CoDET: A Benchmark for *Co*ntrastive *D*ialectal *E*valuation of Machine *T*ranslation

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Abstract

Neural machine translation (NMT) systems exhibit limited robustness in handling source-side linguistic variations. Their performance tends to degrade when faced with even slight deviations in language usage, such as different domains or variations introduced by second-language speakers. It is intuitive to extend this observation to encompass dialectal variations as well, but the work allowing the community to evaluate MT systems on this dimension is limited. To alleviate this issue, we compile and release CoDET, a contrastive dialectal benchmark encompassing 882 different variations from nine different languages. We also quantitatively demonstrate the challenges large MT models face in effectively translating dialectal variants. We are releasing all code and data.[1]

Standard Italian Variant:		
Source:	*Hanno rubato il quadro*	
GTranslate:	They stole the painting	✓
Alassio Variant:		
Source:	*I han rubbau u quaddru*	
GTranslate:	I han rubbau u quaddru	✗

Table 1: While it properly translates standard Italian into English, a popular translation system utterly fails to translate the Alassio variety. *Contrastive dialectal* examples like this one, even if short, allow for revealing and properly quantifying such inadequacies in MT performance.

1 Introduction

Progress in natural language processing (NLP) and other varieties of human language technology throughout the 2010s has been undeniably swift. However, such advances are not only limited to a set of languages with largely available resources (Joshi et al., 2020; Blasi et al., 2022); they have focused solely on dominant, "standard" language varieties. But no language is a monolith; languages vary richly across countries, regions, social classes, and other factors.[2]

For modern *linguae francae* such as English, Spanish, or French, some commercial systems do apply coarse localization, e.g., Google Assistant supports speech recognition for English in at least seven locales.[3] This, however, is not the case for the majority of the world's languages, even if they exhibit large variations across dialects and regions, often corresponding to millions of speakers. As a result, we have a limited understanding of how well modern NLP systems can handle (or not) such data. It is crucial that we first quantify such disparities in as many languages as possible before we may explore ways of mitigating any performance imbalances we identify.

Language variants can vary along several dimensions. In this work, we focus on the robust *understanding* of lexical and morphosyntactic variations, which show up in the written form of languages and hence can be evaluated through a downstream task like text-based machine translation. If one wanted to capture phonological variation additionally, one should work directly on audio and tasks like automatic speech recognition or speech translation; we leave this vein of work for the future.

Consider the case study presented in Table 1: given two sentences that have the same meaning,[4] Google Translate produces very different results. In the first, in "standard" Italian, it produces a perfect translation. The second, from the variety spoken in Alassio in Northwest Italy, the MT system fails to

[1] https://github.com/mahfuzibnalam/dialect_mt

[2] In this paper, we will use the terms "dialect" and "language variety" interchangeably for readability reasons. The distinction between what is named a language and what a dialect or variety is a complex socioeconomic phenomenon rather than a purely linguistic one. We add a bit of discussion in Section 2 for each variety/language we work with.

[3] (AU, CA, GB, IN, BE, SG, US)

[4] Correct translation: *"They stole the painting"*.

English Outputs on three German Varieties	
Standard	Once, the north wind and the sun were arguing about who was stronger, when a traveler, wrapped in a warm ...
Saxony	And the north wind blew, and the sun was divided, and the two were as heavy as a great sea, which was full
Danube Bavarian	The sun is shining and the north wind is blowing, and we are both stronger than the other two.
Standard	They agreed that the stronger one would be the one to force the traveler to take off his coat.
Saxony	I'm sure that's the only way that guy can get rid of the man.
Danube Bavarian	And if the two become one, the one who is stronger will take away his armor in Wåndara.
Standard	The north wind was blowing with all its might, but the more it blew, the more tightly the other wrapped himself
Saxony	The north wind blew as hard as it could, but the more it blew, the more grimly the murmured voice
Danube Bavarian	The north wind blows with all its might, but the more it blows, the more the walls of the mountains are blo
English Outputs on four Norwegian Varieties	
Standard	Noravinn and Sola argued over which of the dams was the strongest.
Eastern	The north wind and the sun argued about which of them was stronger.
Setesdal	The north wind carries the winds of the spring, when it is stronger than the winds of the summer, and its co
Southwestern	The north wind and the sun fought over who would be the strongest.
Standard	Just then a man in a white coat came forward.
Eastern	Just then a man in a robe came walking by.
Setesdal	Some said that if by then the strongest had succeeded in taking the throne, it would be considered the strongest.
Southwestern	Just then a man came walking around in a robe.
Standard	They agreed that the first man who could get a man to take off his coat should pay for the stronger man.
Eastern	They decided that the strongest among them would be the one who first got the man to take off his coat.
Setesdal	The wind blows where it cannot, but the wind blows where it cannot, and the man is torn to pieces.
Southwestern	They agreed that the one who could get the man to take off his coat and shoes would be considered the strongest of them.

Table 2: Translation failures for dialectal input in three German and four Norwegian Varieties for excerpts from an Aesop's fable. The "Standard" variety input in all cases produces excellent translation outputs, but dialectal input leads to almost complete translation failures, especially for Saxony German and Setesdal Norwegian.

produce any English translation whatsoever, simply copying the source. Our assumption for evaluating the system is that both of these inputs should yield the same translated output. This example effectively illustrates the limitations of general MT systems in comprehending and accurately translating dialectal variations.

Another example is in Table 2. In these brief examples, taken from the various German and Norwegian translations of Aesop's fable of "The Sun and the Wind" from the Aesop Language Bank,[5] we highlight the inaccuracies suffered due to dialectal input as opposed to "standard" one.[6]

To properly evaluate such inadequacies in the context of machine translation, one needs *contrastive* examples between varieties so that the evaluation metrics are comparable. Our work attempts to fill this gap. In summary, our contributions are as follows:

- we extract contrastive data from previous dialectology studies in three languages: Italian (439 locales), Basque (39 locales), and Swiss German (368 locales);
- we re-purpose contrastive data from various sources in five languages: Arabic (25 vernaculars), French (1 variety), Greek (1 variety), Tigrinya (2 varieties), and Yoruba (1 variety);
- we create a limited amount of contrastive data in additional languages: Bengali and Central Kurdish.
- We benchmark the selected distinct dialects of the target language using state-of-the-art machine translation models and quantify the performance discrepancies across language varieties.

2 The CoDET Benchmark

Given a sentence in one dialectal variant and another in the standard variant of the same language as in Table 1, if these two sentences have the same meaning, we can call this *contrastive* of each other. While these data are also *parallel*, we prefer to point to the contrast between the two, as is common in the comparative dialectology literature. Given that little has been done in this vein, we focus on creating constructive datasets following three ap-

[5] https://www.aesoplanguagebank.com/

[6] Source sentences are available in Appendix A.1

Languages/Varieties	# Sentences	# Varieties
Arabic Vernaculars	12,000	25
Basque Varieties	370	39
Bengali Varieties	200	5
Central Kurdish	300	2
Occitan	379	1
Italian Varieties	792	439
Swiss German Varieties	118	368
Tigrinya	3071	2
Griko	163	1
Seed data (not used for eval):		
Cretan Greek	32	1
Yoruba	25	2

Table 3: Number of contrastive sentences in CoDET.

proaches, namely repurposing previous dialectological work on syntactic variations for Basque, Italian, Swiss German, Occitan, and Yoruba; manual translation by native dialect speakers for Bengali, Modern Greek, Central Kurdish; and finally, exploiting some existing resources for Arabic and Tigrinya. Table 3 provides the number of sentences along with the number of varieties that the dataset covers.

Utilizing Existing Datasets A small amount of work has already provided contrastive examples for varieties of some languages. Some of these were created as part of dialectological work, which we manually scraped from dissertations and theses; some of them were created as part of other efforts, such as the TICO-19 and the MADAR corpora.[7]

Scraping Syntactic Atlases Traditionally, researchers and fieldworkers employ the method of administering questionnaires to individuals fluent in specific dialects to gather the necessary data for dialectological studies. The questionnaires are designed to elicit responses regarding how a particular sentence or phrase would be expressed in their respective dialects, as in "how do you say this sentence... in your dialect?" where the speaker fills the gap based on the target dialect.[8] This systematic approach allows for the collection of dialectal data that serves as a valuable resource for investigating the linguistic changes in different varieties and for comprehensively examining and analyzing the variations that occur between the dialects.

Although describing and documenting dialectal variations in most languages have received limited attention in the research landscape, notable efforts have been made to study variations in some European languages, such as Italian, Basque, and Swiss German, through the creation of syntactic atlases. In this section, we describe the parts of CoDETthat are based on such resources.

New Data Creation For a couple of languages, namely Central Kurdish and Bengali, we did not find any existing dialectal contrastive data, but we were able to construct small evaluation benchmarks by reaching out to native speakers and translators of these varieties.

2.1 The Languages of CoDET

Basque Varieties Our Basque data is sourced from the Basque Syntactic Database.[9] To gather and analyze the data, researchers initially developed specific questionnaires, each focusing on a distinct linguistic phenomenon characterized by syntactic variation, for a total of 370 different questions. These questionnaires were then provided to informants spanning different age groups, carefully selected from various locations, which comprise 39 variants in the Northern Basque Country in France.

By posing identical questions to speakers of different Basque dialects, this methodology creates contrastive data facilitating an n-way comparison among the dialects. One challenge encountered in this process is that the questions themselves are presented in French. Consequently, we lack sentences in the standard variant. This said the provided English translations of French sentences serve as gold-standard reference translations.

Italian Varieties and Languages Our Italian data are obtained from the Italian Syntactic Atlas[10] which functions similarly to the Basque one. However, in the Italian Syntactic Atlas, the questions are presented in standard Italian. This extensive dataset consists of 792 questions that speakers of various Italian dialects have answered. The dataset encompasses a rich collection of 439 dialects from different regions across Italy. Additionally, the dataset provides information about the specific locations where these dialects are spoken. This comprehensive resource enables in-depth analysis and

[7] See details below.

[8] An alternative approach pre-constructs sentence examples and elicits grammaticality responses from the informants.

[9] http://ixa2.si.ehu.eus/atlas2/index.php

[10] http://svrims2.dei.unipd.it:8080/asit-maldura/pages/search.jsp

exploration of the dialectal variations found within the Italian language.

It is important to note that many of the vernaculars spoken around Italy are recognized as officially distinct languages (e.g., Neapolitan, Ligurian, and Venetian, to name a few). Some of these also have a distinct online presence (e.g. with decent Wikipedias), and some MT research is devoted to them (NLLB Team et al., 2022). However, this "discretization" of the language continuum observed in the Italian peninsula, where each city/village is said to have its dialect, is far from realistic. Hence we focus on the fine-grained evaluation that our data from over 439 regions allows.

Swiss German Varieties Our Swiss German data was obtained by scraping the Syntactic Atlas of German Switzerland (SADS).[11] The SADS website hosts a total of 118 questionnaires, each accompanied by answers provided in 368 different locales. This dataset allows for an n-way comparison between the dialects and the standard (Swiss) German variant, providing valuable contrastive information. However, the data available on the website primarily focuses on highlighting the changes present in the sentences, necessitating manual annotation to identify instances where alterations occur in standard German sentences. Through this manual annotation process, we captured the specific linguistic variations exhibited by the Swiss German dialects.

Bengali Varieties Anecdotally, Bangladesh witnesses a linguistic transition approximately every 10 miles. This work specifically focuses on five prominent dialects from five locales of Bangladesh: Jessore, Khulna, Kushtia, Barisal, and Dhaka. The selection of these dialects was strategic, encompassing regions both close to the origin of standard Bengali (Jessore, Kushtia) and those situated farther away.

Our approach involved initially gathering 200 standard Bengali sentences from the Bengali-English translation dataset presented in Hasan et al. (2020), a high-quality dataset comprising 2.75 million parallel sentence pairs. From this dataset, we selected short sentences comprising 6 to 7 words, facilitating ease of translation for the language speakers. Initially, there were 200,000 sentences to choose from, and we randomly selected 200 sentences for our dataset.

Our initial step involved recruiting proficient annotators fluent in the standard and in one of the dialects. Subsequently, we requested these annotators to provide their respective dialectal renditions of specific sentences. Given that dialects primarily exist in spoken form without standardized orthography, we instructed the annotators to transcribe the sentences in Bengali script based on the acoustic signals they perceived. This process is called dialectal writing (Nigmatulina et al., 2020), which entails creating phonemic transcriptions that closely align grapheme labels with the acoustic signals, despite their inherent inconsistency. This approach, in our view, mimics what speakers of the varieties would do should they attempt to write them. It took the annotators about four hours to annotate 200 sentences each.

Central Occitan Occitan is a Romance language spoken in southern France, Monaco, Italy, and Catalonia, also known as Provençal or Languedocian (*lange d'oc*), and acknowledged as a language continuum with multiple variations. In this work, we use data from the dissertation of (Dansereau, 1985) who studied the syntax of central Occitan, providing additional translations of all examples to "standard" French. In total, we have 379 in the Occitan portion of CoDET. Note, of course, that French and Occitan are widely accepted as different languages; nevertheless, most Occitan speakers live in France, and therefore most systems will direct these speakers' input to a French model.

Griko Griko is a Greek dialect spoken in southern Italy, in the Grecìa Salentina area southeast of Lecce. It is also known as *Italiot Greek* when combined with the Greko variety of Calabria. For CoDET, we use a sample of Griko data from (Anastasopoulos et al., 2018), for which we also create "translations" into modern standard Greek, ending up with a total of 163 sentences.

Central Kurdish Varieties Kurdish is known as a dialect continuum and is mainly classified into Northern, Central, and Southern dialects and is closely related to Zaza-Gorani languages, Laki and Lori (Ahmadi et al., 2023). In this project, we focus on the varieties of Central Kurdish, also known as Sorani, which are mainly spoken in Kurdistan, Iran, and Iraq. Although more extensive studies on Kurdish dialectology are needed to describe Central Kurdish varieties, the following local names are generally and broadly used to refer to the dialects of Central Kurdish spoken in regions of the cities

[11] https://dialektsyntax.linguistik.uzh.ch

specified in parentheses: Babanî (Sulaymaniyah, Iraq) (McCarus, 1956), Ardalanî (Sanandaj, Iran), Cafî (Javanrud, Iran), Mukriyanî or Mukrî (Mahabad, Iran) (De Chiara, 2018) and Hewlêrî (Erbil, Iraq). Among these, the variant of Sulaymaniyah is the most studied one, which is also widely used as a standard variant of Central Kurdish in the press and media (Thackston, 2006).

According to various linguistic analyses of fieldwork data, Matras (2019) classifies Central Kurdish varieties into Northern and Southern Sorani, with their epicenters being based on the dialects of Erbil (*Hewlêr* in Kurdish) and Sulaymaniyah (*Silêmanî* in Kurdish). Based on this classification, Babanî, Ardalanî, and Cafî belong to Southern Sorani, while Mukriyanî and Hewlêrî belong to Northern Sorani. Similarly, we believe that the selected varieties can further elucidate the distinctiveness of the varieties and the classification quantitatively.

Given that there are no corpora documenting varieties of Central Kurdish, we resort to movies where speakers of these varieties play a role. To that end, we transcribe movies in Babanî, Ardalanî, and Mukriyanî. Since none of these movies are available in other varieties, we perform a dialect translation by a native speaker of Ardalanî and Mukriyanî by randomly selecting and translating 300 sentences in Babanî transcriptions. To mitigate the impact of orthography on the dialect, we normalize and standardize the sentences based on the common orthography of Kurdish using KLPT (Ahmadi, 2020).

Arabic Vernaculars Arabic, as a macro-language, encompasses a range of dialects within its language continuum. Modern Standard Arabic (MSA) is a standardized form of the language used across various regions, encompassing cultural, media, and educational domains from Morocco to the west to Oman to the east. However, it is important to note that MSA is not the native language of Arabic speakers. In informal and spontaneous settings where spoken MSA is typically expected, such as in TV talk shows, speakers often code-switch between their respective vernaculars and MSA.

To examine MT performance in Arabic dialects, we use the MADAR corpus (Bouamor et al., 2018). This extensive corpus consists of 12000 sentences on varieties from 25 different Arabic-speaking cities. The corpus is created by translating selected sentences from the Basic Traveling Expression Corpus (BTEC; Takezawa et al., 2007) into various dialects and MSA. This unique dataset is highly suitable for conducting contrastive machine translation (MT) research for Arabic dialects, but to our knowledge has not been extensively used for this purpose.

Tigrinya Tigrinya is an Ethio-Semitic language predominantly spoken in Eritrea and by the Tigrayan people in the Tigray Region of northern Ethiopia. Within Tigrinya, two major varieties exist the Eritrean dialect and the Ethiopian dialect. To explore and compare these two, we leverage the dataset available from TICO-19 (Anastasopoulos et al., 2020). The TICO-19 dataset emerged as a translation initiative during the COVID-19 pandemic, aiming to enhance society's readiness to respond to the ongoing crisis through the utilization of translation technologies effectively. This dataset specifically focuses on the COVID-19 domain, containing translations of the same content in multiple languages. The same 3071 English sentences were professionally translated into both varieties of Togrinya, making it ideal for our purposes.

2.2 Additional Seed Data

For a couple of varieties, we have identified small contrastive datasets that could be used as seeds for small-scale experiments but are not yet large enough to be used for meaningful evaluation of MT systems. Nevertheless, we list their details below.

Cretan Greek Cretan Greek is the variety of Greek spoken on the island of Crete. Its distinction from modern standard Greek is largely phonological. Still, it has additionally retained lexical and morphosyntactic elements of medieval Greek that render it diverse enough to fit the requirements of our project. Here we compile a small seed dataset taken from the "Erotokritos" romance, which was originally composed in the 17th century. We use a sample of 32 sentences (from a total of more than 10,000 verses), for which we manually created gold English and "standard" modern Greek translations.

Central Yorùbá The language of the ethnic Yoruba people, Yoruba is a Niger-Congo language primarily spoken in a dialectal area spanning Nigeria, Benin, and Togo. For this project, we use examples from Olánrewájú (2022), which provides several contrastive examples between Standard Yoruba (SY) and Central Yoruba (CY), examining the syntactic differences in how interrogatives are formed in both dialects. We manually extracted sentences and their English translations from the paper, compiling a set of 25 contrastive examples along with gold translations.

3 Evaluation

To assess the quality of any MT system on dialectal variations, it is crucial to compare its outputs with a reference standard. One approach is to have a gold, human-created translation available that represents the desired translation in a standard setting. However, among the nine languages considered, we only have gold translations for Basque, Bengali, and Tigrinya.

Evaluating Without References Our goal is to evaluate the robustness of MT systems concerning dialectal variation. While access to human-created gold translations can certainly reveal a complete picture of the model's performance, thankfully, it is not a hard requirement.

In this work, we adapt the ideas of Michel and Neubig (2018); Michel et al. (2019) and Anastasopoulos (2019), which presented frameworks for evaluating the robustness of MT systems to adversarial or non-native noisy inputs. Concretely, consider the following notation:

- $\mathbf{x}$: the dialectal input sentence.
- $\tilde{\mathbf{x}}$: the contrastive sentence in the "standard" variety. This is deemed to be similar to what MT systems have been trained on and can likely decently translate.
- $\mathbf{y}$: the output of the NMT system when $\mathbf{x}$ is provided as input.
- $\tilde{\mathbf{y}}$: the output of the NMT system when $\tilde{\mathbf{x}}$ is provided as input.

The core of the idea is that we can treat $\tilde{\mathbf{y}}$, the output of the MT system on the "standard" input, as a *pseudo-reference* for the translation. Intuitively, a robust system should produce the same output for inputs with similar meanings regardless of the small dialectal variations. Hence, we can calculate any MT metric such as BLEU (Papineni et al., 2002) or COMET (Rei et al., 2020) by comparing $\mathbf{y}$ to $\tilde{\mathbf{y}}$.

Important Implementation Notes In this work, we focus on two metrics, BLEU and COMET. BLEU compares the n-grams of the candidate translation's n-grams with the reference translation, counting the number of matches to determine similarity. We calculate BLEU using SacreBLEU (Post, 2018). On the other hand, COMET is a neural framework designed for training multilingual machine translation evaluation models. It leverages information from both the source input and a target-language reference translation to provide more accurate predictions of MT quality, correlating with human judgments. These metrics offer quantitative measures to evaluate and compare the quality of dialectal translations against the reference standards.

