERT** (Chan et al., 2020) was pre-trained on a range of different German language corpora. The exposure of **GBERT** to dialects is not mentioned explicitly.
- **GBERT-large-sts-v2**[9] is a version of **GBERT** fine-tuned the semantic textual similarity (STS) datasets of German sentence pairs.
- **LaBSE** (Feng et al., 2022) was pre-trained on the concatenation of mono-lingual Wikipedia and bilingual translation pairs. **LaBSE** supports German but not its dialects.

We used `[CLS]` and `[mean]` pooling to obtain sentence representations from **MBERT** and **GBERT**. **GBERT-large-sts-v2** and **LaBSE** are sentence models and can be used out of the box to compute the similarity between sentences. **LaBSE** is the current state-of-the-art-model for bitext mining (Reimers and Gurevych, 2020).

Human evaluation. We sampled two random sets of 1,500 bitext instances with **LaBSE** similarity values in the $[0.4; 0.95]$ range to be manually labeled for semantic similarity. The annotation schema is the five-point Likert scale, where 5 indicates the equivalence between dialect sentence and sentence in German and 1 indicates no relation. Appendix A provides the annotation instruction. The annotations were carried out by a native German speaker with a linguistic background and

[2] `bar.wikipedia.org/`, as of 01 Nov 2022
[3] `als.wikipedia.org/`, as of 01 Nov 2022
[4] `de.wikipedia.org/`, as of 01 Nov 2022
[5] `github.com/GermanT5/wikipedia2corpus`
[6] `github.com/tsproisl/SoMaJo`
[7] `https://www.sbert.net`
[8] `https://huggingface.co`
[9] `https://hf.co/deepset/gbert-large-sts`

Bavarian	**German**	✎	COS
Da Geiselbach speist ob da Omersbachmindung oanige Weiher.	Der Geiselbach speist ab der Omersbachmündung einige Weiher.	5	0.94
Alemannic	**German**	✎	COS
Dr Film verzellt d'Geschichte vume Polizistepaar, dem si Idealismus im Lauf vu dr Handlig schwindet.	Der Film erzählt die Geschichte eines Polizistenpaares, deren Idealismus im Laufe der Handlung schwindet.	5	0.92

Table 2: Examples of parallel sentences in Bavarian and German (top) and Alemannic and German (bottom). ✎ denotes a human score (see Section 4 for more details on human evaluation), COS stands for the cosine similarity between **LaBSE** embeddings.

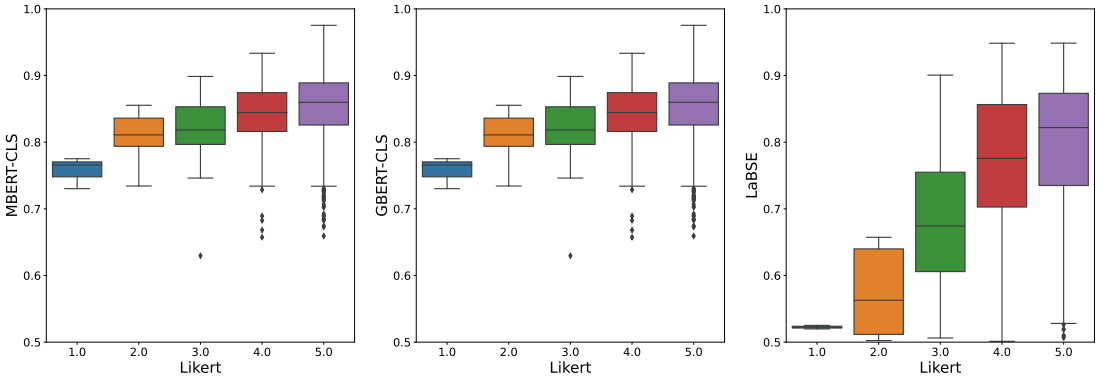

Figure 1: Cosine similarity values (OY) with respect to human scores (OX) for Bavarian. Left: **MBERT** + `[CLS]`, middle: **GBERT** + `[CLS]`, right: **LaBSE**. The gap between unrelated and similar sentences is the most evident using **LaBSE** model.

significant exposure to dialects.[10] To ensure the annotation quality, a smaller sample of 200 sentences was labeled by the second annotator, who is fluent in German. The annotators were able to not label a sentence pair if they do not understand it to a full extent, if the sentence is not written in the dialect, and if the sentence mixes with standard German. The inter-annotator agreement between the two annotators is 0.80 / 0.78 exact match / Pearson correlation for Bavarian and 0.9 / 0.6 for Alemannic. The major source of confusion between the two annotators is labels that are near, namely, (2,3) and (3,4). There are no cases in which annotators disagree and label sentences with opposite scores of 1 and 5. The annotators were asked reject incomplete sentences, or sentences not written in dialect. There were 83 and 162 sentences rejected, respectively.

