Cross-neutralising: Probing for joint encoding of linguistic information in multilingual models

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Abstract

Multilingual sentence encoders are widely used to transfer NLP models across languages. The success of this transfer is, however, dependent on the model’s ability to encode the patterns of cross-lingual similarity and variation. Yet, little is known as to how these models are able to do this. We propose a simple method to study how relationships between languages are encoded in two state-of-the-art multilingual models (i.e. M-BERT and XLM-R). The results provide insight into their information sharing mechanisms and suggest that linguistic properties are encoded jointly across typologically-similar languages in these models.

1 Introduction

Earlier work in multilingual NLP focused on creating task-specific models, and can be divided into two main approaches: language transfer (Täckström et al., 2013; Tiedemann et al., 2014; Banea et al., 2008) and multilingual joint learning (Ammar et al., 2016a,b; Zhou et al., 2015). The former learning method enables the transfer of models or data from high-resource to low-resource languages, hence porting information across languages, while the latter jointly learns models from annotated examples in multiple languages aiming to leverage language interdependencies. Both methods relied on the fact that there are dependencies between processing different languages from a typological perspective. For instance, some syntactic properties are universal across languages (e.g. nouns take adjectives and determiners as dependents, but not adverbs), but others are influenced by the typological properties of each language (e.g. the order of these dependents with respect to the head) (Naseem et al., 2012). We hypothesize that the pretrained general-purpose multilingual models (e.g. M-BERT (Devlin et al., 2019)) rely on these same concepts, and that some of the effectiveness of these models stems from the fact that they learn to efficiently encode and share information about linguistic properties across typologically-similar languages. Hence, in this paper we investigate how different types of language-specific information interact within M-BERT and XLM-R (Conneau et al., 2019). For instance, some properties that are shared across languages may be encoded jointly in the model, while others may be encoded separately in their individual subspaces.

To investigate this, we develop a simple and yet novel method to probe for joint encoding of linguistic information, which we refer to as cross-neutralising. Our work takes inspiration from Choenni and Shutova (2020), who present a set of probing tasks to evaluate the extent to which multilingual models capture typological properties of languages, as defined in the World Atlas of Language Structures (WALS) (Dryer and Haspelmath, 2013). We use the probing tasks introduced by Choenni and Shutova (2020), but expand on their work by developing a method to probe for joint encoding of typological features. Previous research (Libovický et al., 2020; Gonen et al., 2020) demonstrated that representations produced by M-BERT are projected to separate language-specific subspaces. Hence, they can be dissected into a language-neutral component, containing the semantic meaning, and a language-specific component. We exploit this property to test for information sharing between the language-specific subspaces. In particular, we hypothesize that these subspaces jointly encode shared properties across typologically similar languages.

To probe for joint encoding, we test to what extent removing language-specific information negatively affects the probing classifier performance on the probing tasks in typologically-related languages. Our results show that by localizing infor-
Table 1: Probing task example of feature 86A: Order of Genitive and Noun. Labels are Genitive-Noun (GN), Noun-Genitive (NG) and No Dominant Order (NDO).

| Languages (ISO 639-1) | GN | NG | NDO |
|-----------------------|----|----|-----|
| da, hi, sv, mar        |    | ✓  |     |
| cs, mk, bg             |     | ✓  | ✓   |
| pt, it, pl, es, fr     | ✓  | ✓  |     |

Table: Probing task example of feature 86A: Order of Genitive and Noun. Labels are Genitive-Noun (GN), Noun-Genitive (NG) and No Dominant Order (NDO.).

information crucial for encoding the typological properties of one language, we are able to remove this same information from the representations of related languages (that share the same typological feature value). This indicates that the models jointly encode these typological properties across languages.

2 Related work

Several studies investigate language relationships within multilingual models. For instance, by reconstructing phylogenetic trees to analyze the relations they preserve (e.g. in terms of genetic and structural differences) (Bjerva et al., 2019; Beinborn and Choenni, 2020), or by probing them for typological properties of languages (Qian et al., 2016; Şahin et al., 2019; Choenni and Shutova, 2020). To the best of our knowledge, our work comes closest to that of Chi et al. (2020) who search for shared grammatical relations in M-BERT. They use the structural probe from Hewitt and Manning (2019) to show that they are able to perform zero-shot transfer across languages to successfully recover syntax. Their results suggest that the probe is able to pick up on features that are jointly encoded in M-BERT across languages. We expand on this work by linking these features to linguistic typology and demonstrating that individual lexical, morphological and syntactic properties of languages are jointly encoded across all languages that share the property.