Note that BLEU and COMET, and corpus-level scores. For some collections of varieties, though, we have a different number of contrastive sentences (p) for a particular dialectal variation compared to the number of standard dialectal sentences (n). In such a case, we can still perform individual translations and score each sentence separately. Each contrastive sentence is translated and scored individually using the chosen evaluation metric. Once the scores for all the p sentences are obtained, we calculate the average metric score.

This approach enables us to evaluate the quality of translation on a sentence level. However, a limitation arises from the varying number of p for different dialects, resulting in variations in sentence combinations. Consequently, scores cannot be directly compared between dialects. This scenario applies to varieties in four languages: Arabic, Basque, Italian, and Swiss German. To establish comparability, one solution is to create a subset of sentences that are present in all dialects. Unfortunately, the only case where this leads to a decently-sized test set is in Arabic (2000 sentences are shared among all vernaculars). The number of subset sentences among all dialects is presented in Appendix A.2.

For the remaining three languages, we employ an alternative approach by selecting a subset of sentences with high dialectal coverage and evaluating the translations exclusively on those dialects. In the case of Basque, we can exclude one variety that comprises only two sentences, resulting in 34 common sentences among the remaining dialects. Similarly, for Swiss German, we can remove three dialects that contain only one sentence each, leaving us with 87 common sentences.

However, for Italian, we implement an alternative approach because the data intersection of all varieties is empty. First, we exclude 18 dialects that consist of fewer than 50 sentences. Next, for each of the remaining dialects, we randomly select

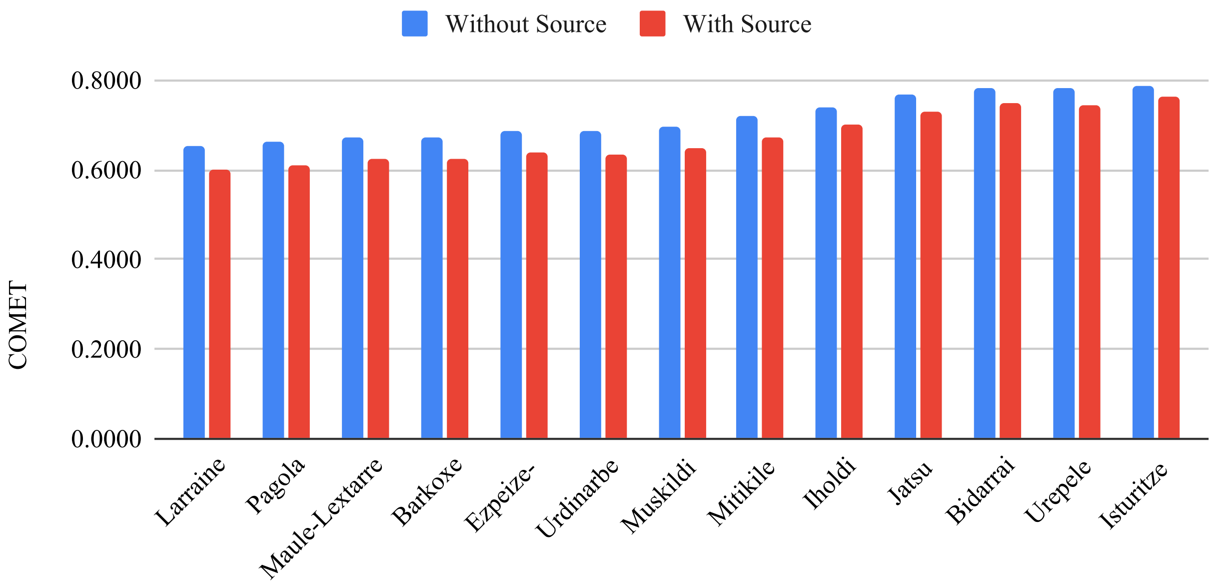

Figure 1: Ablation study of the source sentence usage in dialects of Basque during COMET measurement. COMET scores for Basque varieties when we use the source range from 0.60 to 0.76, but when we don't use the source, it range from 0.65 to 0.79

50 sentences and evaluate the translations based on these samples. We calculate the score for each set of 50 sentences, repeating this process 100 times. Subsequently, we compute the average of the 100 scores obtained from these different runs, representing the final score for that particular dialect.

4 Results and Analysis

Preliminaries For all language varieties, we benchmark MT systems in the X-to-English direction. The choice of English as a target language is a pragmatic one. Still, we note that for future work, a more comprehensive evaluation should consider many other target languages, especially since we do not require gold references to perform our analyses.

We present baseline results in all languages using four different-sized NLLB-200 (NLLB Team et al., 2022) models using the HuggingFace (Wolf et al., 2020) toolkit. For Italian, we also fine-tune the DeltaLM-large (Ma et al., 2021) model with Italian-English OPUS (Tiedemann, 2012) parallel data using the Fairseq (Ott et al., 2019) toolkit.

The COMET evaluation framework relies on XLM-RoBERTa (Conneau et al., 2020), a multilingual language model, to generate embeddings for each token in the input source, machine-translated (mt) sentence, and reference sentence. However, since XLM-RoBERTa was trained on texts of the standard dialect, the quality of the embeddings created for source sentences in different dialectal variants may be compromised. To investigate this, an ablation study was conducted with and without the source sentence as input to the COMET scorer.

Figure 1 presents the results of this ablation study for 13 Basque dialects. The dialectal sentences were translated to English using the NLLB-200-dis-600M model. The blue bars represent COMET scores when the source sentences were replaced with blank sentences, while the orange lines represent COMET scores when the source sentences were included. In all cases, the COMET scores decrease when the source sentences are introduced, supporting the initial hypothesis. The general trends through are very similar with and without using the source sentence. Based on these findings, to ensure more reliable evaluations, for all subsequent COMET calculations in this paper, the source sentence will not be used.

4.1 Analysis

Italian Varieties The dataset used in this study comprises a total of 439 Italian dialects, which are associated with 290 communes. The COMET scores for four different NLLB-200 models, along with the number of contrastive sentences available for each commune compared to the standard variation, are presented in Table A.6 in Appendix A. As mentioned early, these results are not directly comparable to each other but can be thought of as a rough estimation of the expected quality. We

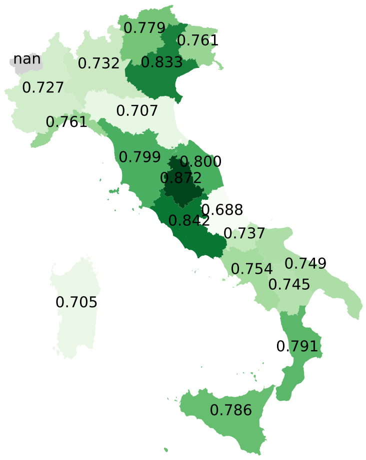

Figure 2: Map of Italy with COMET scores for different regions.

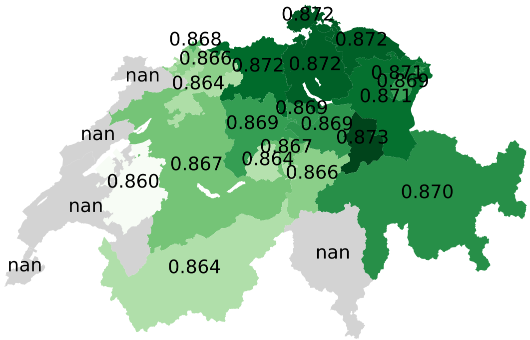

Figure 3: Map of Switzerland with COMET scores for different regions.

present the comparable results among all the dialects in Table A.7 in Appendix A.

These 290 communes are further categorized into 78 provinces. Additionally, these 78 provinces are distributed among 19 regions. The comparable COMET scores for these 19 regions can be found in Table A.9. We also provide the non-directly-comparable results using all the sentences in Table A.9 in Appendix A.

Upon examining the top five COMET scores of the NLLB-Dis-1.3B model, indicated in bold in the table, it is evident that these dialects exhibit a strong resemblance to the standard variation. This is particularly true for the Tuscany variety, as standard Italian is based on this region. Similarly, the proximity of the other three regions (Umbria, Lazio, Marche) to Tuscany suggests that the similarity of these varieties to the now-standard one is reflected in the MT quality.

Based on the obtained scores, it is possible to visualize them on the map of Italy using geojson information, such as the one available here.[12] Figure 2 illustrates the COMET scores of various regions represented on the map of Italy. A darker shade of green indicates a higher COMET score. From the visualization, it becomes evident that regions close to Tuscany exhibit a darker green color, indicating higher scores. However, the scores gradually decrease as we move further away from those regions.

Swiss German Varieties In Appendix A, Tables A.10 and A.11 present the benchmark scores for Swiss German dialects in non-comparable and comparable formats, respectively. These tables provide valuable information on the dialects and their respective regions. Additionally, Table A.12 and Table A.13 in the same appendix display the benchmark scores for different regions of Switzerland in non-comparable and comparable formats, respectively. Similar to the approach taken with Italy, these scores can be geographically visualized on a map. We point the reader to Figure 3, which showcases the map of Switzerland. The map reveals a consistent pattern where the northern regions, being closer to Germany (and consequently speaking varieties closer to High German), obtain higher COMET scores. In contrast, the scores gradually decrease as one moves further south.[13]

Bengali Varieties Table 5 presents the COMET scores of Bengali across the five varieties. These scores are comparable as they were evaluated using the same set of 200 sentences. These dialects are spoken in various regions of Bangladesh, and we visualize their distribution on a map in Figure 4. Interestingly, a similar pattern emerges in this case as well. Notably, Jessore, one of the dialects from which standard Bengali originated, exhibits relatively higher COMET scores. Conversely, as we move away from Jessore, the COMET scores gradually decrease, reflecting a relative decline in translation quality.

Arabic Vernaculars Table A.3 and Table 4 showcase the benchmark scores for Arabic vernaculars. These vernaculars are spoken in different cities. If we take the score of the NLLB-3.3B model, we see that the worst-scoring city is Sfax, and the

[12] https://github.com/openpolis/geojson-italy

[13] Note that "nan" regions are ones which we do not have enough data for, and they mainly correspond to French or Italian-speaking Swiss cantons.

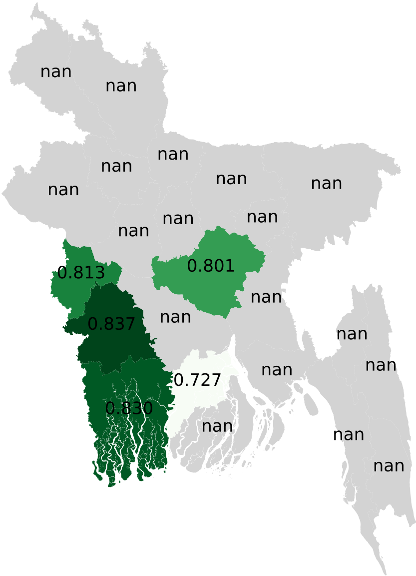

Figure 4: Map of Bangladesh with COMET scores for different regions.

best-scoring city is Riyadh. The difference is 0.1 COMET score, and all the scores are above 0.8. So, we can infer that most Arabic vernaculars are well represented by the baseline systems. Also, let's look at the top four scoring cities (Riyadh, Alexandria, Muscat, and Cairo) and the bottom four scoring cities (Sfax, Tunis, Algiers, and Rabat). We will see that the top-scoring cities are geographically close, and the bottom-scoring cities are also geographically close to each other. But the top-scoring cities are close to Asia or Asia, but the bottom-scoring cities are in Africa, close to Europe. This shows us intuitively that the modern standard Arabic originated mostly from that part of the globe.

Other Languages Table 5 displays the results for languages encompassing only 1-3 dialects. [14] We benchmark 39 dialects of Basque. The lowest-scoring dialect for Basque is Maule-Lextarre for the model NLLB-Dis-1.3B. The highest-scoring dialect is Hendaia. The difference of 0.2 COMET score shows that further work is needed to make a good MT system for that dialect.

Specifically, we benchmark three dialects of Central Kurdish: Babani (Sulaymaniyah) as the standard language, along with Ardalani and Mukryani. We get a better score for Mehabad than Sine. Additionally, we include Occitan, a French dialect. We also contrast standard Greek to Griko.

Lastly, we benchmark two dialects for Tigrinya. Note that, for Tigrinya, we have access to English gold references. Hence we do not need to "define" one of the two varieties (Ethiopian and Eritrean) as the "standard" one. From the results, we see that the Ethiopian dialect has a higher COMET score than the Eritrean dialect. Even though Tigrinya is mostly spoken in Eritrea, the model seems to be more accustomed to the Ethiopian dialect.

In Figure 5, the average COMET scores of different languages are depicted. The results indicate that Swiss German and Arabic exhibit higher scores compared to other languages, suggesting that the baseline system performs well for the various dialects within these languages. The blue bar represents our smallest model, while the yellow bar represents the smallest dense model. Notably, the yellow and blue bars consistently lag behind the red and green bars in terms of performance. The green bar represents our largest model, while the red bar represents our largest distilled model, which is a distillation of a 54.5B Sparsely Gated Mixture-of-Experts model. These findings highlight that models with more parameters tend to represent the nuances of the language better, resulting in improved performance.

5 Related Work

MT is one of the most studied and pioneering tasks in the NLP realm. Many previous studies have focused on proposing more efficient methods, particularly with recent advances in sequence-to-sequence models (Sutskever et al., 2014), attention mechanism (Bahdanau et al., 2014), and transformers (Vaswani et al., 2017) that have left their impact on other tasks in NLP as well. Although creating MT models for languages around the globe has received much attention, as in FLORES-200 benchmark and No Language Left Behind (NLLB) models (Costa-jussà et al., 2022), we have a considerable stretch remaining to create models that can translate dialects and varieties efficiently.

Most of the previous work on developing MT technologies for dialects and varieties address Arabic (Zbib et al., 2012; Harrat et al., 2019), Swiss German (Garner et al., 2014; Honnet et al., 2017), Kurdish (Ahmadi et al., 2022), Portuguese (Fan-

[14] In the appendix, we present the benchmark results for various dialects. Tables A.4 and A.5 contain the benchmark scores for Basque dialects. Due to space constraints, these results are provided in the appendix.

Arabic	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Sfax	2000	0.7815	0.8015	0.7990	0.8010
Tunis	2000	0.7942	0.8124	0.8062	0.8159
Algiers	2000	0.8162	0.8330	0.8276	0.8357
Rabat	2000	0.8205	0.8400	0.8358	0.8457
Tripoli	2000	0.8271	0.8406	0.8380	0.8465
Beirut	2000	0.8285	0.8518	0.8363	0.8503
Benghazi	2000	0.8336	0.8496	0.8452	0.8520
Aleppo	2000	0.8311	0.8518	0.8389	0.8537
Doha	2000	0.8389	0.8591	0.8520	0.8595
Jerusalem	2000	0.8450	0.8632	0.8559	0.8666
Jeddah	2000	0.8420	0.8653	0.8615	0.8683
Damascus	2000	0.8457	0.8660	0.8545	0.8686
Khartoum	2000	0.8488	0.8656	0.8626	0.8695
Basra	2000	0.8436	0.8640	0.8575	0.8700
Baghdad	2000	0.8445	0.8649	0.8595	0.8711
Sanaa	2000	0.8452	0.8704	0.8633	0.8733
Mosul	2000	0.8430	0.8649	0.8619	0.8753
Fes	2000	0.8594	0.8750	0.8695	0.8769
Salt	2000	0.8569	0.8767	0.8650	0.8772
Aswan	2000	0.8496	0.8736	0.8680	0.8800
Amman	2000	0.8618	0.8767	0.8683	0.8811
Cairo	2000	0.8583	0.8790	0.8724	0.8853
Muscat	2000	0.8639	0.8839	0.8790	0.8855
Alexandria	2000	0.8655	0.8895	0.8811	0.8947
Riyadh	2000	0.8859	0.9011	0.8966	0.9028

Table 4: Comparable COMET score of different Arabic dialects on a subset of 2000 sentences.

Standard Language	Variety	# Sentences	COMET			
			NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Bengali	**Barisal**	200	0.7038	0.7089	0.7176	0.7266
	Dhakaiya	200	0.7876	0.8006	0.7969	0.8012
	Jessore	200	0.8226	0.8395	0.8332	0.8365
	Khulna	200	0.8121	0.8193	0.8241	0.8295
	Kushtia	200	0.7922	0.7992	0.8144	0.8132
Central Kurdish	**Ardalani**	300	0.7373	0.7577	0.7407	0.7330
	Mukryani	300	0.7994	0.8189	0.8077	0.7965
French	**Occitan**	379	0.7050	0.7400	0.7425	0.5439
Greek	**Griko**	163	0.4877	0.4969	0.4964	0.5065
Tigrinya	**Ethiopian**	3071	0.8017	0.8232	0.8173	0.8245
	Eritrean	3071	0.7782	0.7998	0.7972	0.8039

Table 5: COMET score of different languages' dialects.

cellu et al., 2014) and French (Garcia and Firat, 2022). In this regard, one of the main challenges is to find possible sources of translation and create corpora and datasets for the translation of varieties and dialects (Zampieri et al., 2020). In the same vein, exploring the translation of varieties in a few-short or zero-shot setting has received attention (Riley et al., 2022). Similarly, fine-tuning translation models trained on closely-related languages has been proposed as a remedy (Kumar et al., 2021).

Given that there is currently no benchmark for the existing data on MT of dialects and varieties, our paper aims to provide one with the sole objective of evaluating varieties and the performance and resilience of MT models to dialectal variations. We also believe that this work will increase awareness

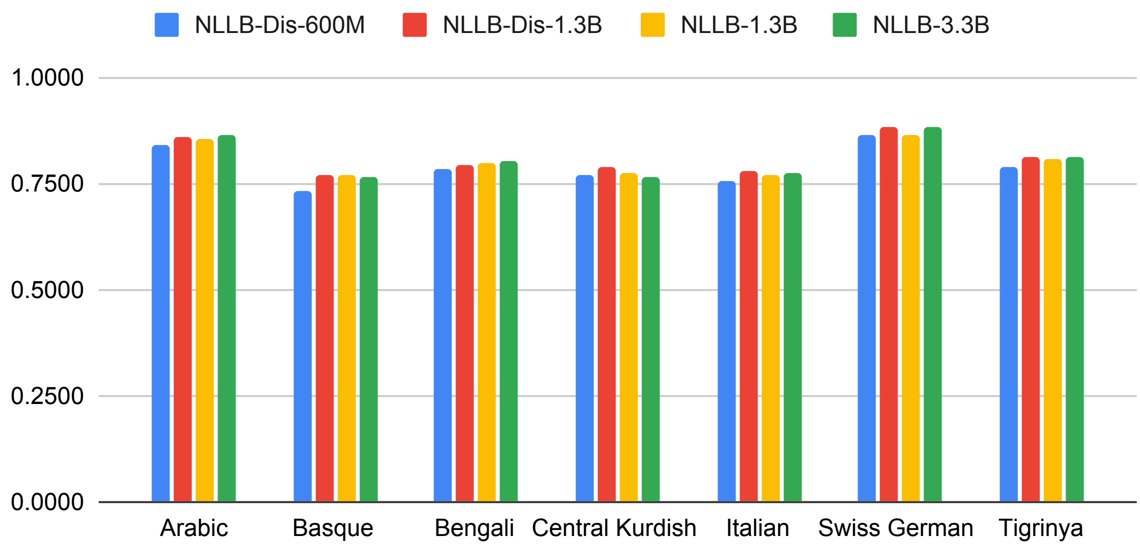

Figure 5: Average COMET score of all the dialects of languages with more than one variety.

regarding this task and motivate future efforts.

6 Conclusion

This study compiles a benchmark of contrastive examples between standard and dialectal variants of nine languages, to facilitate the evaluation of MT systems' robustness along this variation. Our findings demonstrate that MT systems excel at handling standard variants, but as the dialectal varieties start differing from the standard, the quality of the translations declines. In essence, this work emphasizes the need for further research and development in dialectal MT. Excluding a significant portion of the population from the benefits of language transition cannot be considered a satisfactory solution, underscoring the importance of addressing dialectal variations within MT systems.