The results from the human annotation show that the distribution of labels is different for the two dialects: 1,254 sentences were labeled as similar (5) or near similar (4) for Bavarian and almost twice less 644 – for Alemannic. In the 250 Alemannic sentences marked with the label 3, the annotator pointed out that bitext sentences differ in minor details. Sentences in Bavarian differ less from their German counterparts, so that fewer than 100 sentences are marked as having differences in minor details. There are 250/350 Bavarian/Alemannic sentences labeled as using different grammatical structures such as active VS passive, imperfect VS perfect. In summary, based on this annotation study, we conclude that the authors of the Bavarian Wikipedia are more inclined towards literal translation, while the authors of the Alemannic Wikipedia rely less on translation.

Model comparison. Many of the retrieved sentence pairs have high similarity values. For instance, **LaBSE** assigns the scores of 0.8 or above to 42% and 24% of the dataset for Bavarian and Alemannic, correspondingly. Overall, the distribution of cosine values tends to be skewed to higher values for all embedders. **GBERT-large-sts-v2** shows the least reasonable performance: the average similarity value is 0.98 and the standard deviation is close to 0.01 for both

[10]The annotator was hired and received fair compensation according to the local employment regulations.

dialects, leaving no discriminative power to select a precise cutoff threshold. This may happen due to overfitting to semantic similarity tasks. The choice of pooling strategy does not affect the performance of **MBERT**: **MBERT+**`[CLS]` and **MBERT+**`[mean]` output strongly correlated cosine values (0.81 and 0.82 for Bavarian and Alemannic). This is not the case for **GBERT**, for which pooling strategies lead to less correlated results (≈0.5 for both dialects).

The resulting annotated dataset helps to evaluate whether the embedders can judge semantic similarity and assign lower scores to unrelated sentences. At the same time, we may use it to calibrate the cutoff threshold, which distinguishes between similar and unrelated sentence pairs. Figure 1 shows the cosine similarity values, derived with **MBERT+**`[CLS]`, **GBERT+**`[CLS]`, and **LaBSE** models, grouped according to Likert scale values. Although none of these models can divide the data into five groups, there is more evidence that **LaBSE** better separates unrelated sentences (scores 1, 2) from nearly similar or similar sentences (scores 4, 5) leaving somewhat similar sentences (score 3) in between. Based on Figure 1, we decided to use **LaBSE** in further experiments and set the cutoff at the lower bound of the cosine similarity of nearly similar sentences to 0.7.

Results bitext mining. We end up with 17k and 50k parallel Bavarian-German and Alemannic-German sentence pairs. We will release the code to mine bitext sentences along with the resulting bitext dataset. The amount of parallel sentences matches the intuition that many Wikipedia authors translate from German. Future work in this direction can explore bitext mining from Wikipedia in English and other European languages. Next, we describe how we use the obtained bitext to induce bilingual lexicons.

5 Bilingual lexicon induction

Method We use the state-of-the-art awesome-align toolkit[11] (Dou and Neubig, 2021) with **MBERT** and **GBERT** as backbone models. Awesome-align supports an unsupervised mode, so there is no need to fine-tune the models on the parallel data. The word alignments are extracted from parallel sentences by evaluating the similarity between word representations. Awesome-align produces one-to-one alignment by default. When the source dialect sentence uses the perfect tense and the target German sentence uses the preterite tense, in the vast majority of cases, the auxiliary verbs align with the preterite verb.

[11] https://github.com/neulab/awesome-align

Bavarian	**German**	**#**	P
Eihgmoant	Eingemeindet	112	0.99
Sidlichn	Südlichen	71	0.96
Augschburg	Augsburg	39	0.91
Alemannic	**German**	**#**	P
Dytsche	Deutsche	290	0.77
Ywohner	Bewohner	189	0.83
Uniwersidäät	Universität	126	0.95

Table 3: Examples of aligned word pairs in Bavarian and German (top) and Alemannic and German (bottom). # notes the frequency of the word pair. P stands for alignment probability. **MBERT** is the backbone model.