In our work, we draw inspiration from Libovický et al. (2020) who show that M-BERT relies on a language-specific component that is similar across all representations in a language and can thus be approximated by its language centroid. They show that removing the respective centroid drastically decreases performance on language identification, while improving performance on parallel sentence retrieval, indicating a stronger language-neutrality. Hence, this method successfully removes language-specific features from representations produced by a number of BERT-based models (including M-BERT and XLM-R ), without a substantial loss of semantic meaning. While Libovický et al. (2020) demonstrate the existence of the language-neutral component, similar experiments to investigate the language-specific component are left out. Yet, Gonen et al. (2020) explicitly demonstrate the possibility to decompose the representations into a language-specific and language-neutral component, thereby supporting the existence of the language-specific component.

3 Multilingual models

Both models are 12 layer bidirectional Transformers with 12 attention heads and a hidden state size of 768. We use the Multilingual Cased version of M-BERT that supports 104 languages, uses a 110K WordPiece vocabulary and is trained on Masked Language modelling (MLM) and Next Sentence Prediction (NSP). XLM-R is the multilingual variant of RoBerta (Liu et al., 2019) that omits NSP and is trained with more data and compute power than M-BERT. It supports 100 languages and uses a Sentence Piece model (with a 250K vocabulary) for tokenization. To obtain fixed-length sentence representations, we perform mean-pooling over the hidden states of the top layer of the models.

4 Methods

Probing methods We use the 25 language-level probing tasks from Choenni and Shutova (2020) and adapt their paired language evaluation set-up using the same 7 typologically diverse language pairs: 1. (Russian, Ukrainian), 2. (Danish, Swedish), 3. (Czech, Polish), 4. (Portuguese, Spanish), 5. (Hindi, Marathi), 6. (Macedonian, Bulgarian), 7. (Italian, French). For each language, we retrieve 10K input sentences from the Tatoeba corpora¹ and annotate them with the WALS feature value for the corresponding language and probing task \( \tau \). The 25 features we probe for span a wide range of linguistic properties pertaining to lexical, morphological and syntactic structure, classified under the following codes and categories²:

1. [37A, 38A, 45A, 47A, 51A] (Nominal categories), [70A, 71A, 72A, 79A, 79B] (Verbal categories), [81A, 82A, 83A, 85A, 86A, 87A, 88A, 89A]

¹Tatoeba corpora available at: https://tatoeba.org
²For full feature names see Appendix D Table 4, for descriptions see: https://wals.info/
Figure 1: Change in performance for all test languages when cross-neutralising with Spanish. Languages are categorized by an identical (blue) or different (orange) feature value from Spanish for the respective task.

92A, 93A, 95A, 97A, 143F, 144D, 144J (Word order) and [115A, 116A] (Simple clauses). See Table 1 for an example of a probing task.

For each language pair, we use the first language for training and the second for testing. Note that not all features have annotations for all languages, in which case we omit the language from the task. Thus, given that a feature covers language-pairs, we train on $n \times 10K$ sentences from the training languages. Following Choenni and Shutova (2020), we use a one-layer MLP with 100 hidden units, ReLU activation, and an output layer that uses the softmax function to predict the feature values. The parameters of the sentence encoder are frozen during training such that all learning can be ascribed to the probing classifier $P_{\tau}$. We then use $P_{\tau}$ to predict the feature values for the $n \times 10K$ test sentences.

Restructuring the vector space Following Libovický et al. (2020), we approximate the language centroid for each language in our test set $x \in L$, by obtaining a mean language vector $\bar{u}_x \in \mathbb{R}^m$ from a set of $N$ sentence representations $u_1, \ldots, u_n \in \mathbb{R}^m$ from that language. The intuition behind localizing language-specific information this way, is that by averaging representations, core linguistic properties remain prominent in the language centroid. At the same time, we average out the infrequent phenomena that varies depending on sentence meaning. We are then able to obtain a set of language-neutral M-BERT representations $v_1, \ldots, v_n \in \mathbb{R}^m$ for a language by subtracting the corresponding language centroid:

$$v_i \text{ for } x \in L = v_i - \bar{u}_x$$

This means that we remove language-specific information by re-structuring the vector space such that the average of the representations for each language is centered at the origin of the vector space. From now on we refer to this method as self-neutralising.