Future Work This study highlights the unequal support for different language dialects within machine translation (MT) systems. Some dialects exhibit impressive COMET scores due to their close relationship with the standard variant. However, this work primarily focuses on creating a dataset to assess the performance of various dialects rather than conducting experiments on strategies to enhance the MT system's robustness to those dialects. This limitation primarily stems from the scarcity of training data. The datasets created for this study are relatively small and mainly serve as test data.

For future research, the MT community needs to prioritize the development of training datasets for dialects. With an adequate dataset, several strategies can be explored, such as dialect-specific adaptation through finetuning or phylogeny-based adapter approaches (Alam and Anastasopoulos, 2022). This approach could leverage the similarities between dialects, offering a potential solution to improve the translation quality for dialects within the MT system.

Limitations

One of the major limitations of our study is the lack of a qualitative analysis of various lexical and morphosyntactic variations among dialects and varieties that may affect machine translation. Moreover, some of the selected languages, like Kurdish being spoken in different countries, deal with code-switching phenomena more prevalently than others due to socio-linguistic factors. In the same vein, standard orthographies, if existent for a language, implicitly create a bias in transcription and inaccuracy in the translation of vernaculars. Since this is not peculiar to the selected languages or even less-resourced ones, we believe that it may have an effect on machine translation systems. Analyzing all these factors should be addressed in the future.

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A Appendix

German	
Standard	Einst stritten sich Nordwind und Sonne, wer von ihnen beiden wohl der Stärkere wäre, als ein Wanderer, der in einen warmen Mantel gehüllt war, des Weges daherkam.
Saxony	Eema' ham sisch dor Nordwind und de Sonne geschdridden, währ vunn deen beeden dor Schdärgre is, als ä Wandror, där nen wahrm Manddl anhadde, däs Wägs gohm.
Danube Bavarian	Amoi håbn si die Sunn und da Nurdwind gstrittn wea von de beidn woi da Sterkare warat, wia pletzlich a Wåndara mit aan woamen Måntl vurbeikemma is.
Standard	Sie wurden einig, dass derjenige für den Stärkeren gelten sollte, der den Wanderer zwingen würde, seinen Mantel abzunehmen.
Saxony	Se einischdn sisch druff, dass där dor Schdärgre is, där's schaffd, dähm Gerl d'n Manndl abzunähm.
Danube Bavarian	Då saan se de beidn einig wuarn, dås derjenige da Sterkare is, der in Wåndara sein Måntel wegnehma kåa.
Standard	Der Nordwind blies mit aller Macht, aber je mehr er blies, desto fester hüllte sich der anderer in seinen Mantel ein.
Saxony	Dor Nordwind blies so schdarg wie'r gunnde, aber je märer bließ, desdo gramfhafder mummelde sisch dor Wandror in sei Manndl ein.
Danube Bavarian	Da Nurdwind håt mit ålla Kråft blåsn, aber je mehr a blåsn håt, desto festa håt si der Wåndara sein Måntel zuazoogn.
Norwegian	
Standard	Noravinn og sola krangla om kem av dæm som va den stærkaste.
Eastern	Nordavinden og sola krangla om hvem av dem som var den sterkeste.
Setesdal	Nórdavinden å sólí drógest om kvæ som vår' sterkast'e då der kåm enn mann'e gangandi, mæ a tykk frakke på si.
Southwestern	Nordavinden og sole krangla om kem så va den sterkaste.
Standard	Da kom det en mann gåanes me en varm frakk på sæ.
Eastern	Da kom det en mann gåandes med en varm frakk på seg.
Setesdal	Da vurte einige om at den av da som fysst'e greidde å få frakkā av mannæ, sill' reiknast for å vèr' sterkast'e.
Southwestern	Då kom dar en mann gåandes med en varme frakk på seg.
Standard	Di ble enig om at den som først kunne få mann te å ta av sæ frakken skulle gjella for stærkar enn d'n andre.
Eastern	Dem ble enig om at den som først kunne få mannen til å ta av seg frakken skulle regnes som den sterkeste av dem.
Setesdal	Nórdavinden blés så fælt 'an kunna, men ti' mei' 'an blés, ti' mei' nappa mannen att'e frakka sí.
Southwestern	Di blei enige om at den så fysst kunne få mannen te ta av seg frakken sko reknas så den sterkaste av di.

Table A.1: Dialectal inputs in three German and four Norwegian varieties that create the translations of Table2.

Language	# Sentences (common)	# Sentences (coverage)
Arabic	2000	
Basque	0	34
Italian	0	
Swiss German	0	87

Table A.2: The subset of common sentences and those with the highest coverage in all dialects of the indicated languages. Except for Arabic, there is no common sentence for the other languages.

Arabic	**# of Sentences**	**COMET**			
		NLLB-Dis-600M	**NLLB-Dis-1.3B**	**NLLB-1.3B**	**NLLB-3.3B**
Alexandria	2000	0.8655	0.8895	0.8811	0.8947
Baghdad	2000	0.8445	0.8649	0.8595	0.8711
Doha	12000	0.8380	0.8572	0.8509	0.8588
Benghazi	2000	0.8336	0.8496	0.8452	0.8520
Khartoum	2000	0.8488	0.8656	0.8626	0.8695
Sfax	2000	0.7815	0.8015	0.7990	0.8010
Muscat	2000	0.8639	0.8839	0.8790	0.8855
Mosul	2000	0.8430	0.8649	0.8619	0.8753
Riyadh	2000	0.8859	0.9011	0.8966	0.9028
Sanaa	2000	0.8452	0.8704	0.8633	0.8733
Aswan	2000	0.8496	0.8736	0.8680	0.8800
Algiers	2000	0.8162	0.8330	0.8276	0.8357
Tripoli	2000	0.8271	0.8406	0.8380	0.8465
Jeddah	2000	0.8420	0.8653	0.8615	0.8683
Rabat	12000	0.8181	0.8366	0.8318	0.8418
Cairo	12000	0.8578	0.8805	0.8735	0.8839
Jerusalem	2000	0.8450	0.8632	0.8559	0.8666
Beirut	12000	0.8315	0.8553	0.8391	0.8512
Basra	2000	0.8436	0.8640	0.8575	0.8700
Tunis	12000	0.7931	0.8134	0.8061	0.8152
Damascus	2000	0.8457	0.8660	0.8545	0.8686
Salt	2000	0.8569	0.8767	0.8650	0.8772
Fes	2000	0.8594	0.8750	0.8695	0.8769
Aleppo	2000	0.8311	0.8518	0.8389	0.8537
Amman	2000	0.8618	0.8767	0.8683	0.8811

Table A.3: COMET score of different Arabic dialects on all sentences.

Basque	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Ahetze	197	0.8045	0.8058	0.8073	0.8050
Aloze	2	0.8320	0.8701	0.8536	0.7822
Amenduze-Unaso	198	0.8109	0.8111	0.8180	0.8095
Arbona	196	0.8188	0.8032	0.8168	0.8056
Azkaine	198	0.8276	0.8279	0.8314	0.8225
Baigorri	198	0.8009	0.8088	0.8070	0.7961
Barkoxe	198	0.6728	0.7014	0.6904	0.6878
Behorlegi	198	0.8225	0.8151	0.8269	0.8176
Beskoitze	197	0.8156	0.8109	0.8144	0.8174
Bidarrai	198	0.7812	0.7882	0.7949	0.7903
Bidarte	197	0.7955	0.7969	0.7991	0.7968
Donibane-Lohizune	198	0.8009	0.8102	0.8045	0.7980
Ezpeize-Undureine	167	0.6847	0.7124	0.7121	0.6906
Gabadi	196	0.7967	0.7958	0.8018	0.7962
Garruze	198	0.8217	0.8252	0.8215	0.8185
Hazparne	180	0.8445	0.8409	0.8433	0.8302
Heleta	198	0.8084	0.8098	0.8075	0.8013
Hendaia	176	0.8027	0.8143	0.8016	0.8015
Iholdi	198	0.7405	0.7440	0.7473	0.7506
Isturitze	109	0.7875	0.7954	0.7965	0.7922
Itsasu	198	0.7927	0.7994	0.8047	0.7886
Jatsu	198	0.7662	0.7643	0.7608	0.7654
Jutsi	198	0.8165	0.8144	0.8223	0.8171
Larraine	162	0.6540	0.6935	0.6723	0.6686
Larzabale-Arroze-Zibitze	198	0.7966	0.7979	0.7988	0.7993
Luhuso	198	0.8167	0.8278	0.8248	0.8201
Maule-Lextarre	198	0.6703	0.6931	0.6712	0.6802
Mitikile	147	0.7195	0.7391	0.7399	0.7328
Mugerre	198	0.8046	0.8181	0.8017	0.8143
Muskildi	184	0.6946	0.7168	0.7062	0.7007
Pagola	197	0.6633	0.6941	0.6834	0.6873
Sara	198	0.8113	0.8118	0.8161	0.8098
Senpere	198	0.8181	0.8246	0.8086	0.8234
Suhuskune	198	0.7964	0.7868	0.8004	0.7975
Uharte-Garazi	198	0.7964	0.7868	0.8004	0.7975
Urdinarbe	217	0.6857	0.7088	0.6897	0.6966
Urepele	197	0.7831	0.7838	0.7873	0.7832
Urruna	197	0.8591	0.8523	0.8593	0.8480
Ziburu	237	0.8263	0.8255	0.8296	0.8236

Table A.4: COMET score of different Basque dialects on all sentences.

Basque	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Ahetze	34	0.7602	0.7890	0.7890	0.7776
Amenduze-Unaso	34	0.7455	0.7776	0.7948	0.7850
Arbona	34	0.8037	0.8099	0.8154	0.8091
Azkaine	34	0.7943	0.8164	0.8387	0.8039
Baigorri	34	0.7588	0.7951	0.7860	0.7624
Barkoxe	34	0.6306	0.7092	0.6906	0.6852
Behorlegi	34	0.7510	0.7785	0.8006	0.7853
Beskoitze	34	0.7793	0.8046	0.8129	0.8158
Bidarrai	34	0.7240	0.7637	0.7646	0.7678
Bidarte	34	0.7745	0.7740	0.7907	0.7983
Donibane-Lohizune	34	0.7536	0.7988	0.7838	0.7765
Ezpeize-Undureine	34	0.5928	0.6883	0.6702	0.6611
Gabadi	34	0.7494	0.7885	0.7752	0.7836
Garruze	34	0.7984	0.8195	0.7958	0.7977
Hazparne	34	0.8165	0.8394	0.8423	0.8256
Heleta	34	0.7883	0.7938	0.8046	0.7899
Hendaia	34	0.7981	0.8544	0.8320	0.8336
Iholdi	34	0.6771	0.7252	0.7281	0.7374
Isturitze	34	0.7444	0.7801	0.7847	0.7864
Itsasu	34	0.7392	0.7789	0.7787	0.7657
Jatsu	34	0.7299	0.7737	0.7727	0.7912
Jutsi	34	0.7735	0.8157	0.8024	0.7899
Larraine	34	0.5854	0.6722	0.6681	0.6678
Larzabale-Arroze-Zibitze	34	0.7818	0.7826	0.8028	0.8034
Luhuso	34	0.8036	0.8284	0.8008	0.8131
Maule-Lextarre	34	0.5896	0.6686	0.6406	0.6616
Mitikile	34	0.5998	0.6989	0.7146	0.6953
Mugerre	34	0.7605	0.8028	0.7861	0.7907
Muskildi	34	0.6391	0.7022	0.6914	0.6856
Pagola	34	0.6116	0.6764	0.6762	0.6778
Sara	34	0.7675	0.7962	0.7904	0.7916
Senpere	34	0.7826	0.7939	0.7668	0.7797
Suhuskune	34	0.7526	0.7714	0.7845	0.7634
Uharte-Garazi	34	0.7526	0.7714	0.7845	0.7634
Urdinarbe	34	0.6141	0.6961	0.6967	0.6980
Urepele	34	0.7125	0.7452	0.7528	0.7441
Urruna	34	0.8268	0.8386	0.8506	0.8444
Ziburu	34	0.7940	0.8160	0.8341	0.8055

Table A.5: Comparable COMET score of different Basque dialects on a subset of 34 sentences.

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Albosaggia	268	0.6218	0.6954	0.7058	0.7132	0.7209
Aldeno	1448	0.7473	0.8199	0.8426	0.8390	0.8434
Altare	292	0.5701	0.6370	0.6748	0.6659	0.6764
Arcola	305	0.6846	0.7438	0.7672	0.7721	0.7805
Arenzano	304	0.6004	0.6926	0.7294	0.7118	0.7239
Ne	286	0.6130	0.7384	0.7704	0.7489	0.7733
Bergantino	570	0.6291	0.6981	0.7226	0.7134	0.7142
Bologna	294	0.5697	0.6386	0.6637	0.6473	0.6667
Bondeno	274	0.6211	0.7259	0.7443	0.7439	0.7447
Borgofranco d'Ivrea	107	0.6202	0.7200	0.7564	0.7413	0.7386
Borgomanero	234	0.6007	0.6707	0.7101	0.6844	0.6962
Calizzano	302	0.6565	0.7018	0.7347	0.7318	0.7380
Casalmaggiore	94	0.6137	0.6870	0.7136	0.6969	0.7212
Casarza Ligure	289	0.6257	0.7356	0.7673	0.7511	0.7621
Villa Lagarina	107	0.7642	0.8342	0.8800	0.8627	0.8594
Cencenighe Agordino	292	0.6289	0.7198	0.7522	0.7440	0.7481
Cesena	304	0.6027	0.6770	0.7082	0.6937	0.7115
Cicagna	291	0.5936	0.7082	0.7384	0.7317	0.7344
Cividale del Friuli	296	0.6059	0.7086	0.7337	0.7244	0.7563
Colle di Val d'Elsa	255	0.8325	0.8320	0.8580	0.8478	0.8569
Comano	288	0.6454	0.7226	0.7416	0.7451	0.7564
Farra di Soligo	567	0.7573	0.8184	0.8432	0.8396	0.8399
Favale di Malvaro	286	0.6499	0.7414	0.7578	0.7450	0.7532
Finale Ligure	302	0.6141	0.6953	0.7365	0.7157	0.7300
Firenze	305	0.9090	0.9230	0.9281	0.9239	0.9309
Forlì	293	0.6141	0.6985	0.7209	0.7148	0.7153
La Spezia	305	0.6560	0.7270	0.7613	0.7581	0.7688
Lecco	304	0.6197	0.7445	0.7653	0.7589	0.7681
Longare	151	0.7146	0.8008	0.8250	0.8318	0.8177
Malonno	304	0.6179	0.6824	0.7146	0.7174	0.7156
Mantova	107	0.6122	0.7212	0.7417	0.7418	0.7420
Venezia	459	0.7540	0.8435	0.8647	0.8558	0.8608
Milano	911	0.6173	0.7362	0.7608	0.7612	0.7719
Moimacco	305	0.6428	0.7386	0.7587	0.7601	0.7765
Moncalieri	107	0.5986	0.7149	0.7569	0.7275	0.7295
Mondovì	111	0.6225	0.6861	0.7089	0.7019	0.7150
Monno	304	0.5998	0.6603	0.6993	0.6833	0.7100
Sover	107	0.7606	0.8299	0.8494	0.8563	0.8552
Motta di Livenza	305	0.7594	0.8405	0.8620	0.8583	0.8586
Novi Ligure	33	0.5701	0.6275	0.6503	0.6404	0.6732
Imperia	277	0.6494	0.7421	0.7772	0.7500	0.7782
Padova	1773	0.7533	0.8285	0.8486	0.8473	0.8497
Palazzolo dello Stella	107	0.5510	0.7098	0.7277	0.7344	0.7370
Palmanova	107	0.7584	0.8580	0.8910	0.8788	0.8775
Poirino	302	0.6107	0.6864	0.7089	0.7029	0.7167
Pontinvrea	304	0.6392	0.6965	0.7333	0.7209	0.7288
Pramaggiore	305	0.7784	0.8340	0.8604	0.8583	0.8499
Chiomonte	444	0.5139	0.6424	0.6455	0.6397	0.6549
Fontanigorda	290	0.6507	0.7696	0.8035	0.7815	0.7902
Remanzacco	305	0.6064	0.6951	0.7207	0.7201	0.7381
Rimini	107	0.6020	0.6801	0.7024	0.6839	0.7141
Riomaggiore	305	0.6245	0.7263	0.7638	0.7544	0.7528
Chieri	291	0.6204	0.6858	0.7168	0.7056	0.7145
Rivarossa	107	0.6197	0.7207	0.7539	0.7343	0.7505
Prali	291	0.5476	0.6665	0.6746	0.6741	0.6859
Rovereto	107	0.7706	0.8489	0.8723	0.8698	0.8548
Salzano	374	0.7187	0.8297	0.8515	0.8476	0.8491
San Michele al Tagliamento	885	0.6457	0.7382	0.7596	0.7557	0.7585
Scorzè	107	0.7627	0.8262	0.8627	0.8585	0.8548
Selva di Val Gardena	203	0.5652	0.6430	0.6712	0.6676	0.6632
Tezze sul Brenta	304	0.7396	0.8245	0.8475	0.8416	0.8384
Torino	1484	0.6348	0.7135	0.7493	0.7377	0.7435
Trecate	107	0.5553	0.6102	0.6357	0.6196	0.6540

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Treviso	107	0.7397	0.8254	0.8629	0.8476	0.8517
Montecchio Maggiore	127	0.7650	0.8364	0.8633	0.8576	0.8567
Amblar	127	0.6629	0.7417	0.7620	0.7638	0.7687
Andreis	127	0.6368	0.7156	0.7507	0.7189	0.7439
Aquileia	198	0.6151	0.7236	0.7421	0.7437	0.7457
Arsiero	184	0.7514	0.8455	0.8704	0.8675	0.8697
Bagnolo San Vito	185	0.6133	0.7147	0.7249	0.7214	0.7396
Barcis	127	0.6749	0.7417	0.7607	0.7631	0.7621
Biancavilla	199	0.7619	0.8461	0.8575	0.8485	0.8493
Borghetto di Vara	197	0.6834	0.7667	0.7828	0.7729	0.7870
Corte Franca	889	0.6489	0.6964	0.7163	0.7087	0.7150
Borgo San Martino	198	0.5918	0.6809	0.7174	0.7003	0.7078
Bormio	269	0.5800	0.6929	0.7379	0.7232	0.7364
Bovolone	127	0.7650	0.8233	0.8389	0.8394	0.8373
Noale	254	0.7593	0.8227	0.8445	0.8344	0.8402
Brione	195	0.6705	0.7475	0.7732	0.7676	0.7775
Cairo Montenotte	198	0.6614	0.7160	0.7416	0.7278	0.7382
Calalzo di Cadore	152	0.7259	0.7766	0.8000	0.7924	0.7967
Calcinate	127	0.6142	0.6728	0.6718	0.6830	0.6935
Caldogno	127	0.7682	0.8295	0.8427	0.8357	0.8381
Asti	127	0.6872	0.7261	0.7430	0.7409	0.7469
Camisano Vicentino	127	0.7431	0.8145	0.8506	0.8443	0.8490
Brugine	126	0.7429	0.8324	0.8334	0.8418	0.8342
Carcare	198	0.6673	0.7178	0.7572	0.7562	0.7630
Carmignano di Brenta	442	0.7205	0.8014	0.8158	0.8146	0.8141
Carpi	183	0.6026	0.6891	0.7214	0.7072	0.7225
Carrara	199	0.5266	0.6528	0.6748	0.6736	0.6809
Campitello di Fassa	392	0.6368	0.7121	0.7364	0.7384	0.7374
Cesiomaggiore	184	0.7582	0.8285	0.8513	0.8506	0.8438
Chiavari	382	0.6573	0.7689	0.7948	0.7809	0.7908
Chies d'Alpago	199	0.7700	0.8170	0.8397	0.8311	0.8443
Chioggia	155	0.7562	0.8462	0.8687	0.8674	0.8680
Cimolais	127	0.6620	0.7202	0.7316	0.7233	0.7425
Belluno	227	0.7212	0.7614	0.7941	0.7826	0.7915
Claut	126	0.6583	0.7108	0.7362	0.7434	0.7497
Forni Avoltri	188	0.5309	0.6681	0.6924	0.6698	0.6981
Colognola ai Colli	127	0.7315	0.7773	0.7857	0.7919	0.7801
Cordenons	183	0.6631	0.7462	0.7544	0.7630	0.7683
Corvara in Badia/Corvara	347	0.5774	0.6726	0.6995	0.6860	0.6838
Due Carrare	381	0.7513	0.8277	0.8461	0.8485	0.8527
Erto e Casso	127	0.6359	0.6751	0.7019	0.6828	0.7194
Cittadella	254	0.7463	0.8190	0.8451	0.8423	0.8423
Falcade	153	0.6641	0.7071	0.7305	0.7266	0.7328
Sernaglia della Battaglia	127	0.7291	0.8012	0.8113	0.8081	0.8263
Ferrara	543	0.6014	0.6895	0.7046	0.7055	0.7049
Sondalo	270	0.6289	0.7150	0.7364	0.7511	0.7409
Galliera Veneta	254	0.7480	0.8160	0.8361	0.8324	0.8382
Gazzo	127	0.7261	0.7853	0.8093	0.7968	0.8072
Arcole	127	0.7208	0.7932	0.8221	0.8108	0.8186
Montegaldella	127	0.7590	0.8393	0.8479	0.8383	0.8430
Gorizia	387	0.6525	0.7415	0.7800	0.7649	0.7805
Gradara	153	0.6388	0.7116	0.7222	0.7258	0.7158
Grosio	211	0.6086	0.7485	0.7680	0.7561	0.7772
Illasi	390	0.7029	0.7802	0.7990	0.7929	0.7995
Iseo	1016	0.6513	0.7108	0.7346	0.7252	0.7263
Jesolo	198	0.7562	0.8270	0.8374	0.8411	0.8434
Lamon	154	0.6957	0.7563	0.7822	0.7831	0.7748
Rocca Pietore	391	0.6500	0.7058	0.7269	0.7279	0.7294
Albignasego	127	0.7398	0.8125	0.8338	0.8262	0.8329
Livigno	301	0.5871	0.6750	0.6902	0.6826	0.7005
Lonato del Garda	198	0.6331	0.7255	0.7589	0.7556	0.7442
Sandrigo	127	0.7650	0.8443	0.8603	0.8479	0.8506