We feed the extracted parallel dialect-German sentences to the aligner. The outputs are word pairs, in which one of the words is written in dialect and the other in German. Each word pair is assigned with alignment probability (see Table 3 for sample output).

We disregarded word pairs, in which one of the words is a non-word token (a number, a typographical symbol, or a punctuation mark). For each dialect word, we compute its frequency in Wikipedia. We divide word pairs into four groups based on the dialect word frequency quartiles. From each group, we randomly select 250 word pairs for further analysis.

Dictionary-based evaluation. To the best of our knowledge, there are no high-quality Bavarian-German or Alemannic-German lexicons, that can be easily accessed for computational experiments, so we turn to community-based resources. Glosbe[12] is a collection of community-maintained dictionaries, including Bavarian-German and Alemannic-German dictionaries. Since Glosbe does not provide an API, we manually look up German words and record the suggested translations into dialects.

Table 4 shows, that the Glosbe dictionary provides better coverage for high-frequency words. The ratio of obtained translation sinks from

[12] https://glosbe.com/

Q.	Dictionary ✍	Dictionary ✔	Human ✎
Bavarian			
1	5%	50%	0.85%
2	6%	50%	0.95%
3	16%	65%	0.90%
4	29%	60%	0.65%
Alemannic			
1	4%	70%	0.94%
2	5%	63%	0.95%
3	9%	81%	0.80%
4	26%	43 %	0.40%

Table 4: Dictionary-based evaluation of induced bilingual lexicons, created from sentences, aligned with **LaBSE**. The results are grouped according to the frequency quartile of German words (Q). 1 stands for the low-frequency bin, and 4 stands for the high-frequency bin. There are 250 words in each bin. ✍ stands for the percentage of words, found in the Glosbe dictionary. ✔ denotes the percentage of correct word pairs. ✎ denotes the percentage of correct word pairs according to human evaluation.

29% to 5% from high-frequency words to low-frequency words. The mismatch between the induced translation and the dictionary-based translation is mainly caused by orthographic variations (see Table 5 for examples, in which both the induced and the Glosbe translations appear to be correct, but different from each other). The low coverage of the Glosbe dictionary can be partially attributed to the absence of compounds, which are naturally present in Wikipedia writing. For instance, words such as *Laubwoidgebiet* (Bavarian, deciduous forest region) do not exist in Glosbe.

Human evaluation. Along with the dictionary-based evaluation, we annotate the same word pairs in German on a binary scale for semantic similarity. The task is to determine whether a word in German is a correct translation of a dialect word. Appendix B contains the annotation guidelines. The markup is performed by the same annotators who participated in the evaluation of the bitext (section 4). The word pairs are provided without the surrounding context. Annotators may reject labeling a word pair if they do not understand the dialect word. The control sample for assessing agreement between annotators consists of 200 word pairs for each dialect. The exact match between annotators makes 0.96 and 0.85 for Bavarian and Alemannic, respectively. Disagreements between annotators are mainly caused by judgments of overlapping words (*Turm – Kirchturm*, steeple – church steeple, Bavarian).

Bavarian	**German**	**Glosbe** $_{(de \rightarrow bar)}$
Obapfäjza	Oberpfälzer	Obapfejza
Zamm	Zusammen	Z'samm, zaum
Bavarian	**German**	**MUSE**$_{(de \rightarrow bar)}$
Vagressade	Vergrößerte	Großhadern
Freizeidzentrum	Freizeitzentrum	Sportpark
Alemannic	**German**	**Glosbe**$_{(de \rightarrow als)}$
Barlemäntarischi	Parlamentarische	Parlamentarischi
Nobelprys	Nobelpreis	Nobelpreis
Alemannic	**German**	**MUSE**$_{(de \rightarrow als)}$
Flüssige	Flüssiger	Wassermolekül
Epos	Heldengedicht	Heldenepos

Table 5: Differences between word pairs induced with **MBERT** and (top) the Glosbe dictionary, (bottom) **MUSE** synonyms.