Testing for information-sharing Using this self-neutralising method we study how typological properties are shared, i.e. are they jointly encoded across languages in a localizable manner or rather in independent ways for each language. We do this by adapting the self-neutralising method to a cross-neutralising scenario in which we test whether removing a language-centroid from a language $x \in L$ will also cause performance on representations from a related language $y \in L$ where $y \neq x$, to deteriorate. Thus, we approximate typological information from one language by computing $\bar{u}_x$ and subtract this from the representations of all languages in $L \setminus \{x\}$, after which we test the trained classifier on the neutralised representations. The intuition behind this is that if these encoders were to learn language structures in independent ways, we expect only the performance for the language $x$ that corresponds to the centroid $\bar{u}_x$, to deteriorate. However, if performance for multiple languages deteriorates instead, this indicates that information about the typological property is jointly encoded for these languages. We refer to this method as cross-neutralising.

5 Experiments and results

To summarise, we evaluate the trained probing classifier using the following two methods:

- **Self-neutralising**, where we compute a language centroid $\bar{u}_x$ for each test language $x$ and subtract this from the sentence representations of the corresponding language $x$.

- **Cross-neutralising**, where we compute a language centroid $\bar{u}_x$ for a test language $x \in L$.
Table 2: The average change in performance per task $\tau$ and cross-neutralising language $x$ for M-BERT categorized by languages that have the same and those that have a different feature value from language $x$. Note, the blank spaces indicate the cases in which $x$ was omitted from the task due to a lack of coverage in WALS.

| $\tau$ | Ukrainian | Swedish | Polish | Spanish | Marathi | Bulgarian | French |
|-------|-----------|---------|--------|---------|---------|-----------|--------|
|       | same | diff | same | diff | same | diff | same | diff | same | diff | same | diff | same | diff |
| 37A   | -0.45 | -0.22 | -0.76 | -0.01 | -0.62 | 0.03 | -0.62 | 0.02 | -0.74 | 0.04 | -0.46 | 0.02 | -0.15 | 0.01 |
| 38A   | -0.8 | 0.0 | 0.41 | 0.0 | -0.67 | 0.0 | -0.47 | 0.0 | -0.82 | 0.05 | - | -0.34 | 0.0 |
| 45A   | -0.4 | 0.0 | - | - | -0.44 | 0.0 | -0.61 | 0.0 | - | -0.21 | 0.0 |
| 47A   | - | -0.32 | 0.01 | - | -0.58 | 0.0 | -0.82 | 0.01 | - | -0.18 | 0.0 |
| 51A   | -0.22 | 0.14 | 0.18 | -0.23 | -0.26 | 0.17 | -0.3 | 0.0 | -0.75 | 0.44 | - | - |
| 70A   | -0.58 | 0.33 | -0.38 | 0.0 | -0.26 | 0.12 | 0.08 | -0.22 | -0.1 | -0.54 | -0.61 | 0.21 | -0.51 | 0.05 |
| 71A   | -0.15 | 0.04 | -0.55 | 0.05 | -0.45 | 0.05 | -0.68 | 0.08 | 0.08 | -0.06 | -0.28 | -0.12 | -0.13 | -0.11 |
| 72A   | -0.07 | 0.05 | -0.36 | 0.39 | -0.35 | 0.39 | -0.5 | 0.48 | 0.24 | -0.18 | -0.23 | 0.0 | -0.81 | 0.54 |
| 79A   | -0.2 | 0.05 | - | - | -0.68 | 0.07 | - | - | - | - | -0.43 | 0.01 | - |
| 79B   | 0.14 | 0.07 | - | - | - | - | - | - | - | - | - | - | - |
| 81A   | -0.1 | 0.0 | -0.62 | 0.0 | -0.28 | 0.0 | -0.73 | 0.0 | -0.57 | 0.0 | -0.46 | 0.0 | -0.38 | 0.0 |
| 82A   | -0.4 | 0.35 | -0.39 | 0.32 | 0.32 | -0.36 | 0.1 | -0.16 | -0.53 | 0.42 | 0.71 | -0.82 | -0.06 | 0.03 |
| 83A   | -0.08 | 0.0 | -0.6 | 0.0 | -0.27 | 0.0 | -0.8 | 0.0 | -0.6 | 0.0 | -0.41 | 0.0 | -0.47 | 0.0 |
| 85A   | -0.07 | 0.0 | -0.41 | 0.0 | -0.27 | 0.0 | -0.69 | 0.0 | -0.64 | 0.0 | -0.4 | 0.0 | -0.38 | 0.0 |
| 86A   | - | -0.34 | 0.0 | 0.09 | -0.11 | -0.5 | 0.01 | -0.84 | 0.0 | -0.6 | 0.06 | -0.42 | 0.01 |
| 87A   | -0.29 | 0.02 | -0.32 | 0.02 | -0.16 | 0.02 | -0.73 | 0.0 | -0.8 | 0.02 | -0.67 | 0.02 | -0.34 | 0.0 |
| 92A   | 0.26 | -0.05 | -0.35 | 0.15 | 0.28 | -0.33 | 0.15 | -0.18 | - | - | - | - | - |
| 93A   | - | - | -0.29 | 0.0 | 0.19 | -0.21 | - | - | - | - | -0.53 | 0.13 | - |
| 95A   | -0.12 | 0.0 | -0.65 | 0.0 | -0.28 | 0.0 | -0.76 | 0.0 | -0.53 | 0.0 | -0.47 | 0.0 | -0.43 | 0.0 |
| 97A   | -0.24 | 0.0 | -0.7 | 0.0 | -0.48 | 0.0 | -0.76 | -0.03 | -0.72 | -0.03 | -0.87 | 0.0 | -0.42 | -0.02 |
| 115A  | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 116A  | -0.47 | 0.4 | -0.22 | 0.19 | 0.11 | -0.02 | 0.26 | -0.14 | -0.27 | 0.28 | -0.36 | 0.34 | - |
| 143F  | -0.75 | 0.66 | -0.21 | 0.0 | -0.23 | 0.52 | -0.25 | 0.53 | 0.24 | -0.03 | -0.25 | 0.53 | 0.16 | -0.02 |
| 144D  | -0.62 | 0.0 | -0.47 | 0.0 | - | -0.47 | 0.0 | - | - | - | - | - | - |
| 144J  | -0.74 | 0.0 | -0.54 | 0.0 | -0.32 | 0.0 | -0.45 | 0.0 | - | - | - | - | - |