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Luzzara	127	0.6210	0.6771	0.6869	0.6821	0.7054
Marostica	326	0.7271	0.8047	0.8283	0.8239	0.8247
Maserà di Padova	127	0.7527	0.8239	0.8394	0.8464	0.8471
Mason Vicentino	199	0.7272	0.8074	0.8441	0.8331	0.8311
Arsiè	308	0.7072	0.7742	0.8055	0.8042	0.8105
Mirano	853	0.7695	0.8380	0.8589	0.8529	0.8549
Monselice	127	0.7483	0.8248	0.8367	0.8362	0.8312
Montecchio Precalcino	127	0.7617	0.8284	0.8338	0.8282	0.8341
Montereale Valcellina	126	0.6577	0.7413	0.7538	0.7595	0.7599
Nimis	153	0.5986	0.6943	0.7285	0.7217	0.7671
Tassullo	152	0.6590	0.7412	0.7668	0.7640	0.7640
Ortisei/St. Ulrich	33	0.5974	0.6730	0.6505	0.6623	0.6602
Osimo	126	0.7491	0.8033	0.8190	0.8086	0.8287
Comelico Superiore	199	0.5796	0.6753	0.7107	0.6941	0.7007
Vodo Cadore	153	0.6713	0.7341	0.7595	0.7548	0.7713
Pianiga	508	0.7643	0.8241	0.8443	0.8368	0.8404
Piove di Sacco	379	0.7537	0.8344	0.8470	0.8500	0.8514
Pozza di Fassa	75	0.6365	0.7202	0.7049	0.7241	0.7064
Pieve di Cadore	351	0.7120	0.7662	0.7983	0.7908	0.7993
Angrogna	40	0.6083	0.6932	0.6664	0.6969	0.7055
Puos d'Alpago	199	0.7381	0.7958	0.8140	0.8154	0.8151
Reana del Rojale	247	0.6138	0.7309	0.7542	0.7391	0.7578
Quinto Vicentino	127	0.7666	0.8395	0.8442	0.8446	0.8415
Redondesco	393	0.6111	0.7052	0.7297	0.7299	0.7214
Revò	127	0.6594	0.7329	0.7515	0.7526	0.7462
Romano d'Ezzelino	199	0.7656	0.8474	0.8705	0.8524	0.8609
Ronzone	254	0.6661	0.7337	0.7451	0.7645	0.7514
Rovigo	184	0.7855	0.8500	0.8786	0.8696	0.8785
Rovolon	184	0.7605	0.8393	0.8527	0.8515	0.8529
Badia/Abtei	153	0.6068	0.6895	0.7206	0.7186	0.7169
San Martino di Lupari	1016	0.7448	0.8194	0.8377	0.8306	0.8324
San Pietro in Gu	453	0.7403	0.8183	0.8455	0.8347	0.8363
Santa Maria di Sala	845	0.7623	0.8272	0.8463	0.8425	0.8434
Savona	197	0.6238	0.7518	0.7799	0.7667	0.7900
Samolaco	199	0.5184	0.6388	0.6634	0.6747	0.6817
Schio	127	0.7303	0.8245	0.8478	0.8429	0.8341
Selvazzano Dentro	127	0.7468	0.8195	0.8416	0.8483	0.8322
Valdidentro	250	0.6609	0.7356	0.7532	0.7482	0.7472
Solesino	127	0.7747	0.8379	0.8578	0.8513	0.8353
Calasetta	232	0.5135	0.6465	0.6885	0.6835	0.6751
Taggia	198	0.7107	0.7856	0.8086	0.8006	0.8119
Taglio di Po	374	0.6952	0.7832	0.7863	0.7840	0.7907
Teglio Veneto	198	0.6639	0.7722	0.7850	0.7669	0.7920
Teolo	127	0.7391	0.8104	0.8292	0.8428	0.8350
Pieve d'Alpago	184	0.7593	0.8055	0.8366	0.8291	0.8214
Tollegno	153	0.6083	0.7028	0.7160	0.7092	0.7195
Treia	126	0.7318	0.7789	0.7963	0.8010	0.8011
Triggiano	199	0.5890	0.6631	0.7206	0.6898	0.7067
Valdagno	154	0.7634	0.8228	0.8545	0.8491	0.8389
Valfurva	479	0.6489	0.7317	0.7536	0.7485	0.7523
Vallarsa	149	0.7293	0.8143	0.8333	0.8299	0.8200
Verona	184	0.7453	0.8251	0.8390	0.8288	0.8378
Vicenza	226	0.7633	0.8369	0.8563	0.8408	0.8461
Vidor	226	0.7607	0.8315	0.8415	0.8380	0.8508
Villa di Chiavenna	185	0.5199	0.6785	0.6960	0.6983	0.7022
Stazzona	241	0.5904	0.7407	0.7599	0.7511	0.7570
Villafranca Padovana	113	0.7330	0.8232	0.8490	0.8447	0.8325
Villaverla	113	0.7623	0.8168	0.8507	0.8334	0.8355
Villorba	144	0.6997	0.8177	0.8355	0.8339	0.8396
Zero Branco	113	0.7437	0.8253	0.8480	0.8344	0.8426

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Correzzola	122	0.7767	0.8450	0.8570	0.8594	0.8692
Agugliaro	11	0.7494	0.8134	0.8253	0.8239	0.8457
Vittorio Veneto	56	0.7933	0.8322	0.8561	0.8640	0.8768
Ariano Irpino	218	0.6570	0.7970	0.8180	0.8154	0.8051
Avellino	1088	0.6058	0.7226	0.7509	0.7293	0.7375
Bari	107	0.6520	0.7072	0.7322	0.7242	0.7321
Bitti	218	0.5791	0.6624	0.6951	0.6767	0.6926
Castrignano del Capo	218	0.6701	0.7549	0.7703	0.7518	0.7724
Catania	762	0.6482	0.7615	0.7730	0.7632	0.7708
Corigliano d'Otranto	214	0.7370	0.8081	0.8267	0.8149	0.8213
Corleone	218	0.7068	0.8064	0.8277	0.8246	0.8257
Cosenza	109	0.6327	0.7708	0.7876	0.7781	0.7864
Crotone	218	0.5663	0.7157	0.7635	0.7366	0.7291
Gallipoli	218	0.6493	0.7258	0.7548	0.7401	0.7486
Laino Castello	109	0.7335	0.8044	0.8150	0.8001	0.8027
Locorotondo	215	0.5814	0.6781	0.7007	0.7016	0.6929
Locri	195	0.6904	0.7886	0.8033	0.8052	0.8068
Macerata	217	0.6930	0.7814	0.8199	0.8050	0.8146
Marcianise	218	0.7822	0.8393	0.8464	0.8454	0.8495
Melfi	108	0.4740	0.7297	0.7855	0.7696	0.7647
Messina	654	0.6683	0.7937	0.8154	0.8056	0.8027
Molfetta	1524	0.6239	0.6891	0.7093	0.6992	0.7016
Monasterace	436	0.6655	0.7675	0.7926	0.7781	0.7846
Montella	217	0.7004	0.7599	0.7665	0.7523	0.7725
Ortelle	218	0.6944	0.7836	0.8021	0.7997	0.8000
Ossi	217	0.6271	0.7209	0.7440	0.7423	0.7431
Paciano	218	0.8516	0.8703	0.8822	0.8718	0.8817
Palermo	1048	0.6336	0.7334	0.7592	0.7551	0.7444
Papasidero	108	0.6486	0.7621	0.8087	0.7888	0.7823
Pennapiedimonte	109	0.3908	0.6113	0.6781	0.6387	0.6599
Posada	216	0.5834	0.6889	0.7181	0.7167	0.7136
San Cesario di Lecce	216	0.7471	0.7990	0.8260	0.8138	0.8178
San Marco in Lamis	364	0.7139	0.7736	0.7886	0.7964	0.7909
San Martino in Pensilis	50	0.4177	0.6113	0.6813	0.6888	0.6990
Sciacca	78	0.7356	0.7745	0.7989	0.7780	0.7917
Terravecchia	146	0.5984	0.7332	0.7579	0.7474	0.7591
Trepuzzi	177	0.6702	0.7281	0.7539	0.7412	0.7406
Trevico	218	0.6588	0.7362	0.7453	0.7466	0.7498
Troina	2174	0.6887	0.7924	0.8090	0.7991	0.8031
Venosa	218	0.5879	0.6840	0.7023	0.7127	0.6928
Santa Cesarea Terme	108	0.6852	0.7477	0.7578	0.7589	0.7737
Termoli	76	0.7099	0.7574	0.7844	0.7591	0.7662
Tricase	109	0.6965	0.7714	0.7872	0.7789	0.7610
Capurso	159	0.4442	0.6721	0.7348	0.7242	0.7217
Lesina	177	0.4330	0.7151	0.7795	0.7656	0.7629
Bagnoregio	194	0.8065	0.8371	0.8504	0.8438	0.8581
Campi Salentina	104	0.6995	0.7689	0.7973	0.7672	0.7857
Campobasso	103	0.6206	0.7231	0.7426	0.7073	0.7315
Cardito	502	0.5173	0.7105	0.7564	0.7505	0.7633
Carosino	103	0.6615	0.7293	0.7565	0.7157	0.7498
Castiglione Messer Marino	101	0.5652	0.6345	0.6836	0.6333	0.6579
Copertino	93	0.6701	0.6887	0.7372	0.7014	0.7299
Cutrofiano	104	0.6672	0.7325	0.7674	0.7403	0.7528
Faggiano	104	0.6673	0.7357	0.7562	0.7314	0.7415
Francavilla Fontana	104	0.6736	0.7264	0.7498	0.7154	0.7624
Gragnano	102	0.6010	0.6961	0.7234	0.6917	0.7035
Grottaglie	104	0.6526	0.7050	0.7469	0.7026	0.7366
Iglesias	104	0.5972	0.6776	0.7122	0.6797	0.6898
Lanciano	104	0.6028	0.7301	0.7529	0.7334	0.7480
L'Aquila	96	0.7356	0.7632	0.7799	0.7746	0.7703
Lecce	206	0.6852	0.7590	0.7865	0.7597	0.7621
Liscia	95	0.4443	0.6048	0.6367	0.6236	0.6303

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Lubriano	96	0.7452	0.7883	0.8033	0.7904	0.7980
Maglie	102	0.7212	0.7843	0.8233	0.8071	0.7984
Civitanova Marche	95	0.8129	0.8387	0.8424	0.8372	0.8506
Martina Franca	103	0.5450	0.6082	0.6240	0.6116	0.6123
Trieste	637	0.7718	0.8510	0.8703	0.8578	0.8689
Trissino	234	0.7560	0.8370	0.8696	0.8661	0.8593
Vallecrosia	304	0.6358	0.7324	0.7655	0.7475	0.7636
Vaprio d'Adda	220	0.6028	0.6963	0.7068	0.7006	0.7077
Vione	107	0.6159	0.6889	0.7286	0.7325	0.7307
Alassio	127	0.6924	0.7542	0.7747	0.7708	0.7724
Alba	128	0.6069	0.7144	0.7347	0.7288	0.7217
Altavilla Vicentina	198	0.7514	0.8182	0.8530	0.8514	0.8478
Martinsicuro	101	0.4688	0.6454	0.7070	0.6871	0.6933
Massafra	104	0.6091	0.6817	0.6730	0.6915	0.6731
Mazara del Vallo	104	0.6471	0.7314	0.7504	0.7495	0.7432
Monteiasi	208	0.6539	0.7128	0.7485	0.7013	0.7375
Monteroni di Lecce	95	0.7016	0.7291	0.7457	0.7305	0.7374
Monterotondo	78	0.8446	0.8797	0.8837	0.8912	0.9018
Morolo	95	0.8095	0.8265	0.8304	0.8260	0.8434
Mussomeli	104	0.6454	0.7525	0.7809	0.7538	0.7649
Napoli	100	0.5049	0.6871	0.7357	0.7190	0.7408
Nardò	103	0.6903	0.7576	0.7720	0.7397	0.7471
Orvieto	85	0.8006	0.8515	0.8622	0.8489	0.8574
Pescara	104	0.5258	0.7069	0.7611	0.7348	0.7420
Pianella	967	0.5875	0.7114	0.6724	0.6982	0.6993
Ragusa	80	0.5543	0.6769	0.6993	0.6592	0.6894
Roma	63	0.7994	0.8359	0.8387	0.8501	0.8576
Salerno	80	0.5654	0.6721	0.6821	0.6633	0.6669
San Valentino in Abruzzo Citeriore	108	0.5562	0.6585	0.6817	0.6732	0.7005
Sinagra	79	0.6447	0.7576	0.7896	0.7757	0.7610
Soleto	80	0.7362	0.7889	0.8173	0.7882	0.7929
Squinzano	79	0.6712	0.7403	0.7575	0.7266	0.7298
Taranto	80	0.6212	0.6799	0.6816	0.6766	0.6522
Torre del Greco	158	0.5032	0.7053	0.7505	0.7396	0.7420
Villacidro	78	0.5875	0.6642	0.6686	0.6591	0.6939
Sutrio	3	0.5225	0.7665	0.7952	0.8134	0.8578
Lizzano	1	0.5552	0.7724	0.6567	0.7650	0.7241
Abano Terme	3	0.8638	0.8676	0.8671	0.8895	0.8891
Udine	2	0.6183	0.5971	0.6708	0.5565	0.6937
Selva di Progno	3	0.4775	0.5217	0.5354	0.5498	0.5672
Luserna	3	0.5484	0.5623	0.5307	0.5497	0.6571
Palù del Fersina	3	0.5072	0.6096	0.5241	0.5473	0.5886
Casale sul Sile	1	0.9824	0.9896	0.9879	0.9896	0.9927

Table A.6: COMET score of different Italian communes on all sentences.

Itlaian	COMET				
	DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Albosaggia	0.6226	0.6966	0.7068	0.7138	0.7234
Aldeno	0.7480	0.8190	0.8422	0.8383	0.8439
Altare	0.5717	0.6393	0.6755	0.6650	0.6778
Arcola	0.6846	0.7449	0.7659	0.7734	0.7796
Arenzano	0.6039	0.6936	0.7280	0.7128	0.7239
Ne	0.6119	0.7339	0.7709	0.7446	0.7691
Bergantino	0.6269	0.6992	0.7181	0.7108	0.7135
Bologna	0.5667	0.6395	0.6643	0.6471	0.6676
Bondeno	0.6198	0.7245	0.7432	0.7416	0.7435
Borgofranco d'Ivrea	0.6214	0.7203	0.7572	0.7447	0.7391
Borgomanero	0.5992	0.6670	0.7071	0.6807	0.6941
Calizzano	0.6621	0.7053	0.7379	0.7349	0.7405
Casalmaggiore	0.6128	0.6838	0.7130	0.6960	0.7187
Casarza Ligure	0.6243	0.7355	0.7670	0.7504	0.7631
Villa Lagarina	0.7628	0.8354	0.8811	0.8641	0.8597
Cencenighe Agordino	0.6288	0.7171	0.7483	0.7418	0.7457
Cesena	0.5907	0.6655	0.6989	0.6823	0.7005
Cicagna	0.5934	0.7073	0.7382	0.7298	0.7333
Cividale del Friuli	0.6067	0.7097	0.7357	0.7224	0.7575
Colle di Val d'Elsa	0.8311	0.8288	0.8550	0.8443	0.8540
Comano	0.6452	0.7241	0.7421	0.7444	0.7563
Farra di Soligo	0.7575	0.8173	0.8441	0.8388	0.8391
Favale di Malvaro	0.6488	0.7432	0.7572	0.7459	0.7553
Finale Ligure	0.6126	0.6915	0.7329	0.7104	0.7272
Firenze	0.9085	0.9227	0.9266	0.9234	0.9302
Forlì	0.6166	0.6967	0.7206	0.7133	0.7137
La Spezia	0.6558	0.7253	0.7588	0.7566	0.7690
Lecco	0.6224	0.7443	0.7650	0.7585	0.7687
Longare	0.7171	0.8018	0.8239	0.8291	0.8162
Malonno	0.6191	0.6797	0.7167	0.7176	0.7172
Mantova	0.6124	0.7220	0.7421	0.7422	0.7417
Venezia	0.7551	0.8437	0.8645	0.8557	0.8607
Milano	0.6199	0.7383	0.7628	0.7655	0.7765
Moimacco	0.6390	0.7351	0.7533	0.7572	0.7741
Moncalieri	0.5986	0.7167	0.7598	0.7294	0.7292
Mondovì	0.6264	0.6890	0.7096	0.7033	0.7163
Monno	0.6008	0.6594	0.7017	0.6850	0.7111
Sover	0.7591	0.8275	0.8457	0.8559	0.8534
Motta di Livenza	0.7602	0.8388	0.8585	0.8563	0.8576
Imperia	0.6475	0.7417	0.7768	0.7483	0.7767
Padova	0.7549	0.8275	0.8485	0.8464	0.8499
Palazzolo dello Stella	0.5528	0.7126	0.7284	0.7354	0.7385
Palmanova	0.7586	0.8578	0.8914	0.8797	0.8764
Poirino	0.6131	0.6886	0.7111	0.7054	0.7180
Pontinvrea	0.6374	0.6948	0.7318	0.7200	0.7289
Pramaggiore	0.7798	0.8336	0.8594	0.8574	0.8500
Chiomonte	0.5121	0.6411	0.6444	0.6391	0.6551
Fontanigorda	0.6510	0.7698	0.8022	0.7828	0.7885
Remanzacco	0.6086	0.6962	0.7190	0.7192	0.7371
Rimini	0.6026	0.6823	0.7050	0.6880	0.7157
Riomaggiore	0.6243	0.7251	0.7645	0.7549	0.7555
Chieri	0.6208	0.6887	0.7163	0.7093	0.7162
Rivarossa	0.6253	0.7241	0.7582	0.7367	0.7529
Prali	0.5471	0.6656	0.6740	0.6720	0.6835