Table 4 provides human evaluation results for BLI. The quality of the alignment of low-frequency and mid-frequency words ranges from 0.85% to 0.95%, but drops significantly for high-frequency words to 0.65%. This can be explained by a higher ratio of high-frequent prepositions, pronouns, and forms of auxiliary verbs, that get wrongly aligned. Interestingly, for mid-frequency words one of the main sources of errors appears as the alignment of such words, that may be used in similar contexts, but are not synonyms (*Soizsään – Mineralquellen*, Bavarian, salt lakes - mineral springs). Overall, the annotation study identified 860 and 774 synonym word pairs between Bavarian and German, and Alemannic and German, respectively.

Baseline. We use supervised **MUSE** embeddings (Lample et al., 2018) as a baseline for bilingual lexicon induction. We employ fasttext embeddings, pre-trained on mono-lingual Wikipedia (Bojanowski et al., 2017), and use identical character words as seeds. Following the project's guidelines,[13] we set up the dialect embeddings as the source space and German embeddings as the target space. For each dialect word, we retrieve

[13] https://github.com/facebookresearch/MUSE

the nearest neighbor according to cosine similarity.

The **MUSE** embeddings retrieve 48 (out of 860) and 74 (out of 774) word pairs (Bavarian/Alemannic), identified as correct in the annotation study. Table 5 shows examples of cases, in which **MUSE** embeddings induce words that are different from those induced from bitext. These words have a similar spelling or can be used in similar contexts, but are not synonyms of source dialect words. Note, that the two-step approach for bitext mining and bilingual lexicon induction and the baseline **MUSE** embeddings leverage upon the same data source, namely, Wikipedia. However, the two-step approach leads to inducing more literal synonyms due to accessing larger contexts.

Model comparison. We compare two backbone models for the awesome-align toolkit in the binary classification setup. To this end, we loop over a threshold on alignment probability in the $[0.7; 0.99]$ range. Word pairs given with a probability below the threshold are considered negative, and word pairs given with a probability above the threshold are considered positive. Next, we compare these predictions to human yes/no labels and record the F_1 score. Figure 2 shows the dependence of F_1 score on the threshold values. First, **MBERT** consistently outperforms **GBERT**. Second, the **MBERT** performance is on the plateau in the $[0.7; 0.8]$ range and slowly degrades with higher thresholds. Thus, it seems reasonable to set the cut-off threshold at 0.8.

Edit distance. Following prior works (Hangya et al., 2018), we explore the contribution of the edit distance to the word alignment probability. We compute the edit distance and normalize it with the sum of the number of characters in two words divided by two. The correlation coefficient between the normalized edit distance and the average alignment probability makes -0.4 / -0.38 and $-0.49/-0.56$ for Bavarian with **MBERT** / **GBERT** backbones and Alemannic, respectively. This means, first, that the words, spelled similarly have higher chances to be aligned. Second, both backbone models significantly rely on the surface-level similarity between words.

Results. With the cutoff threshold of 0.8 for **MBERT** alignment probability we end up with the bilingual lexicons of 11k and 68k word pairs in Bavarian and Alemannic. We will release the code

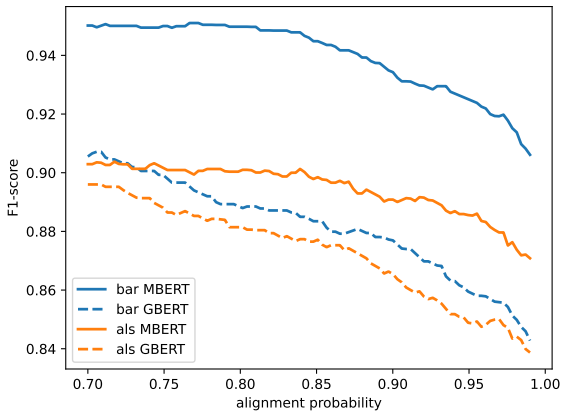

Figure 2: Comparison of two backbone models for Bavarian (blue) and Alemannic (orange). OX: the cut-off threshold for alignment probability. OY: F_1 scores. The solid line stands for **MBERT**, and the dashed line stands for **GBERT**. **MBERT** consistently outperforms **GBERT** for both dialects.

to bilingual lexicon induction along with the resulting bilingual lexicons. By design, the resulting bilingual lexicons suffer from excessive repetition of different word forms. We are unable to merge different forms of the same words due to the lack of dialect stemmers or lemmatizers. Besides, in some cases, words of different parts of speech got aligned. Likewise, we can not control the part of speech consistency, due to the lack of dialect taggers. Finally, the resulting lexicon exhibits several cases, in which a single German word is linked to multiple dialect words due to the high variety in dialect spelling (see Figure 3).