and subtract this from the sentence representations from all other languages in our test set $L \setminus \{x\}$.

5.1 Self-neutralising
First, we test to what extent our approximated language centroids $\bar{u}_x$ successfully capture the typological properties of the language. We do this by evaluating whether the self-neutralising method results in a substantial loss of information about the typological properties of the languages in our test set. When evaluating the change in probing classifier performance before and after applying this method, we observe that each time we self-neutralise with a language, the performance on that language deteriorates to chance accuracy. This shows that the self-neutralising method successfully removes all typological information from the encodings. Moreover, the language identity, approximated by the language centroid, plays a key role in the encoding of typological properties. This suggests that typological information is largely encoded in the relative positioning of the language-specific subspaces of our models.

5.2 Cross-neutralising
Now that we know that computing $\bar{u}_x$ is a viable method to localise the typological properties of a language $x$, we apply our cross-neutralising method. From the results we see that depending on the language we cross-neutralise with (i.e. language $x$ from which we compute $\bar{u}_x$): 1. performance on a different set of languages is affected, and 2. this set of languages varies per task. Upon further inspection, we observe that the languages affected tend to share the same feature value as $x$ for the respective task. Figure 1 shows the change in performance on all test languages when cross-neutralised with Spanish (see Appendix A for cross-neutralisation with other languages). We categorize these languages based on whether their feature value is identical (blue) or different (orange) from the feature value of Spanish in the respective task. Interestingly, we indeed see that the performance on the set of languages that contain the same feature value ($L_{diff}$) tend to deteriorate, while the performance on languages with a different feature value ($L_{diff}$) remains mostly constant.

Moreover, we find that in cases where the classifier incorrectly predicts the feature value of a language $y \in L_{diff}$, the languages in $L_{diff}$ that share this different feature value are affected instead. For instance, for task 116A: ‘Polar Questions’ the label ‘Question particle’ is always incorrectly predicted for the Spanish representations
(even before neutralising). Consequently, when cross-neutralising with Spanish, the performance for languages that share this feature value deteriorate (note in the figure that the orange dots drop in this case). This indicates that in the sentence encoder the feature value ‘Question particle’ is encoded for Spanish. Thus, when we compute $\tilde{u}_i$, we capture information for removing this feature value instead of the correct one ‘Interrogative word order’.