Itlaian	COMET				
	DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Rovereto	0.7717	0.8507	0.8739	0.8725	0.8572
Salzano	0.7228	0.8309	0.8510	0.8483	0.8495
San Michele al Tagliamento	0.6534	0.7436	0.7621	0.7584	0.7616
Scorzè	0.7609	0.8233	0.8615	0.8583	0.8530
Selva di Val Gardena	0.5664	0.6448	0.6731	0.6686	0.6652
Tezze sul Brenta	0.7400	0.8240	0.8440	0.8394	0.8364
Torino	0.6316	0.7139	0.7528	0.7382	0.7465
Trecate	0.5574	0.6133	0.6416	0.6236	0.6560
Treviso	0.7399	0.8242	0.8628	0.8479	0.8525
Trieste	0.7694	0.8488	0.8676	0.8562	0.8662
Trissino	0.7569	0.8357	0.8698	0.8666	0.8611
Vallecrosia	0.6392	0.7336	0.7665	0.7486	0.7619
Vaprio d'Adda	0.6020	0.6951	0.7062	0.7002	0.7069
Vione	0.6171	0.6890	0.7286	0.7317	0.7315
Alassio	0.6923	0.7520	0.7745	0.7700	0.7726
Alba	0.6071	0.7141	0.7331	0.7270	0.7219
Altavilla Vicentina	0.7549	0.8177	0.8515	0.8498	0.8483
Montecchio Maggiore	0.7669	0.8383	0.8646	0.8564	0.8589
Amblar	0.6623	0.7373	0.7577	0.7607	0.7647
Andreis	0.6340	0.7128	0.7476	0.7167	0.7432
Aquileia	0.6134	0.7220	0.7406	0.7423	0.7437
Arsiero	0.7510	0.8437	0.8706	0.8675	0.8710
Bagnolo San Vito	0.6111	0.7114	0.7190	0.7172	0.7360
Barcis	0.6723	0.7387	0.7560	0.7597	0.7604
Biancavilla	0.7570	0.8432	0.8530	0.8445	0.8452
Borghetto di Vara	0.6814	0.7664	0.7823	0.7737	0.7862
Corte Franca	0.6497	0.7013	0.7164	0.7111	0.7170
Borgo San Martino	0.5914	0.6816	0.7190	0.7021	0.7099
Bormio	0.5787	0.6928	0.7385	0.7229	0.7356
Bovolone	0.7645	0.8217	0.8382	0.8358	0.8376
Noale	0.7611	0.8237	0.8456	0.8339	0.8417
Brione	0.6719	0.7460	0.7718	0.7667	0.7781
Cairo Montenotte	0.6597	0.7136	0.7376	0.7272	0.7351
Calalzo di Cadore	0.7260	0.7763	0.7988	0.7919	0.7974
Calcinate	0.6144	0.6737	0.6714	0.6845	0.6974
Caldogno	0.7677	0.8277	0.8440	0.8337	0.8379
Asti	0.6851	0.7250	0.7424	0.7385	0.7454
Camisano Vicentino	0.7453	0.8151	0.8517	0.8435	0.8488
Brugine	0.7444	0.8331	0.8315	0.8412	0.8346
Carcare	0.6680	0.7141	0.7535	0.7541	0.7595
Carmignano di Brenta	0.7331	0.8090	0.8262	0.8199	0.8270
Carpi	0.6020	0.6892	0.7202	0.7054	0.7227
Carrara	0.5239	0.6503	0.6727	0.6724	0.6801
Campitello di Fassa	0.6371	0.7109	0.7350	0.7398	0.7370
Cesiomaggiore	0.7568	0.8264	0.8491	0.8480	0.8431
Chiavari	0.6599	0.7714	0.7974	0.7824	0.7927
Chies d'Alpago	0.7712	0.8181	0.8404	0.8335	0.8455
Chioggia	0.7580	0.8475	0.8682	0.8677	0.8662
Cimolais	0.6565	0.7198	0.7297	0.7206	0.7426
Belluno	0.7029	0.7476	0.7819	0.7661	0.7782
Claut	0.6577	0.7116	0.7372	0.7452	0.7504
Forni Avoltri	0.5290	0.6686	0.6921	0.6676	0.6975
Colognola ai Colli	0.7329	0.7771	0.7854	0.7933	0.7816
Cordenons	0.6603	0.7439	0.7522	0.7613	0.7641
Corvara in Badia/Corvara	0.5767	0.6732	0.6994	0.6859	0.6843
Due Carrare	0.7524	0.8264	0.8463	0.8464	0.8528
Erto e Casso	0.6354	0.6748	0.7003	0.6812	0.7206

Itlaian	COMET				
	DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Cittadella	0.7455	0.8175	0.8455	0.8408	0.8422
Falcade	0.6657	0.7095	0.7326	0.7264	0.7342
Sernaglia della Battaglia	0.7268	0.7978	0.8102	0.8064	0.8285
Ferrara	0.6116	0.7036	0.7163	0.7194	0.7190
Sondalo	0.6281	0.7172	0.7390	0.7525	0.7412
Galliera Veneta	0.7470	0.8158	0.8367	0.8318	0.8396
Gazzo	0.7250	0.7846	0.8110	0.7952	0.8092
Arcole	0.7208	0.7935	0.8218	0.8095	0.8208
Montegaldella	0.7627	0.8365	0.8508	0.8386	0.8454
Gorizia	0.6415	0.7409	0.7770	0.7617	0.7784
Gradara	0.6388	0.7123	0.7216	0.7253	0.7151
Grosio	0.6078	0.7498	0.7666	0.7575	0.7759
Illasi	0.7016	0.7798	0.8000	0.7916	0.7968
Iseo	0.6531	0.7145	0.7351	0.7265	0.7282
Jesolo	0.7572	0.8250	0.8349	0.8386	0.8412
Lamon	0.6934	0.7558	0.7808	0.7821	0.7735
Rocca Pietore	0.6488	0.7056	0.7266	0.7264	0.7271
Albignasego	0.7402	0.8113	0.8360	0.8249	0.8322
Livigno	0.5816	0.6754	0.6921	0.6784	0.6959
Lonato del Garda	0.6349	0.7282	0.7597	0.7550	0.7456
Sandrigo	0.7669	0.8430	0.8607	0.8453	0.8511
Luzzara	0.6221	0.6779	0.6873	0.6826	0.7073
Marostica	0.7282	0.8045	0.8274	0.8221	0.8234
Maserà di Padova	0.7542	0.8235	0.8400	0.8449	0.8483
Mason Vicentino	0.7259	0.8065	0.8417	0.8298	0.8280
Arsiè	0.7065	0.7723	0.8036	0.8023	0.8086
Mirano	0.7703	0.8374	0.8571	0.8503	0.8530
Monselice	0.7504	0.8223	0.8374	0.8335	0.8307
Montecchio Precalcino	0.7618	0.8274	0.8377	0.8295	0.8370
Montereale Valcellina	0.6570	0.7416	0.7545	0.7606	0.7593
Nimis	0.5996	0.6980	0.7306	0.7229	0.7684
Tassullo	0.6615	0.7400	0.7653	0.7607	0.7599
Osimo	0.7502	0.8048	0.8216	0.8109	0.8306
Comelico Superiore	0.5817	0.6742	0.7099	0.6933	0.6995
Vodo Cadore	0.6698	0.7331	0.7573	0.7550	0.7713
Pianiga	0.7637	0.8241	0.8447	0.8360	0.8412
Piove di Sacco	0.7534	0.8347	0.8462	0.8487	0.8517
Pozza di Fassa	0.6381	0.7205	0.7050	0.7252	0.7076
Pieve di Cadore	0.7172	0.7704	0.7996	0.7936	0.8007
Puos d'Alpago	0.7377	0.7940	0.8118	0.8141	0.8151
Reana del Rojale	0.6129	0.7306	0.7538	0.7381	0.7578
Quinto Vicentino	0.7679	0.8386	0.8465	0.8449	0.8439
Redondesco	0.6105	0.7022	0.7268	0.7263	0.7211
Revò	0.6586	0.7320	0.7496	0.7513	0.7431
Romano d'Ezzelino	0.7643	0.8459	0.8687	0.8486	0.8586
Ronzone	0.6626	0.7300	0.7403	0.7612	0.7477
Rovigo	0.7838	0.8492	0.8789	0.8699	0.8792
Rovolon	0.7608	0.8391	0.8534	0.8523	0.8543
Badia/Abtei	0.6108	0.6902	0.7209	0.7181	0.7176
San Martino di Lupari	0.7437	0.8187	0.8385	0.8289	0.8334
San Pietro in Gu	0.7384	0.8167	0.8444	0.8305	0.8349
Santa Maria di Sala	0.7630	0.8277	0.8469	0.8425	0.8441
Savona	0.6235	0.7539	0.7814	0.7684	0.7890
Samolaco	0.5217	0.6423	0.6634	0.6774	0.6850
Schio	0.7303	0.8240	0.8467	0.8417	0.8344

Itlaian	COMET				
	DeltaLM	**NLLB-Dis-600M**	**NLLB-Dis-1.3B**	**NLLB-1.3B**	**NLLB-3.3B**
Selvazzano Dentro	0.7490	0.8178	0.8426	0.8465	0.8331
Valdidentro	0.6587	0.7375	0.7555	0.7494	0.7488
Solesino	0.7757	0.8358	0.8600	0.8503	0.8367
Calasetta	0.5142	0.6494	0.6897	0.6862	0.6756
Taggia	0.7094	0.7870	0.8093	0.8023	0.8109
Taglio di Po	0.6965	0.7822	0.7858	0.7836	0.7909
Teglio Veneto	0.6641	0.7713	0.7829	0.7656	0.7913
Teolo	0.7390	0.8101	0.8296	0.8419	0.8361
Pieve d'Alpago	0.7583	0.8049	0.8351	0.8286	0.8213
Tollegno	0.6104	0.7024	0.7156	0.7115	0.7214
Treia	0.7319	0.7762	0.7957	0.7994	0.7999
Triggiano	0.5882	0.6586	0.7160	0.6848	0.7038
Valdagno	0.7646	0.8217	0.8545	0.8475	0.8381
Valfurva	0.6492	0.7313	0.7555	0.7469	0.7509
Vallarsa	0.7300	0.8130	0.8340	0.8292	0.8196
Verona	0.7445	0.8235	0.8379	0.8267	0.8345
Vicenza	0.7635	0.8346	0.8543	0.8381	0.8437
Vidor	0.7580	0.8285	0.8387	0.8346	0.8482
Villa di Chiavenna	0.5190	0.6802	0.6962	0.6997	0.7036
Stazzona	0.5864	0.7389	0.7566	0.7500	0.7558
Villafranca Padovana	0.7288	0.8213	0.8480	0.8434	0.8320
Villaverla	0.7614	0.8128	0.8461	0.8295	0.8319
Villorba	0.7013	0.8139	0.8308	0.8295	0.8380
Zero Branco	0.7426	0.8225	0.8464	0.8319	0.8401
Correzzola	0.7774	0.8485	0.8582	0.8592	0.8715
Vittorio Veneto	0.7917	0.8298	0.8555	0.8649	0.8767
Ariano Irpino	0.6546	0.7992	0.8190	0.8148	0.8056
Avellino	0.6034	0.7219	0.7511	0.7289	0.7378
Bari	0.6564	0.7082	0.7322	0.7262	0.7327
Bitti	0.5822	0.6628	0.6973	0.6771	0.6946
Castrignano del Capo	0.6694	0.7528	0.7689	0.7491	0.7716
Catania	0.6472	0.7613	0.7728	0.7625	0.7720
Corigliano d'Otranto	0.7331	0.8075	0.8263	0.8135	0.8209
Corleone	0.7080	0.8060	0.8311	0.8241	0.8246
Cosenza	0.6294	0.7708	0.7892	0.7792	0.7872
Crotone	0.5641	0.7165	0.7640	0.7372	0.7283
Gallipoli	0.6518	0.7290	0.7585	0.7431	0.7503
Laino Castello	0.7324	0.8037	0.8141	0.7995	0.8028
Locorotondo	0.5842	0.6784	0.7023	0.7036	0.6964
Locri	0.6919	0.7881	0.8040	0.8048	0.8060
Macerata	0.6914	0.7793	0.8179	0.8043	0.8120
Marcianise	0.7828	0.8411	0.8471	0.8458	0.8504
Melfi	0.4775	0.7318	0.7878	0.7729	0.7672
Messina	0.6684	0.7932	0.8139	0.8024	0.8001
Molfetta	0.6223	0.6870	0.7080	0.6981	0.7022
Monasterace	0.6654	0.7672	0.7947	0.7768	0.7858
Montella	0.6972	0.7597	0.7655	0.7517	0.7725
Ortelle	0.6974	0.7844	0.8055	0.8005	0.8010
Ossi	0.6287	0.7227	0.7452	0.7420	0.7441
Paciano	0.8500	0.8696	0.8818	0.8692	0.8813
Palermo	0.6342	0.7306	0.7571	0.7546	0.7432
Papasidero	0.6504	0.7645	0.8087	0.7904	0.7819
Pennapiedimonte	0.3926	0.6138	0.6808	0.6418	0.6643
Posada	0.5856	0.6904	0.7148	0.7154	0.7150

Itlaian	COMET				
	DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
San Cesario di Lecce	0.7481	0.8000	0.8274	0.8143	0.8181
San Marco in Lamis	0.7022	0.7617	0.7746	0.7848	0.7788
San Martino in Pensilis	0.4193	0.6121	0.6844	0.6908	0.7033
Sciacca	0.7333	0.7744	0.7986	0.7775	0.7911
Terravecchia	0.5993	0.7373	0.7617	0.7517	0.7633
Trepuzzi	0.6663	0.7262	0.7512	0.7376	0.7365
Trevico	0.6577	0.7361	0.7433	0.7466	0.7498
Troina	0.6874	0.7912	0.8078	0.7968	0.8020
Venosa	0.5869	0.6817	0.7024	0.7109	0.6920
Santa Cesarea Terme	0.6853	0.7503	0.7603	0.7607	0.7762
Termoli	0.7107	0.7580	0.7846	0.7623	0.7662
Tricase	0.6949	0.7716	0.7860	0.7806	0.7622
Capurso	0.4462	0.6763	0.7376	0.7271	0.7248
Lesina	0.4325	0.7157	0.7794	0.7637	0.7623
Bagnoregio	0.8077	0.8390	0.8514	0.8445	0.8592
Campi Salentina	0.6986	0.7667	0.7940	0.7648	0.7831
Campobasso	0.6200	0.7205	0.7425	0.7041	0.7321
Cardito	0.5164	0.7089	0.7538	0.7499	0.7625
Carosino	0.6616	0.7296	0.7533	0.7148	0.7452
Castiglione Messer Marino	0.5617	0.6325	0.6805	0.6280	0.6576
Copertino	0.6710	0.6906	0.7378	0.7020	0.7306
Cutrofiano	0.6657	0.7289	0.7635	0.7382	0.7498
Faggiano	0.6666	0.7357	0.7561	0.7312	0.7409
Francavilla Fontana	0.6723	0.7245	0.7479	0.7120	0.7625
Gragnano	0.5968	0.6932	0.7234	0.6872	0.7029
Grottaglie	0.6540	0.7040	0.7469	0.7015	0.7353
Iglesias	0.5955	0.6758	0.7118	0.6780	0.6862
Lanciano	0.5973	0.7290	0.7497	0.7300	0.7455
L'Aquila	0.7293	0.7603	0.7773	0.7707	0.7673
Lecce	0.6833	0.7591	0.7864	0.7593	0.7629
Liscia	0.4427	0.6018	0.6330	0.6218	0.6292
Lubriano	0.7441	0.7876	0.8037	0.7914	0.7985
Maglie	0.7224	0.7860	0.8247	0.8083	0.7999
Civitanova Marche	0.8143	0.8385	0.8410	0.8357	0.8503
Martina Franca	0.5456	0.6068	0.6224	0.6093	0.6097
Martinsicuro	0.4640	0.6435	0.7047	0.6854	0.6911
Massafra	0.6079	0.6811	0.6729	0.6919	0.6737
Mazara del Vallo	0.6471	0.7283	0.7471	0.7466	0.7435
Monteiasi	0.6530	0.7095	0.7472	0.7007	0.7359
Monteroni di Lecce	0.7036	0.7308	0.7453	0.7311	0.7380
Monterotondo	0.8490	0.8825	0.8842	0.8925	0.9026
Morolo	0.8074	0.8228	0.8268	0.8214	0.8404
Mussomeli	0.6468	0.7562	0.7813	0.7568	0.7683
Napoli	0.4984	0.6833	0.7326	0.7162	0.7382
Nardò	0.6885	0.7575	0.7736	0.7425	0.7482
Orvieto	0.7979	0.8526	0.8623	0.8496	0.8565
Pescara	0.5246	0.7046	0.7583	0.7326	0.7383
Pianella	0.5828	0.7100	0.6714	0.6960	0.6983
Ragusa	0.5573	0.6814	0.7011	0.6603	0.6910
Roma	0.7983	0.8341	0.8363	0.8491	0.8577
Salerno	0.5656	0.6697	0.6822	0.6618	0.6661
San Valentino in Abruzzo Citeriore	0.5789	0.6609	0.6851	0.6777	0.7057
Sinagra	0.6446	0.7574	0.7901	0.7754	0.7605
Soleto	0.7405	0.7936	0.8187	0.7917	0.7949
Squinzano	0.6722	0.7424	0.7582	0.7295	0.7313
Taranto	0.6226	0.6795	0.6808	0.6762	0.6516
Torre del Greco	0.5041	0.7054	0.7494	0.7395	0.7417
Villacidro	0.5859	0.6655	0.6688	0.6583	0.6941

Table A.7: Comparable COMET score of different Italian communes.

Italian	# of Sentences	COMET				
		DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Lombardia	8027	0.6209	0.7091	0.7319	0.7281	0.7342
Trentino Alto Adige	3787	0.6871	0.7637	0.7859	0.7845	0.7834
Liguria	5939	0.6404	0.7277	0.7588	0.7467	0.7578
Veneto	21723	0.7330	0.8066	0.8280	0.8234	0.8255
Emilia Romagna	2125	0.6028	0.6854	0.7071	0.6997	0.7091
Piemonte	4264	0.6048	0.6914	0.7179	0.7074	0.7166
Friuli Venezia Giulia	3878	0.6526	0.7439	0.7675	0.7598	0.7760
Toscana	1047	0.7452	0.7943	0.8116	0.8086	0.8174
Sicilia	5500	0.6700	0.7752	0.7941	0.7849	0.7857
Marche	717	0.7140	0.7775	0.7977	0.7923	0.7984
Sardegna	1065	0.5778	0.6779	0.7080	0.6987	0.7031
Puglia	6100	0.6470	0.7236	0.7490	0.7343	0.7401
Campania	2901	0.6083	0.7342	0.7614	0.7483	0.7562
Calabria	1321	0.6469	0.7612	0.7883	0.7746	0.7774
Basilicata	326	0.5502	0.6992	0.7299	0.7315	0.7166
Umbria	303	0.8373	0.8650	0.8766	0.8654	0.8748
Abruzzo	1785	0.5633	0.6920	0.6896	0.6931	0.6997
Molise	229	0.6059	0.7101	0.7431	0.7205	0.7359
Lazio	526	0.8007	0.8324	0.8417	0.8386	0.8509

Table A.8: COMET score of different Italian regions on all sentences.