6 Conclusion and Future Work

In this project, we are developing a two-stage bilingual lexicon induction pipeline for German and its two dialects, Bavarian and Alemannic. First, we extract bitext (parallel) sentences from public data, namely Wikipedia. We then use an alignment tool that induces word pairs from parallel sentences. Both steps heavily rely on pre-trained large language models. We carefully verify the output of each step by human evaluation. To this end, we conduct two annotation studies to judge the semantic similarity between extracted sentences and induced word pairs. The results of annotation studies help to select the best-performing language model and calibrate its parameters. Although none of the large language models considered is fine-tuned on dialect data, we can get decent performance. This may be ex-

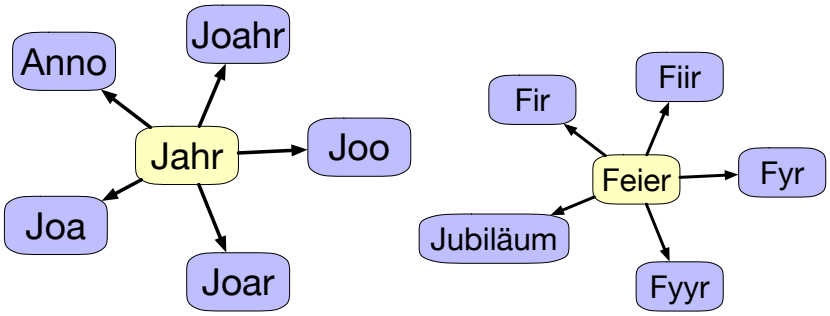

Figure 3: Examples of one-to-many correspondence from Bavarian-German (left) and Alemannic-German (right) bilingual lexicons. German words are in yellow, dialect words are in blue.

plicitly attributed to the ability of language models to transfer from languages, seen during pre-training, such as German. We publish the code used in the experiments, the annotation guidelines, and the evaluation datasets for further uptake.

There are multiple future work directions. Since Wikipedia provides detailed dialect categorization, it is possible to differentiate between several Bavarian / Alemannic dialects instead of treating them as one dialect. This would help build more nuanced bilingual lexicons. Second, one can explore the effect of fine-tuning a cross-lingual language model on German and dialect data on bilingual lexicon induction. Finally, the experiments can be extended to other German dialects and language pairs.

6.1 Limitations.

The limitations of this project come with the low-resource setup. First, there is no large-scale data source available, so we stick to Wikipedia as almost the only reasonable domain. Second, dialect text processing is hindered due to the lack of standard linguistic tools, such as lemmatizers and part-of-speech taggers. Third, the pipeline of bitext mining and word aligning has its own disadvantages, such as resulting in one-to-one sentence / word alignment and over-relying on surface-level features. Finally, the evaluation suffers from the absence of unified lexicons for German dialects.

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A Bitext Annotation. Are these two sentences similar?

Task. Compare two sentences. One sentence is written in a Bavarian dialect. Another sentence is written in the standard German language. Your task is to compare these two sentences and decide how similar or different they are. You will be asked questions about sentence meaning, if one sentence provides more information than the other, and if the dialect sentence can potentially be a translated version of the German sentence.

Meaning. On a scale from 1 to 5, rate how close the meaning of sentences is. Choose the "idk" option if you do not understand the sentence to judge the similarity and skip the rest of the questions. Choose "n/a" if the first sentence is not in a Bavarian dialect and skip the rest of the questions. Choose "incomplete" if the dialect sentence is not complete or some parts of the sentence are missing and skip the rest of the questions. The scores can be interpreted in the following way.

Label	Explanation
idk	I do not understand the dialect sentence.
n/a	The dialect sentence is not written in the dialect.
incomplete	The dialect sentence is not complete (see below).
1	The sentences are completely unrelated.
2	The sentences have minor details in common (shared generic topic).
3	The sentences refer to same entities, but there are major differences (shared specific topic).
4	The sentences refer to same entities, but there are minor differences.
5	The sentences have identical meaning.

Table 6: The markup schema for bitext annotation.

Try to judge the differences between the sentences from the context. Do you learn the same things from these sentences or not? If one sentence adds more information, is it something really important?

Incomplete sentences. might look like these in Table 7 and should be labelled with 5.