Italian	COMET				
	DeltaLM	NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Lombardia	0.6257	0.7103	0.7316	0.7278	0.7341
Trentino Alto Adige	0.6826	0.7584	0.7793	0.7805	0.7763
Liguria	0.6445	0.7311	0.7612	0.7495	0.7604
Veneto	0.7400	0.8117	**0.8330**	0.8276	0.8311
Emilia Romagna	0.6034	0.6848	0.7071	0.6981	0.7109
Piemonte	0.6113	0.6969	0.7266	0.7139	0.7231
Friuli Venezia Giulia	0.6456	0.7378	0.7614	0.7537	0.7695
Toscana	0.7272	0.7815	**0.7991**	0.7961	0.8051
Sicilia	0.6627	0.7654	0.7857	0.7758	0.7764
Marche	0.7253	0.7822	**0.7996**	0.7951	0.8016
Sardegna	0.5820	0.6777	0.7046	0.6928	0.7016
Puglia	0.6507	0.7241	0.7493	0.7323	0.7396
Campania	0.5821	0.7235	0.7545	0.7420	0.7511
Calabria	0.6498	0.7644	0.7914	0.7770	0.7801
Basilicata	0.5322	0.7067	0.7451	0.7419	0.7296
Umbria	0.8240	0.8611	**0.8720**	0.8594	0.8689
Abruzzo	0.5622	0.6915	0.6880	0.6915	0.6990
Molise	0.5833	0.6968	0.7372	0.7191	0.7339
Lazio	0.8024	0.8342	**0.8423**	0.8406	0.8529

Table A.9: Comparable COMET score of different Italian regions.

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Aarau,AG	121	0.8734	0.8787	0.8714	0.8882
Aarberg,BE	117	0.8701	0.8772	0.8616	0.8839
Aarburg,AG	118	0.8706	0.8808	0.8663	0.8905
Adelboden,BE	120	0.8686	0.8684	0.8675	0.8829
Aedermannsdorf,SO	115	0.8655	0.8744	0.8591	0.8806
Aesch,BL	118	0.8712	0.8759	0.8688	0.8865
Aeschi,SO	113	0.8624	0.8761	0.8606	0.8799
Agarn,VS	124	0.8584	0.8650	0.8629	0.8713
Alpnach,OW	115	0.8659	0.8799	0.8641	0.8825
Alpthal,SZ	118	0.8721	0.8751	0.8669	0.8814
Altdorf,UR	115	0.8652	0.8808	0.8646	0.8868
Altstätten,SG	121	0.8705	0.8773	0.8705	0.8874
Amden,SG	115	0.8763	0.8876	0.8761	0.8926
Amriswil,TG	115	0.8697	0.8830	0.8699	0.8854
Andelfingen,ZH	116	0.8786	0.8864	0.8712	0.8912
Andermatt,UR	120	0.8658	0.8717	0.8643	0.8866
Andwil,SG	119	0.8709	0.8783	0.8719	0.8851
Appenzell,AI	116	0.8658	0.8804	0.8704	0.8881
Arosa,GR	119	0.8749	0.8761	0.8689	0.8827
Ausserberg,VS	121	0.8657	0.8689	0.8639	0.8806
Avers,GR	117	0.8763	0.8786	0.8715	0.8894
Bäretswil,ZH	118	0.8736	0.8854	0.8694	0.8866
Baldingen,AG	119	0.8794	0.8842	0.8730	0.8858
Basadingen-Schlattingen,TG	118	0.8752	0.8818	0.8727	0.8882
Basel,BS	116	0.8724	0.8853	0.8682	0.8895
Bassersdorf,ZH	124	0.8769	0.8856	0.8753	0.8889
Bauma,ZH	117	0.8760	0.8799	0.8745	0.8905
Belp,BE	115	0.8755	0.8828	0.8690	0.8899
Benken,SG	110	0.8746	0.8875	0.8712	0.8938
Bern,BE	119	0.8688	0.8801	0.8664	0.8874
Berneck,SG	115	0.8701	0.8785	0.8726	0.8812
Betten,VS	119	0.8599	0.8665	0.8612	0.8769
Bettingen,BS	112	0.8714	0.8810	0.8670	0.8892
Bettlach,SO	117	0.8664	0.8715	0.8641	0.8797
Bibern,SH	116	0.8761	0.8763	0.8663	0.8847
Binn,VS	118	0.8659	0.8746	0.8684	0.8825
Birmenstorf,AG	119	0.8777	0.8810	0.8755	0.8926
Birwinken,TG	117	0.8721	0.8854	0.8702	0.8892
Blatten,VS	126	0.8660	0.8680	0.8624	0.8734
Bleienbach,BE	115	0.8710	0.8810	0.8619	0.8849
Boltigen,BE	109	0.8635	0.8699	0.8566	0.8761
Boniswil,AG	115	0.8727	0.8780	0.8717	0.8852
Boswil,AG	118	0.8697	0.8803	0.8696	0.8822
Bottighofen,TG	116	0.8741	0.8850	0.8714	0.8874
Bremgarten,AG	115	0.8760	0.8883	0.8729	0.8917
Brienz,BE	121	0.8714	0.8800	0.8756	0.8877
Brig-Glis,VS	122	0.8608	0.8687	0.8590	0.8780
Rüte,AI	115	0.8669	0.8798	0.8677	0.8875
Brugg,AG	120	0.8745	0.8837	0.8724	0.8955
Brunnadern,SG	118	0.8770	0.8828	0.8698	0.8871
Ingenbohl,SZ	120	0.8709	0.8742	0.8690	0.8862
Buchberg,SH	121	0.8758	0.8835	0.8726	0.8864
Buckten,BL	118	0.8658	0.8678	0.8591	0.8786
Bühler,AR	116	0.8734	0.8818	0.8754	0.8881
Bülach,ZH	121	0.8770	0.8917	0.8763	0.8940
Bürchen,VS	119	0.8638	0.8685	0.8622	0.8803
Büren an der Aare,BE	121	0.8683	0.8704	0.8606	0.8791
Buochs,NW	116	0.8640	0.8768	0.8629	0.8782
Busswil bei Büren,BE	116	0.8708	0.8721	0.8673	0.8849
Chur,GR	116	0.8735	0.8771	0.8708	0.8863
Churwalden,GR	117	0.8712	0.8883	0.8700	0.8880
Dagmersellen,LU	118	0.8695	0.8754	0.8678	0.8836
Davos,GR	118	0.8741	0.8834	0.8682	0.8912
Degersheim,SG	113	0.8706	0.8840	0.8722	0.8859

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Densbüren,AG	121	0.8732	0.8762	0.8704	0.8866
Diemtigen,BE	118	0.8676	0.8775	0.8674	0.8850
Diepoldsau,SG	113	0.8732	0.8849	0.8719	0.8898
Diessbach bei Büren,BE	115	0.8657	0.8771	0.8635	0.8867
Düdingen,FR	114	0.8679	0.8765	0.8633	0.8881
Ebnat-Kappel,SG	122	0.8757	0.8783	0.8738	0.8873
Egg,ZH	120	0.8714	0.8847	0.8690	0.8870
Eglisau,ZH	116	0.8769	0.8902	0.8740	0.8948
Einsiedeln,SZ	115	0.8745	0.8787	0.8724	0.8853
Elfingen,AG	117	0.8828	0.8853	0.8768	0.8912
Elgg,ZH	118	0.8749	0.8826	0.8731	0.8906
Ellikon an der Thur,ZH	116	0.8730	0.8887	0.8705	0.8915
Elm,GL	122	0.8720	0.8813	0.8736	0.8943
Engelberg,OW	116	0.8725	0.8813	0.8638	0.8849
Engi,GL	121	0.8759	0.8800	0.8711	0.8881
Entlebuch,LU	117	0.8760	0.8820	0.8773	0.8900
Erlach,BE	119	0.8704	0.8746	0.8654	0.8840
Ermatingen,TG	113	0.8707	0.8811	0.8726	0.8877
Erschwil,SO	112	0.8639	0.8746	0.8588	0.8802
Eschenbach,LU	115	0.8724	0.8837	0.8697	0.8893
Escholzmatt,LU	116	0.8726	0.8732	0.8670	0.8848
Ettingen,BL	114	0.8717	0.8731	0.8684	0.8862
Fällanden,ZH	117	0.8701	0.8820	0.8647	0.8863
Trub,BE	114	0.8688	0.8790	0.8640	0.8856
Spiez,BE	118	0.8730	0.8684	0.8668	0.8853
Ferden,VS	122	0.8645	0.8622	0.8582	0.8706
Fiesch,VS	116	0.8613	0.8698	0.8654	0.8769
Fischingen,TG	114	0.8766	0.8871	0.8748	0.8906
Flaach,ZH	117	0.8746	0.8827	0.8760	0.8890
Fläsch,GR	117	0.8789	0.8809	0.8718	0.8864
Flawil,SG	116	0.8717	0.8821	0.8686	0.8870
Flühli,LU	117	0.8651	0.8710	0.8615	0.8793
Flums,SG	120	0.8706	0.8836	0.8717	0.8873
Maur,ZH	121	0.8758	0.8801	0.8739	0.8877
Frauenfeld,TG	114	0.8735	0.8826	0.8685	0.8864
Frauenkappelen,BE	118	0.8751	0.8758	0.8673	0.8850
Fribourg,FR	118	0.8692	0.8738	0.8646	0.8823
Frick,AG	121	0.8759	0.8779	0.8700	0.8852
Frutigen,BE	118	0.8679	0.8725	0.8686	0.8839
Gadmen,BE	118	0.8724	0.8827	0.8744	0.8921
Gächlingen,SH	119	0.8724	0.8805	0.8700	0.8835
Gais,AR	118	0.8707	0.8836	0.8728	0.8893
Gelterkinden,BL	119	0.8689	0.8696	0.8622	0.8833
Giffers,FR	115	0.8691	0.8789	0.8627	0.8847
Giswil,OW	113	0.8718	0.8773	0.8659	0.8863
Glarus,GL	123	0.8760	0.8880	0.8728	0.8930
Göschenen,UR	118	0.8757	0.8765	0.8666	0.8848
Grabs,SG	116	0.8758	0.8846	0.8788	0.8886
Grafenried,BE	119	0.8681	0.8714	0.8674	0.8821
Grindelwald,BE	119	0.8757	0.8846	0.8715	0.8918
Grosswangen,LU	117	0.8688	0.8747	0.8679	0.8830
Gossau,ZH	121	0.8720	0.8738	0.8683	0.8858
Gsteig,BE	116	0.8659	0.8717	0.8653	0.8834
Guggisberg,BE	114	0.8633	0.8754	0.8620	0.8817
Gurmels,FR	118	0.8656	0.8789	0.8614	0.8836
Gurtnellen,UR	117	0.8756	0.8764	0.8675	0.8830
Guttannen,BE	121	0.8666	0.8737	0.8677	0.8819
Guttet-Feschel,VS	122	0.8692	0.8727	0.8652	0.8794
Habkern,BE	113	0.8694	0.8749	0.8662	0.8783
Hägglingen,AG	115	0.8753	0.8803	0.8716	0.8896
Hallau,SH	117	0.8736	0.8781	0.8679	0.8882

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Schlatt-Haslen,AI	112	0.8656	0.8806	0.8685	0.8847
Hedingen,ZH	116	0.8710	0.8821	0.8660	0.8862
Heiden,AR	118	0.8707	0.8825	0.8724	0.8909
Heitenried,FR	118	0.8622	0.8710	0.8538	0.8740
Herisau,AR	113	0.8729	0.8826	0.8731	0.8894
Hölstein,BL	120	0.8711	0.8735	0.8644	0.8858
Homburg,TG	110	0.8730	0.8828	0.8721	0.8891
Horw,LU	116	0.8728	0.8785	0.8711	0.8915
Hünenberg,ZG	116	0.8753	0.8793	0.8725	0.8837
Hütten,ZH	120	0.8748	0.8784	0.8713	0.8863
Hüttwilen,TG	114	0.8772	0.8893	0.8738	0.8958
Huttwil,BE	116	0.8661	0.8806	0.8674	0.8840
Illnau-Effretikon,ZH	122	0.8744	0.8806	0.8715	0.8842
Inden,VS	122	0.8686	0.8772	0.8692	0.8861
Innerthal,SZ	113	0.8701	0.8788	0.8689	0.8843
Innertkirchen,BE	121	0.8682	0.8792	0.8689	0.8891
Ins,BE	113	0.8645	0.8714	0.8600	0.8823
Interlaken,BE	116	0.8725	0.8767	0.8716	0.8881
Iseltwald,BE	120	0.8672	0.8715	0.8682	0.8826
Isenthal,UR	117	0.8769	0.8832	0.8697	0.8912
Ittigen,BE	114	0.8774	0.8813	0.8724	0.8907
Jaun,FR	118	0.8665	0.8679	0.8585	0.8757
Jenins,GR	113	0.8751	0.8715	0.8678	0.8830
Kaiserstuhl,AG	117	0.8751	0.8849	0.8673	0.8899
Kaisten,AG	119	0.8749	0.8901	0.8733	0.8939
Kandersteg,BE	114	0.8705	0.8750	0.8719	0.8894
Kappel am Albis,ZH	116	0.8750	0.8880	0.8690	0.8891
Kesswil,TG	115	0.8739	0.8854	0.8715	0.8864
Reichenbach im Kandertal,BE	115	0.8646	0.8786	0.8691	0.8848
Kirchberg,SG	112	0.8739	0.8895	0.8751	0.8903
Kirchleerau,AG	120	0.8787	0.8797	0.8730	0.8896
Kleinlützel,SO	116	0.8729	0.8743	0.8679	0.8850
Klosters-Serneus,GR	121	0.8719	0.8847	0.8738	0.8883
Konolfingen,BE	116	0.8724	0.8731	0.8683	0.8848
Krauchthal,BE	117	0.8740	0.8775	0.8717	0.8903
Krinau,SG	114	0.8704	0.8852	0.8717	0.8877
Küblis,GR	113	0.8733	0.8880	0.8689	0.8903
Küsnacht,ZH	122	0.8733	0.8903	0.8694	0.8866
Küssnacht am Rigi,SZ	119	0.8774	0.8831	0.8753	0.8912
Lachen,SZ	115	0.8760	0.8860	0.8737	0.8945
Langenbruck,BL	112	0.8663	0.8778	0.8679	0.8817
Langenthal,BE	113	0.8692	0.8758	0.8622	0.8885
Langnau im Emmental,BE	119	0.8699	0.8734	0.8714	0.8847
Langnau am Albis,ZH	118	0.8752	0.8857	0.8708	0.8899
Langwies,GR	110	0.8690	0.8813	0.8644	0.8890
Laufen,BL	114	0.8652	0.8716	0.8567	0.8818
Laupen,BE	115	0.8689	0.8727	0.8636	0.8844
Lauterbrunnen,BE	125	0.8711	0.8738	0.8721	0.8845
Leibstadt,AG	120	0.8787	0.8839	0.8762	0.8909
Leissigen,BE	118	0.8686	0.8699	0.8590	0.8777
Lenk,BE	120	0.8643	0.8711	0.8599	0.8770
Lenzburg,AG	120	0.8731	0.8759	0.8704	0.8877
Liesberg,BL	121	0.8689	0.8741	0.8672	0.8819
Liestal,BL	116	0.8690	0.8726	0.8642	0.8815
Ligerz,BE	111	0.8686	0.8694	0.8652	0.8801
Linthal,GL	119	0.8741	0.8792	0.8675	0.8879
Luchsingen,GL	123	0.8787	0.8913	0.8762	0.8988
Lützelflüh,BE	118	0.8653	0.8702	0.8629	0.8808
Lungern,OW	115	0.8672	0.8724	0.8630	0.8798
Lupfig,AG	112	0.8718	0.8834	0.8710	0.8912
Thundorf,TG	116	0.8745	0.8896	0.8736	0.8926
Luzern,LU	119	0.8714	0.8760	0.8673	0.8849
Silenen,UR	117	0.8750	0.8804	0.8668	0.8881

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Magden,AG	114	0.8729	0.8739	0.8663	0.8852
Maisprach,BL	116	0.8705	0.8725	0.8666	0.8836
Malans,GR	114	0.8772	0.8802	0.8750	0.8879
Malters,LU	117	0.8711	0.8729	0.8664	0.8856
Mammern,TG	120	0.8776	0.8821	0.8738	0.8881
Marbach,LU	121	0.8769	0.8793	0.8732	0.8899
Marthalen,ZH	115	0.8747	0.8799	0.8757	0.8884
St.Stephan,BE	117	0.8681	0.8779	0.8648	0.8829
Meikirch,BE	115	0.8607	0.8740	0.8592	0.8804
Meilen,ZH	124	0.8746	0.8829	0.8742	0.8869
Meiringen,BE	120	0.8718	0.8785	0.8718	0.8880
Melchnau,BE	112	0.8711	0.8826	0.8668	0.8939
Kerns,OW	116	0.8669	0.8776	0.8607	0.8814
Mels,SG	125	0.8690	0.8822	0.8739	0.8851
Brunegg,AG	113	0.8742	0.8887	0.8732	0.8938
Menzingen,ZG	116	0.8733	0.8849	0.8722	0.8920
Merenschwand,AG	115	0.8731	0.8795	0.8725	0.8843
Merishausen,SH	118	0.8780	0.8846	0.8734	0.8901
Metzerlen,SO	111	0.8670	0.8758	0.8649	0.8835
Möhlin,AG	121	0.8739	0.8759	0.8685	0.8853
Mörel,VS	124	0.8683	0.8776	0.8706	0.8832
Mörschwil,SG	117	0.8701	0.8801	0.8685	0.8876
Mollis,GL	125	0.8793	0.8821	0.8757	0.8923
Mosnang,SG	117	0.8718	0.8790	0.8668	0.8813
Mümliswil-Ramiswil,SO	113	0.8662	0.8780	0.8634	0.8857
Münchenbuchsee,BE	114	0.8694	0.8773	0.8655	0.8894
Muhen,AG	114	0.8753	0.8786	0.8690	0.8897
Muotathal,SZ	117	0.8599	0.8754	0.8580	0.8788
Murten,FR	114	0.8626	0.8731	0.8578	0.8805
Mutten,GR	112	0.8720	0.8835	0.8675	0.8887
Muttenz,BL	116	0.8790	0.8816	0.8736	0.8901
Näfels,GL	117	0.8765	0.8874	0.8733	0.8932
Uster,ZH	118	0.8733	0.8853	0.8695	0.8863
Neftenbach,ZH	117	0.8776	0.8837	0.8753	0.8888
Neuenegg,BE	115	0.8768	0.8749	0.8692	0.8904
Neuenkirch,LU	113	0.8691	0.8815	0.8666	0.8889
Kradolf-Schönenberg,TG	113	0.8732	0.8832	0.8727	0.8883
Niederbipp,BE	115	0.8715	0.8734	0.8648	0.8881
Niederrohrdorf,AG	120	0.8765	0.8822	0.8726	0.8884
Niederweningen,ZH	124	0.8752	0.8806	0.8715	0.8832
Nunningen,SO	114	0.8672	0.8717	0.8631	0.8792
Oberägeri,ZG	118	0.8666	0.8702	0.8619	0.8786
Oberhof,AG	118	0.8681	0.8758	0.8690	0.8799
Oberiberg,SZ	118	0.8681	0.8737	0.8651	0.8846
Oberriet,SG	117	0.8683	0.8775	0.8647	0.8864
Obersaxen,GR	120	0.8776	0.8766	0.8696	0.8867
Oberwald,VS	117	0.8625	0.8736	0.8635	0.8752
Oberwichtrach,BE	115	0.8639	0.8773	0.8623	0.8859
Obstalden,GL	122	0.8779	0.8792	0.8758	0.8902
Pfäfers,SG	120	0.8745	0.8788	0.8736	0.8868
Pfäffikon,ZH	116	0.8748	0.8837	0.8735	0.8907
Pfaffnau,LU	114	0.8736	0.8837	0.8695	0.8913
Pieterlen,BE	120	0.8716	0.8725	0.8652	0.8807
Plaffeien,FR	116	0.8618	0.8726	0.8560	0.8752
Pratteln,BL	120	0.8666	0.8722	0.8639	0.8828
Quarten,SG	117	0.8765	0.8853	0.8748	0.8920
Rafz,ZH	121	0.8728	0.8801	0.8695	0.8850
Ramsen,SH	116	0.8742	0.8801	0.8711	0.8860
Randa,VS	118	0.8585	0.8676	0.8600	0.8794
Rapperswil,BE	116	0.8724	0.8815	0.8674	0.8910
Reckingen,VS	121	0.8588	0.8732	0.8638	0.8785
Regensberg,ZH	120	0.8761	0.8803	0.8718	0.8872

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Reutigen,BE	118	0.8652	0.8781	0.8688	0.8844
Rheineck,SG	119	0.8695	0.8823	0.8670	0.8877
Medels im Rheinwald,GR	111	0.8760	0.8773	0.8668	0.8843
Wattwil,SG	117	0.8700	0.8826	0.8668	0.8866
Rickenbach,SO	118	0.8697	0.8733	0.8681	0.8843
Rifferswil,ZH	114	0.8731	0.8864	0.8694	0.8927
Murgenthal,AG	120	0.8739	0.8800	0.8696	0.8902
Römerswil,LU	116	0.8706	0.8746	0.8693	0.8852
Röthenbach im Emmental,BE	118	0.8715	0.8797	0.8694	0.8875
Roggenburg,BL	112	0.8754	0.8776	0.8677	0.8883
Roggwil,TG	119	0.8755	0.8791	0.8708	0.8862
Romanshorn,TG	116	0.8731	0.8853	0.8697	0.8910
Rorbas,ZH	120	0.8733	0.8856	0.8719	0.8892
Risch,ZG	116	0.8759	0.8808	0.8740	0.8893
Rubigen,BE	116	0.8717	0.8756	0.8685	0.8899
Rüeggisberg,BE	115	0.8743	0.8871	0.8723	0.8933
Rümlang,ZH	119	0.8783	0.8850	0.8749	0.8924
Ruswil,LU	117	0.8749	0.8798	0.8722	0.8922
Saanen,BE	122	0.8670	0.8671	0.8632	0.8780
Saas Grund,VS	119	0.8639	0.8713	0.8660	0.8776
Safien,GR	117	0.8753	0.8720	0.8685	0.8816
Salgesch,VS	124	0.8633	0.8695	0.8637	0.8782
Sarnen,OW	118	0.8689	0.8713	0.8663	0.8831
Schänis,SG	113	0.8747	0.8879	0.8741	0.8887
Schaffhausen,SH	114	0.8787	0.8868	0.8778	0.8917
Schangnau,BE	111	0.8686	0.8823	0.8670	0.8891
Schiers,GR	113	0.8717	0.8837	0.8752	0.8916
Schleitheim,SH	115	0.8752	0.8812	0.8749	0.8862
Schnottwil,SO	116	0.8697	0.8742	0.8658	0.8840
Schönenbuch,BL	117	0.8702	0.8741	0.8646	0.8827
Schüpfheim,LU	117	0.8680	0.8737	0.8649	0.8852
Schwanden,GL	119	0.8745	0.8865	0.8733	0.8938
Wahlern,BE	113	0.8676	0.8792	0.8653	0.8880
Schwyz,SZ	117	0.8660	0.8822	0.8652	0.8840
Seftigen,BE	110	0.8696	0.8782	0.8664	0.8891
Sempach,LU	117	0.8738	0.8783	0.8712	0.8866
Sennwald,SG	120	0.8721	0.8741	0.8721	0.8846
Sevelen,SG	119	0.8749	0.8796	0.8694	0.8877
Siglistorf,AG	115	0.8801	0.8861	0.8773	0.8886
Signau,BE	111	0.8685	0.8810	0.8677	0.8880
Simplon,VS	123	0.8669	0.8761	0.8662	0.8848
Zihlschlacht-Sitterdorf,TG	116	0.8765	0.8896	0.8755	0.8945
Solothurn,SO	115	0.8662	0.8784	0.8652	0.8828
St.Antönien,GR	116	0.8720	0.8825	0.8734	0.8888
St.Gallen,SG	116	0.8735	0.8868	0.8689	0.8871
St.Niklaus,VS	120	0.8595	0.8664	0.8612	0.8726
Stadel,ZH	118	0.8783	0.8874	0.8723	0.8925
Stallikon,ZH	121	0.8727	0.8764	0.8721	0.8869
Stans,NW	119	0.8729	0.8755	0.8671	0.8887
Steffisburg,BE	116	0.8647	0.8781	0.8643	0.8841
Steg,VS	118	0.8668	0.8778	0.8712	0.8826
Stein,AG	116	0.8725	0.8848	0.8702	0.8889
Stein am Rhein,SH	116	0.8740	0.8865	0.8746	0.8886
Sternenberg,ZH	120	0.8739	0.8809	0.8689	0.8870
Stüsslingen,SO	114	0.8728	0.8831	0.8680	0.8913
Sumiswald,BE	113	0.8664	0.8791	0.8641	0.8842
Sursee,LU	118	0.8694	0.8773	0.8698	0.8850
Täuffelen,BE	118	0.8645	0.8693	0.8618	0.8788
Tafers,FR	115	0.8644	0.8716	0.8557	0.8761
Tamins,GR	122	0.8729	0.8749	0.8668	0.8898
Teufenthal,AG	118	0.8758	0.8820	0.8737	0.8902
Thalwil,ZH	117	0.8782	0.8908	0.8776	0.8944
Thun,BE	116	0.8717	0.8760	0.8675	0.8847
Thusis,GR	117	0.8754	0.8759	0.8657	0.8873

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Triengen,LU	118	0.8692	0.8734	0.8679	0.8840
Trimmis,GR	117	0.8662	0.8803	0.8682	0.8864
Trogen,AR	118	0.8692	0.8825	0.8693	0.8870
Tüscherz-Alfermée,BE	115	0.8706	0.8761	0.8696	0.8865
Tuggen,SZ	120	0.8787	0.8833	0.8741	0.8920
Turbenthal,ZH	124	0.8774	0.8832	0.8755	0.8901
Ueberstorf,FR	116	0.8692	0.8779	0.8640	0.8887
Unterschächen,UR	120	0.8671	0.8686	0.8608	0.8780
Unterstammheim,ZH	115	0.8701	0.8788	0.8716	0.8828
Untervaz,GR	121	0.8687	0.8758	0.8693	0.8860
Urdorf,ZH	115	0.8752	0.8884	0.8705	0.8879
Urnäsch,AR	117	0.8715	0.8757	0.8689	0.8848
Ursenbach,BE	116	0.8661	0.8766	0.8623	0.8842
Utzenstorf,BE	116	0.8709	0.8757	0.8652	0.8869
Vals,GR	120	0.8701	0.8786	0.8676	0.8870
Villigen,AG	117	0.8824	0.8857	0.8743	0.8932
Visp,VS	118	0.8632	0.8748	0.8693	0.8797
Visperterminen,VS	120	0.8620	0.8643	0.8558	0.8736
Wädenswil,ZH	118	0.8788	0.8848	0.8792	0.8917
Wängi,TG	115	0.8733	0.8836	0.8713	0.8898
Walchwil,ZG	116	0.8702	0.8768	0.8683	0.8861
Wald,ZH	116	0.8735	0.8831	0.8707	0.8904
Waldstatt,AR	113	0.8692	0.8809	0.8640	0.8888
Walenstadt,SG	125	0.8732	0.8777	0.8693	0.8831
Wangen an der Aare,BE	119	0.8668	0.8759	0.8613	0.8859
Wartau,SG	123	0.8727	0.8794	0.8731	0.8850
Wegenstetten,AG	121	0.8741	0.8815	0.8751	0.8896
Weggis,LU	118	0.8705	0.8764	0.8671	0.8838
Weinfelden,TG	116	0.8771	0.8864	0.8731	0.8874
Welschenrohr,SO	123	0.8635	0.8706	0.8654	0.8832
Wengi,BE	118	0.8693	0.8728	0.8685	0.8871
Wiesen,GR	116	0.8728	0.8887	0.8733	0.8929
Wil,SG	116	0.8732	0.8858	0.8720	0.8899
Wilchingen,SH	117	0.8728	0.8787	0.8746	0.8866
Wildhaus,SG	115	0.8753	0.8772	0.8743	0.8840
Willisau Stadt,LU	116	0.8752	0.8793	0.8717	0.8899
Winterthur,ZH	125	0.8806	0.8867	0.8748	0.8906
Wolfenschiessen,NW	117	0.8762	0.8744	0.8703	0.8850
Wolhusen,LU	117	0.8717	0.8758	0.8698	0.8873
Wollerau,SZ	121	0.8754	0.8809	0.8753	0.8859
Worb,BE	118	0.8747	0.8786	0.8728	0.8900
Würenlos,AG	113	0.8737	0.8838	0.8739	0.8913
Wynigen,BE	119	0.8678	0.8750	0.8672	0.8835
Zell,LU	111	0.8676	0.8816	0.8652	0.8907
Zermatt,VS	122	0.8636	0.8713	0.8673	0.8774
Ziefen,BL	118	0.8727	0.8777	0.8681	0.8829
Zofingen,AG	119	0.8738	0.8856	0.8694	0.8883
Zürich,ZH	118	0.8735	0.8844	0.8711	0.8900
Zug,ZG	114	0.8693	0.8788	0.8656	0.8863
Zunzgen,BL	116	0.8723	0.8734	0.8672	0.8873
Zweisimmen,BE	118	0.8623	0.8690	0.8647	0.8808
Bibern,SO	1	0.9271	0.8686	0.9271	0.9334
Eschenbach,SG	1	0.6550	0.6364	0.5925	0.5575
Stein,SG	1	0.9271	0.8686	0.9271	0.9334

Table A.10: COMET score of different Swiss-German dialects on all sentences.

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Aarau,AG	87	0.8622	0.8796	0.8635	0.8848
Aarberg,BE	87	0.8675	0.8810	0.8628	0.8855
Aarburg,AG	87	0.8611	0.8800	0.8611	0.8881
Adelboden,BE	87	0.8594	0.8744	0.8648	0.8838
Aedermannsdorf,SO	87	0.8654	0.8800	0.8641	0.8837
Aesch,BL	87	0.8641	0.8844	0.8706	0.8874
Aeschi,SO	87	0.8624	0.8802	0.8652	0.8818
Agarn,VS	87	0.8560	0.8681	0.8608	0.8753
Alpnach,OW	87	0.8645	0.8831	0.8670	0.8845
Alpthal,SZ	87	0.8680	0.8846	0.8706	0.8853
Altdorf,UR	87	0.8634	0.8823	0.8664	0.8864
Altstätten,SG	87	0.8647	0.8845	0.8683	0.8871
Amden,SG	87	0.8691	0.8881	0.8688	0.8886
Amriswil,TG	87	0.8654	0.8848	0.8658	0.8870
Andelfingen,ZH	87	0.8701	0.8879	0.8669	0.8873
Andermatt,UR	87	0.8600	0.8788	0.8650	0.8887
Andwil,SG	87	0.8636	0.8849	0.8694	0.8844
Appenzell,AI	87	0.8587	0.8763	0.8614	0.8833
Arosa,GR	87	0.8652	0.8837	0.8658	0.8785
Ausserberg,VS	87	0.8574	0.8664	0.8610	0.8807
Avers,GR	87	0.8681	0.8809	0.8673	0.8846
Bäretswil,ZH	87	0.8679	0.8881	0.8686	0.8862
Baldingen,AG	87	0.8708	0.8895	0.8683	0.8820
Basadingen-Schlattingen,TG	87	0.8653	0.8859	0.8667	0.8842
Basel,BS	87	0.8671	0.8839	0.8635	0.8843
Bassersdorf,ZH	87	0.8626	0.8860	0.8649	0.8811
Bauma,ZH	87	0.8630	0.8821	0.8679	0.8836
Belp,BE	87	0.8677	0.8824	0.8658	0.8878
Benken,SG	87	0.8671	0.8862	0.8698	0.8872
Bern,BE	87	0.8608	0.8794	0.8667	0.8863
Berneck,SG	87	0.8644	0.8843	0.8674	0.8811
Betten,VS	87	0.8549	0.8692	0.8626	0.8778
Bettingen,BS	87	0.8638	0.8802	0.8641	0.8873
Bettlach,SO	87	0.8599	0.8743	0.8624	0.8794
Bibern,SH	87	0.8683	0.8811	0.8606	0.8825
Binn,VS	87	0.8592	0.8763	0.8685	0.8829
Birmenstorf,AG	87	0.8652	0.8841	0.8699	0.8868
Birwinken,TG	87	0.8631	0.8853	0.8647	0.8835
Blatten,VS	87	0.8544	0.8660	0.8562	0.8730
Bleienbach,BE	87	0.8666	0.8810	0.8628	0.8824
Boltigen,BE	87	0.8643	0.8760	0.8594	0.8821
Boniswil,AG	87	0.8653	0.8834	0.8691	0.8839
Boswil,AG	87	0.8643	0.8870	0.8711	0.8857
Bottighofen,TG	87	0.8668	0.8882	0.8692	0.8855
Bremgarten,AG	87	0.8682	0.8891	0.8699	0.8893
Brienz,BE	87	0.8597	0.8762	0.8707	0.8825
Brig-Glis,VS	87	0.8568	0.8740	0.8623	0.8812
Rüte,AI	87	0.8614	0.8800	0.8640	0.8846
Brugg,AG	87	0.8639	0.8812	0.8677	0.8898
Brunnadern,SG	87	0.8701	0.8838	0.8668	0.8847
Ingenbohl,SZ	87	0.8635	0.8800	0.8677	0.8839
Buchberg,SH	87	0.8664	0.8865	0.8674	0.8844
Buckten,BL	87	0.8625	0.8791	0.8635	0.8832
Bühler,AR	87	0.8680	0.8836	0.8709	0.8866
Bülach,ZH	87	0.8639	0.8887	0.8692	0.8880
Bürchen,VS	87	0.8559	0.8654	0.8548	0.8773
Büren an der Aare,BE	87	0.8600	0.8768	0.8573	0.8787
Buochs,NW	87	0.8655	0.8837	0.8671	0.8829
Busswil bei Büren,BE	87	0.8658	0.8817	0.8702	0.8867
Chur,GR	87	0.8654	0.8791	0.8635	0.8840
Churwalden,GR	87	0.8653	0.8863	0.8671	0.8859
Dagmersellen,LU	87	0.8634	0.8837	0.8683	0.8851

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Davos,GR	87	0.8649	0.8818	0.8636	0.8876
Degersheim,SG	87	0.8648	0.8868	0.8686	0.8854
Densbüren,AG	87	0.8638	0.8808	0.8657	0.8852
Diemtigen,BE	87	0.8617	0.8791	0.8649	0.8859
Diepoldsau,SG	87	0.8670	0.8832	0.8655	0.8864
Diessbach bei Büren,BE	87	0.8620	0.8791	0.8658	0.8883
Düdingen,FR	87	0.8592	0.8740	0.8632	0.8819
Ebnat-Kappel,SG	87	0.8645	0.8813	0.8688	0.8829
Egg,ZH	87	0.8632	0.8859	0.8669	0.8850
Eglisau,ZH	87	0.8694	0.8898	0.8728	0.8929
Einsiedeln,SZ	87	0.8623	0.8762	0.8632	0.8782
Elfingen,AG	87	0.8703	0.8862	0.8695	0.8852
Elgg,ZH	87	0.8618	0.8814	0.8648	0.8833
Ellikon an der Thur,ZH	87	0.8652	0.8870	0.8666	0.8872
Elm,GL	87	0.8676	0.8851	0.8675	0.8946
Engelberg,OW	87	0.8662	0.8816	0.8609	0.8810
Engi,GL	87	0.8671	0.8848	0.8657	0.8846
Entlebuch,LU	87	0.8667	0.8863	0.8741	0.8883
Erlach,BE	87	0.8636	0.8807	0.8628	0.8855
Ermatingen,TG	87	0.8653	0.8854	0.8681	0.8883
Erschwil,SO	87	0.8632	0.8786	0.8645	0.8846
Eschenbach,LU	87	0.8644	0.8834	0.8670	0.8851
Escholzmatt,LU	87	0.8656	0.8808	0.8697	0.8858
Ettingen,BL	87	0.8648	0.8801	0.8674	0.8831
Fällanden,ZH	87	0.8642	0.8840	0.8655	0.8846
Trub,BE	87	0.8625	0.8808	0.8667	0.8849
Spiez,BE	87	0.8644	0.8785	0.8663	0.8859
Ferden,VS	87	0.8561	0.8652	0.8603	0.8748
Fiesch,VS	87	0.8587	0.8726	0.8657	0.8807
Fischingen,TG	87	0.8675	0.8855	0.8716	0.8850
Flaach,ZH	87	0.8650	0.8874	0.8715	0.8846
Fläsch,GR	87	0.8706	0.8817	0.8625	0.8809
Flawil,SG	87	0.8652	0.8847	0.8679	0.8858
Flühli,LU	87	0.8664	0.8833	0.8683	0.8885
Flums,SG	87	0.8639	0.8846	0.8679	0.8891
Maur,ZH	87	0.8666	0.8866	0.8701	0.8874
Frauenfeld,TG	87	0.8663	0.8874	0.8698	0.8874
Frauenkappelen,BE	87	0.8661	0.8835	0.8665	0.8873
Fribourg,FR	87	0.8610	0.8768	0.8620	0.8814
Frick,AG	87	0.8645	0.8827	0.8652	0.8804
Frutigen,BE	87	0.8619	0.8736	0.8674	0.8832
Gadmen,BE	87	0.8610	0.8763	0.8637	0.8851
Gächlingen,SH	87	0.8631	0.8867	0.8648	0.8826
Gais,AR	87	0.8593	0.8796	0.8632	0.8851
Gelterkinden,BL	87	0.8629	0.8810	0.8637	0.8862
Giffers,FR	87	0.8624	0.8773	0.8592	0.8818
Giswil,OW	87	0.8667	0.8798	0.8670	0.8858
Glarus,GL	87	0.8678	0.8849	0.8665	0.8904
Göschenen,UR	87	0.8713	0.8850	0.8671	0.8852
Grabs,SG	87	0.8724	0.8829	0.8714	0.8871
Grafenried,BE	87	0.8614	0.8779	0.8677	0.8830
Grindelwald,BE	87	0.8643	0.8755	0.8603	0.8820
Grosswangen,LU	87	0.8611	0.8819	0.8678	0.8826
Gossau,ZH	87	0.8643	0.8804	0.8661	0.8855
Gsteig,BE	87	0.8578	0.8707	0.8627	0.8777
Guggisberg,BE	87	0.8596	0.8765	0.8658	0.8840
Gurmels,FR	87	0.8561	0.8811	0.8600	0.8815
Gurtnellen,UR	87	0.8708	0.8843	0.8689	0.8838
Guttannen,BE	87	0.8575	0.8688	0.8623	0.8774
Guttet-Feschel,VS	87	0.8568	0.8677	0.8597	0.8751
Habkern,BE	87	0.8665	0.8774	0.8698	0.8793