Sentence	Is it complete?
Bédouès, Cocurès, Florac, Fraissinet-de-Lozère, La Salle-Prunet, Le Pont-de-Montvert, Saint-Andéol-de-Clerguemort, Saint-Frézal-de-Ventalon, Saint-Julien-d'Arpaon.	**No.** Reason: This looks like a part of a list.
House" Haus und des "Mordecai Lincoln House" Haus san historische Gebaide in Springfield und im National Register of Historic Places aufgfiaht.	**No.** Reason: It looks like a few words in the beginning of the sentence are missing.

Table 7: Examples of incomplete sentences.

Identical meaning. We consider sentences like these in Table 2 to have identical meaning.

Bavarian	German	Label
Da Geiselbach speist ob da Omersbachmindung oanige Weiher.	Der Geiselbach speist ab der Omersbachmündung einige Weiher.	5
Am 31. Dezemba 1990 werd Schladerlmühle ois unbewohnt und in Treffelstein aufgonga bezeichnt.	Am 31. Dezember 1990 wird Schladerlmühle als unbewohnt und in Treffelstein aufgegangen bezeichnet.	5
As Gebiet vo da Metropolitanstod Neapel is a bliabds Reisezui vo in- und ausländischn Touristn.	Das Gebiet der Metropolitanstadt Neapel ist ein beliebtes Reiseziel in- und ausländischer Touristen.	5

Table 8: Examples of sentences with identical meaning

Factual similarity. If the sentences do not have identical meaning, choose from the drop down list one of the following explanations, how they differ:

- The dialect sentence misses details.
- The dialect sentence adds details.

Bavarian	German	Meaning	Factual similarity
Seitm 1. Mai 2008 isa Easchta Buagamoasta vo da Gmoa Hafenlohr.	Seit dem 1. Mai 2008 ist er Erster Bürgermeister der Gemeinde Hafenlohr und Kreisrat im Landkreis Main-Spessart.	4	The dialect sentence misses details. Reason: The standard German sentence provides additional information (Kreisrat im Landkreis Main-Spessart).
De Gmoa eastreckt se iwa uma 54km².	Die Gemeinde erstreckt sich über etwa 55km².	4	Minor factual inconsistency. Reason: 54km² does not equal to 55km², but the numbers are almost the same.
Hafenlohr is duach des Zwoate Gmoaedikt am 17. Mai 1818 a Tei vo da Gmoa Hafenlohr gewoadn.	Hafenlohr ist der Hauptort der Gemeinde Hafenlohr.	3	Major factual inconsistency. Reason 1: The dialect sentence provides additional information (duach des Zwoate Gmoaedikt am 17. Mai 1818). Reason 2: The dialect sentence uses ”Tei”. The standard German sentence uses “Hauptort”.
As Spuin hod a recht wichtige Funktion in da Entwicklung vo Menschnkinda.	Von besonderer Bedeutung ist hier der Verlauf der individuellen Wachstumskurve.	2	Minor common details. Factual similarity is not applicable.
A Klassika vo humoristischa Litratua is aa da Ignát Herrmann.	Sein Werk ist ein lyrisches Poem, das hochromantisch und hochdramatisch ist.	1	Unrelated sentences Factual similarity is not applicable.

Table 9: Examples of sentence with scores from 1 to 4.

- Different details: both sentences add some new details and miss different details.
- Minor factual inconsistency.
- Major factual inconsistency.
- n/a: if the sentences are completely unrelated, you can not make a judgment about their factual consistency.

Table 9 shows instructions on how to score less similar sentences.

Grammar differs? This is a checkbox: mark yes, if there is a difference between the grammar structure of two sentences. If there is no difference or you can not tell it, skip this section.

Free form comment. Is there anything else you would like to notice about these two sentences? Can you explain the reason behind your judgment?

B Bilingual Lexicon Annotation. Is the translation acceptable?

Task. This project aims to evaluate bilingual word pairs. Each word pair consists of:

a. a word in Bavarian;
b. a word in Standard German.

The task is to label each word pair as an acceptable translation from Standard German to Bavarian. Label each word pair with:

1. **yes**, if the translation is acceptable;
2. **no**, if it is not acceptable;
3. **idk**, if you can not tell;
4. **check in the box “different part of speech”**, if the two words belong to different parts-of-speech only if you are sure you can tell it without full context.
5. **check in the box “partial match”**, if the words partially match and one word is a part of another (e.g. *Turm - Kirchturm, S'assl – B'rosessel.*

Put down free-form comments when necessary.