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Hägglingen,AG	87	0.8642	0.8826	0.8670	0.8854
Hallau,SH	87	0.8643	0.8843	0.8640	0.8862
Schlatt-Haslen,AI	87	0.8615	0.8795	0.8630	0.8813
Hedingen,ZH	87	0.8642	0.8846	0.8645	0.8847
Heiden,AR	87	0.8633	0.8804	0.8660	0.8868
Heitenried,FR	87	0.8584	0.8737	0.8564	0.8769
Herisau,AR	87	0.8637	0.8829	0.8659	0.8857
Hölstein,BL	87	0.8648	0.8809	0.8628	0.8886
Homburg,TG	87	0.8645	0.8851	0.8672	0.8865
Horw,LU	87	0.8640	0.8842	0.8705	0.8897
Hünenberg,ZG	87	0.8680	0.8850	0.8726	0.8819
Hütten,ZH	87	0.8652	0.8830	0.8664	0.8834
Hüttwilen,TG	87	0.8661	0.8872	0.8672	0.8896
Huttwil,BE	87	0.8638	0.8827	0.8701	0.8867
Illnau-Effretikon,ZH	87	0.8641	0.8828	0.8653	0.8818
Inden,VS	87	0.8532	0.8711	0.8602	0.8805
Innerthal,SZ	87	0.8624	0.8827	0.8666	0.8838
Innertkirchen,BE	87	0.8553	0.8700	0.8616	0.8803
Ins,BE	87	0.8614	0.8770	0.8648	0.8848
Interlaken,BE	87	0.8647	0.8821	0.8688	0.8869
Iseltwald,BE	87	0.8605	0.8788	0.8654	0.8832
Isenthal,UR	87	0.8703	0.8842	0.8691	0.8875
Ittigen,BE	87	0.8669	0.8820	0.8678	0.8870
Jaun,FR	87	0.8641	0.8755	0.8580	0.8780
Jenins,GR	87	0.8664	0.8795	0.8628	0.8801
Kaiserstuhl,AG	87	0.8697	0.8853	0.8643	0.8865
Kaisten,AG	87	0.8663	0.8904	0.8693	0.8887
Kandersteg,BE	87	0.8631	0.8801	0.8651	0.8875
Kappel am Albis,ZH	87	0.8678	0.8851	0.8635	0.8835
Kesswil,TG	87	0.8657	0.8852	0.8683	0.8842
Reichenbach im Kandertal,BE	87	0.8621	0.8836	0.8698	0.8870
Kirchberg,SG	87	0.8640	0.8857	0.8680	0.8869
Kirchleerau,AG	87	0.8688	0.8834	0.8683	0.8852
Kleinlützel,SO	87	0.8639	0.8794	0.8656	0.8826
Klosters-Serneus,GR	87	0.8586	0.8780	0.8650	0.8845
Konolfingen,BE	87	0.8656	0.8818	0.8699	0.8871
Krauchthal,BE	87	0.8628	0.8807	0.8655	0.8870
Krinau,SG	87	0.8644	0.8868	0.8665	0.8869
Küblis,GR	87	0.8653	0.8860	0.8671	0.8861
Küsnacht,ZH	87	0.8659	0.8892	0.8660	0.8868
Küssnacht am Rigi,SZ	87	0.8715	0.8896	0.8731	0.8903
Lachen,SZ	87	0.8671	0.8849	0.8691	0.8891
Langenbruck,BL	87	0.8641	0.8813	0.8688	0.8847
Langenthal,BE	87	0.8635	0.8789	0.8644	0.8906
Langnau im Emmental,BE	87	0.8637	0.8826	0.8721	0.8881
Langnau am Albis,ZH	87	0.8673	0.8872	0.8686	0.8874
Langwies,GR	87	0.8630	0.8825	0.8599	0.8865
Laufen,BL	87	0.8665	0.8805	0.8653	0.8894
Laupen,BE	87	0.8592	0.8787	0.8637	0.8837
Lauterbrunnen,BE	87	0.8604	0.8755	0.8665	0.8810
Leibstadt,AG	87	0.8663	0.8856	0.8686	0.8842
Leissigen,BE	87	0.8638	0.8785	0.8631	0.8832
Lenk,BE	87	0.8633	0.8777	0.8608	0.8824
Lenzburg,AG	87	0.8637	0.8797	0.8679	0.8859
Liesberg,BL	87	0.8613	0.8797	0.8648	0.8819
Liestal,BL	87	0.8645	0.8792	0.8651	0.8846
Ligerz,BE	87	0.8643	0.8800	0.8632	0.8824
Linthal,GL	87	0.8671	0.8858	0.8648	0.8869
Luchsingen,GL	87	0.8695	0.8875	0.8707	0.8933
Lützelflüh,BE	87	0.8592	0.8768	0.8647	0.8855
Lungern,OW	87	0.8645	0.8757	0.8688	0.8810
Lupfig,AG	87	0.8670	0.8839	0.8700	0.8898
Thundorf,TG	87	0.8662	0.8869	0.8679	0.8873
Luzern,LU	87	0.8653	0.8839	0.8679	0.8842
Silenen,UR	87	0.8671	0.8789	0.8647	0.8831

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Magden,AG	87	0.8662	0.8809	0.8630	0.8845
Maisprach,BL	87	0.8656	0.8818	0.8668	0.8873
Malans,GR	87	0.8684	0.8829	0.8677	0.8852
Malters,LU	87	0.8644	0.8814	0.8690	0.8867
Mammern,TG	87	0.8679	0.8871	0.8686	0.8835
Marbach,LU	87	0.8657	0.8814	0.8682	0.8863
Marthalen,ZH	87	0.8652	0.8846	0.8676	0.8859
St.Stephan,BE	87	0.8656	0.8782	0.8656	0.8862
Meikirch,BE	87	0.8599	0.8774	0.8641	0.8841
Meilen,ZH	87	0.8626	0.8870	0.8681	0.8823
Meiringen,BE	87	0.8587	0.8742	0.8669	0.8826
Melchnau,BE	87	0.8614	0.8809	0.8649	0.8913
Kerns,OW	87	0.8650	0.8837	0.8627	0.8850
Mels,SG	87	0.8660	0.8862	0.8703	0.8894
Brunegg,AG	87	0.8661	0.8861	0.8699	0.8899
Menzingen,ZG	87	0.8650	0.8852	0.8707	0.8865
Merenschwand,AG	87	0.8644	0.8843	0.8709	0.8828
Merishausen,SH	87	0.8676	0.8873	0.8708	0.8872
Metzerlen,SO	87	0.8658	0.8818	0.8673	0.8869
Möhlin,AG	87	0.8658	0.8823	0.8646	0.8849
Mörel,VS	87	0.8569	0.8741	0.8649	0.8787
Mörschwil,SG	87	0.8635	0.8817	0.8665	0.8858
Mollis,GL	87	0.8680	0.8851	0.8680	0.8882
Mosnang,SG	87	0.8664	0.8799	0.8625	0.8788
Mümliswil-Ramiswil,SO	87	0.8622	0.8803	0.8668	0.8847
Münchenbuchsee,BE	87	0.8647	0.8811	0.8665	0.8908
Muhen,AG	87	0.8649	0.8805	0.8622	0.8849
Muotathal,SZ	87	0.8577	0.8775	0.8600	0.8805
Murten,FR	87	0.8595	0.8765	0.8605	0.8818
Mutten,GR	87	0.8675	0.8868	0.8645	0.8858
Muttenz,BL	87	0.8665	0.8832	0.8675	0.8851
Näfels,GL	87	0.8714	0.8883	0.8727	0.8934
Uster,ZH	87	0.8667	0.8875	0.8670	0.8838
Neftenbach,ZH	87	0.8653	0.8868	0.8693	0.8828
Neuenegg,BE	87	0.8669	0.8816	0.8693	0.8890
Neuenkirch,LU	87	0.8634	0.8836	0.8692	0.8883
Kradolf-Schönenberg,TG	87	0.8653	0.8796	0.8690	0.8849
Niederbipp,BE	87	0.8655	0.8805	0.8636	0.8877
Niederrohrdorf,AG	87	0.8659	0.8868	0.8663	0.8836
Niederweningen,ZH	87	0.8648	0.8850	0.8654	0.8797
Nunningen,SO	87	0.8623	0.8812	0.8621	0.8838
Oberägeri,ZG	87	0.8634	0.8796	0.8633	0.8824
Oberhof,AG	87	0.8623	0.8821	0.8714	0.8789
Oberiberg,SZ	87	0.8653	0.8808	0.8668	0.8885
Oberriet,SG	87	0.8629	0.8784	0.8635	0.8875
Obersaxen,GR	87	0.8683	0.8785	0.8626	0.8816
Oberwald,VS	87	0.8596	0.8765	0.8668	0.8783
Oberwichtrach,BE	87	0.8605	0.8810	0.8670	0.8891
Obstalden,GL	87	0.8701	0.8852	0.8711	0.8901
Pfäfers,SG	87	0.8665	0.8827	0.8645	0.8850
Pfäffikon,ZH	87	0.8679	0.8844	0.8678	0.8871
Pfaffnau,LU	87	0.8678	0.8860	0.8718	0.8911
Pieterlen,BE	87	0.8610	0.8767	0.8613	0.8787
Plaffeien,FR	87	0.8599	0.8754	0.8629	0.8788
Pratteln,BL	87	0.8622	0.8796	0.8629	0.8861
Quarten,SG	87	0.8680	0.8876	0.8693	0.8930
Rafz,ZH	87	0.8633	0.8844	0.8652	0.8829
Ramsen,SH	87	0.8661	0.8835	0.8655	0.8836
Randa,VS	87	0.8534	0.8701	0.8606	0.8812
Rapperswil,BE	87	0.8666	0.8829	0.8661	0.8890
Reckingen,VS	87	0.8547	0.8772	0.8661	0.8820

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Regensberg,ZH	87	0.8651	0.8831	0.8647	0.8824
Reutigen,BE	87	0.8619	0.8816	0.8688	0.8854
Rheineck,SG	87	0.8628	0.8843	0.8653	0.8865
Medels im Rheinwald,GR	87	0.8682	0.8821	0.8613	0.8803
Wattwil,SG	87	0.8655	0.8879	0.8675	0.8867
Rickenbach,SO	87	0.8647	0.8802	0.8704	0.8858
Rifferswil,ZH	87	0.8620	0.8830	0.8624	0.8864
Murgenthal,AG	87	0.8650	0.8826	0.8663	0.8870
Römerswil,LU	87	0.8652	0.8835	0.8713	0.8857
Röthenbach im Emmental,BE	87	0.8641	0.8825	0.8726	0.8873
Roggenburg,BL	87	0.8642	0.8795	0.8645	0.8855
Roggwil,TG	87	0.8637	0.8827	0.8627	0.8814
Romanshorn,TG	87	0.8658	0.8891	0.8673	0.8879
Rorbas,ZH	87	0.8644	0.8851	0.8679	0.8869
Risch,ZG	87	0.8681	0.8867	0.8718	0.8896
Rubigen,BE	87	0.8603	0.8764	0.8611	0.8854
Rüeggisberg,BE	87	0.8656	0.8845	0.8683	0.8885
Rümlang,ZH	87	0.8656	0.8870	0.8689	0.8868
Ruswil,LU	87	0.8653	0.8880	0.8724	0.8896
Saanen,BE	87	0.8644	0.8747	0.8632	0.8855
Saas Grund,VS	87	0.8608	0.8708	0.8651	0.8767
Safien,GR	87	0.8705	0.8817	0.8682	0.8857
Salgesch,VS	87	0.8550	0.8701	0.8623	0.8785
Sarnen,OW	87	0.8644	0.8803	0.8679	0.8852
Schänis,SG	87	0.8699	0.8900	0.8711	0.8861
Schaffhausen,SH	87	0.8666	0.8867	0.8667	0.8850
Schangnau,BE	87	0.8636	0.8838	0.8672	0.8880
Schiers,GR	87	0.8634	0.8853	0.8691	0.8877
Schleitheim,SH	87	0.8661	0.8882	0.8674	0.8826
Schnottwil,SO	87	0.8637	0.8815	0.8675	0.8859
Schönenbuch,BL	87	0.8682	0.8846	0.8667	0.8866
Schüpfheim,LU	87	0.8610	0.8809	0.8663	0.8866
Schwanden,GL	87	0.8678	0.8848	0.8674	0.8897
Wahlern,BE	87	0.8602	0.8792	0.8647	0.8854
Schwyz,SZ	87	0.8617	0.8824	0.8641	0.8814
Seftigen,BE	87	0.8655	0.8813	0.8696	0.8896
Sempach,LU	87	0.8674	0.8853	0.8722	0.8853
Sennwald,SG	87	0.8654	0.8785	0.8651	0.8818
Sevelen,SG	87	0.8672	0.8821	0.8630	0.8839
Siglistorf,AG	87	0.8705	0.8856	0.8718	0.8839
Signau,BE	87	0.8637	0.8827	0.8685	0.8874
Simplon,VS	87	0.8550	0.8708	0.8585	0.8784
Zihlschlacht-Sitterdorf,TG	87	0.8646	0.8852	0.8680	0.8875
Solothurn,SO	87	0.8627	0.8821	0.8654	0.8825
St.Antönien,GR	87	0.8604	0.8801	0.8661	0.8831
St.Gallen,SG	87	0.8652	0.8869	0.8653	0.8844
St.Niklaus,VS	87	0.8522	0.8663	0.8597	0.8725
Stadel,ZH	87	0.8689	0.8862	0.8651	0.8860
Stallikon,ZH	87	0.8636	0.8830	0.8672	0.8848
Stans,NW	87	0.8626	0.8810	0.8661	0.8882
Steffisburg,BE	87	0.8611	0.8816	0.8669	0.8855
Steg,VS	87	0.8598	0.8770	0.8696	0.8805
Stein,AG	87	0.8657	0.8857	0.8692	0.8860
Stein am Rhein,SH	87	0.8664	0.8869	0.8714	0.8845
Sternenberg,ZH	87	0.8628	0.8840	0.8613	0.8845
Stüsslingen,SO	87	0.8676	0.8838	0.8676	0.8904
Sumiswald,BE	87	0.8629	0.8844	0.8692	0.8867
Sursee,LU	87	0.8640	0.8872	0.8724	0.8859
Täuffelen,BE	87	0.8591	0.8761	0.8628	0.8809
Tafers,FR	87	0.8611	0.8726	0.8598	0.8764
Tamins,GR	87	0.8634	0.8797	0.8624	0.8868
Teufenthal,AG	87	0.8633	0.8832	0.8663	0.8841
Thalwil,ZH	87	0.8648	0.8866	0.8690	0.8853
Thun,BE	87	0.8658	0.8818	0.8676	0.8868

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
Thusis,GR	87	0.8662	0.8807	0.8632	0.8850
Triengen,LU	87	0.8614	0.8821	0.8702	0.8845
Trimmis,GR	87	0.8632	0.8796	0.8615	0.8830
Trogen,AR	87	0.8615	0.8807	0.8613	0.8832
Tüscherz-Alfermée,BE	87	0.8604	0.8782	0.8620	0.8828
Tuggen,SZ	87	0.8672	0.8844	0.8661	0.8860
Turbenthal,ZH	87	0.8651	0.8866	0.8684	0.8861
Ueberstorf,FR	87	0.8608	0.8772	0.8610	0.8846
Unterschächen,UR	87	0.8607	0.8769	0.8641	0.8809
Unterstammheim,ZH	87	0.8644	0.8878	0.8679	0.8853
Untervaz,GR	87	0.8647	0.8799	0.8637	0.8845
Urdorf,ZH	87	0.8674	0.8875	0.8657	0.8834
Urnäsch,AR	87	0.8647	0.8803	0.8653	0.8849
Ursenbach,BE	87	0.8648	0.8835	0.8685	0.8903
Utzenstorf,BE	87	0.8632	0.8808	0.8617	0.8848
Vals,GR	87	0.8608	0.8817	0.8643	0.8841
Villigen,AG	87	0.8704	0.8861	0.8663	0.8854
Visp,VS	87	0.8571	0.8750	0.8695	0.8813
Visperterminen,VS	87	0.8543	0.8640	0.8532	0.8740
Wädenswil,ZH	87	0.8646	0.8859	0.8662	0.8840
Wängi,TG	87	0.8668	0.8859	0.8694	0.8872
Walchwil,ZG	87	0.8654	0.8826	0.8684	0.8861
Wald,ZH	87	0.8653	0.8845	0.8654	0.8863
Waldstatt,AR	87	0.8640	0.8826	0.8627	0.8876
Walenstadt,SG	87	0.8647	0.8825	0.8642	0.8855
Wangen an der Aare,BE	87	0.8637	0.8821	0.8647	0.8921
Wartau,SG	87	0.8677	0.8829	0.8673	0.8862
Wegenstetten,AG	87	0.8644	0.8845	0.8700	0.8842
Weggis,LU	87	0.8648	0.8844	0.8699	0.8861
Weinfelden,TG	87	0.8701	0.8866	0.8693	0.8845
Welschenrohr,SO	87	0.8572	0.8751	0.8639	0.8823
Wengi,BE	87	0.8615	0.8792	0.8660	0.8869
Wiesen,GR	87	0.8625	0.8849	0.8633	0.8855
Wil,SG	87	0.8650	0.8854	0.8681	0.8863
Wilchingen,SH	87	0.8619	0.8855	0.8698	0.8823
Wildhaus,SG	87	0.8679	0.8844	0.8675	0.8827
Willisau Stadt,LU	87	0.8665	0.8849	0.8695	0.8881
Winterthur,ZH	87	0.8662	0.8865	0.8632	0.8835
Wolfenschiessen,NW	87	0.8685	0.8825	0.8724	0.8852
Wolhusen,LU	87	0.8662	0.8850	0.8724	0.8881
Wollerau,SZ	87	0.8641	0.8851	0.8690	0.8827
Worb,BE	87	0.8637	0.8816	0.8687	0.8885
Würenlos,AG	87	0.8653	0.8852	0.8661	0.8887
Wynigen,BE	87	0.8627	0.8839	0.8678	0.8871
Zell,LU	87	0.8626	0.8846	0.8666	0.8893
Zermatt,VS	87	0.8551	0.8683	0.8637	0.8757
Ziefen,BL	87	0.8675	0.8832	0.8696	0.8825
Zofingen,AG	87	0.8650	0.8837	0.8643	0.8851
Zürich,ZH	87	0.8659	0.8879	0.8696	0.8875
Zug,ZG	87	0.8660	0.8810	0.8695	0.8862
Zunzgen,BL	87	0.8631	0.8801	0.8645	0.8857
Zweisimmen,BE	87	0.8609	0.8757	0.8636	0.8849

Table A.11: Compare COMET score of different Swiss-German dialects on a subset of 87 sentences.

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
AG	3881	0.8750	0.8817	0.8717	0.8889
BE	8389	0.8691	0.8758	0.8665	0.8853
SO	1498	0.8672	0.8750	0.8643	0.8831
BL	1867	0.8703	0.8740	0.8657	0.8840
VS	2775	0.8636	0.8707	0.8642	0.8782
OW	693	0.8689	0.8766	0.8640	0.8830
SZ	1293	0.8718	0.8792	0.8694	0.8862
UR	824	0.8716	0.8767	0.8657	0.8855
SG	3522	0.8726	0.8819	0.8714	0.8870
TG	2077	0.8743	0.8846	0.8721	0.8891
ZH	4871	0.8749	0.8838	0.8721	0.8888
AI	343	0.8661	0.8803	0.8688	0.8868
GR	2677	0.8733	0.8800	0.8697	0.8875
BS	228	0.8719	0.8832	0.8676	0.8893
SH	1169	0.8751	0.8816	0.8723	0.8872
AR	813	0.8711	0.8814	0.8709	0.8883
NW	352	0.8711	0.8756	0.8668	0.8840
LU	2565	0.8714	0.8773	0.8689	0.8869
FR	1162	0.8659	0.8742	0.8598	0.8809
GL	1091	0.8761	0.8839	0.8733	0.8924
ZG	696	0.8718	0.8784	0.8691	0.8860

Table A.12: COMET score of different Swiss-German regions on all sentences.

Swiss-German	# of Sentences	COMET			
		NLLB-Dis-600M	NLLB-Dis-1.3B	NLLB-1.3B	NLLB-3.3B
AG	87	0.8658	0.8841	0.8674	0.8855
BE	87	0.8627	0.8792	0.8657	0.8854
SO	87	0.8632	0.8799	0.8656	0.8842
BL	87	0.8645	0.8811	0.8659	0.8855
VS	87	0.8562	0.8705	0.8623	0.8781
OW	87	0.8652	0.8807	0.8657	0.8838
SZ	87	0.8646	0.8826	0.8669	0.8845
UR	87	0.8662	0.8815	0.8665	0.8851
SG	87	0.8660	0.8843	0.8672	0.8858
TG	87	0.8659	0.8857	0.8678	0.8859
ZH	87	0.8652	0.8857	0.8668	0.8851
AI	87	0.8605	0.8786	0.8628	0.8831
GR	87	0.8652	0.8819	0.8644	0.8842
BS	87	0.8654	0.8821	0.8638	0.8858
SH	87	0.8657	0.8857	0.8668	0.8841
AR	87	0.8635	0.8815	0.8651	0.8857
NW	87	0.8655	0.8824	0.8685	0.8854
LU	87	0.8647	0.8839	0.8698	0.8869
FR	87	0.8603	0.8760	0.8603	0.8803
GL	87	0.8685	0.8857	0.8683	0.8901
ZG	87	0.8660	0.8833	0.8694	0.8854

Table A.13: Comparable COMET score of different Swiss-German regions on a subset of 87 sentences.