Table 2 shows the average performance for M-BERT, categorized by feature value, for each language with which we neutralise (see Appendix B, Table 3 for XLM-R results). Cases for which the initial probing task performance on the language (before neutralising) was insufficient (< 75%) are denoted in gray (it is unclear what information these centroids capture thus we can not reasonably expect the same trend to emerge). This table shows that there is a clear overall pattern where the performance in languages with the same feature value suffers, while that in languages with a different feature value remains unharmed. Moreover, it showcases counter-examples for cases where properties are not accurately captured, indicating that the trend does not emerge arbitrarily. These results hold true for all languages we cross-neutralise with and for both encoders. Lastly, in some cases we notice that cross-neutralising on average increases the performance of the languages in $L_{diff}$ (e.g. $x = \text{Ukrainian for task 70A}$). We speculate that removing information about $fv_x$ reduces noise in the representations allowing the classifier to pick up on the right signal instead.

Thus, we find that language centroids capture specific feature values in a localizable and systematically similar way across different languages, indicating that linguistic typological properties are jointly encoded across languages. Moreover, we re-produced all of our experiments using sentence representations retrieved from the other layers of the models and observed similar results in all layers (see Appendix C, Figure 3).

6 Conclusion

We have shown that typological feature values are encoded jointly across languages and are localizable in their respective language centroids. In future work, we will correlate the model’s ability to encode typological features with its performance in downstream tasks by progressively deteriorating the amount of typological information encoded. Moreover, the proposed method enables us to carefully select which set of languages we want to neutralise with respect to certain typological properties. This could inspire work on encouraging selective generalization in large-scale models based on typological knowledge, as opposed to enforcing complete language-agnosticism. Lastly, our method is easily applicable to probing for joint encoding in other scenarios, e.g. encoding of linguistic and visual information in multimodal models.

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A  Cross-neutralising results for M-BERT

Figure 2: Change in performance after cross-neutralising with the other test languages for M-BERT. The performance change for all 25 probing tasks is shown per language used for cross-neutralising.
## B  Averaged performance change over languages for XLM-R

| τ / x | Ukrainian | Swedish | Polish | Spanish | Marathi | Bulgarian | French |
|-------|-----------|---------|--------|---------|---------|-----------|--------|
|       | same      | diff.   | same   | diff.   | same    | diff.     | same   | diff. |
| 37A   | -0.26     | 0.0     | -0.74  | -0.02   | -0.77   | 0.01      | -0.81  | 0.0   | 0.0  | -0.74 | 0.01 | -0.54 | 0.0 | -0.22 | 0.0 |
| 38A   | -0.76     | 0.02    | 0.13   | -0.0    | -0.5    | 0.01      | -0.52  | 0.0   | 0.0  | -0.88 | 0.0 | -0.28 | 0.0 |
| 45A   | -        | -0.72   | 0.0    | -        | -0.34   | 0.0       | -0.52  | 0.0   | -0.48 | -0.64 | 0.0 | -0.28 | 0.0 |
| 47A   | -        | -0.48   | 0.0    | -        | -0.72   | 0.0       | -0.52  | 0.0   | -0.48 | -0.64 | 0.0 | -0.28 | 0.0 |
| 51A   | -0.81     | 0.51    | 0.24   | 0.01    | -0.17   | 0.31      | -0.27  | 0.0   | -0.53 | 0.0  | -0.24 | 0.0 |
| 70A   | -0.63     | 0.02    | -0.36  | 0.01    | -0.16   | 0.02      | 0.11   | 0.01 | 0.1  | -0.57 | 0.0 | -0.62 | 0.0 | -0.19 | 0.0 |
| 71A   | -0.66     | -0.08   | -0.68  | 0.0     | -0.72   | 0.01      | -0.68  | 0.11  | 0.08 | 0.0  | -0.27 | 0.04 | -0.19 | 0.0 |
| 72A   | -0.09     | 0.03    | -0.32  | 0.04    | -0.77   | 0.39      | -0.33  | 0.04 | 0.24 | -0.61 | 0.0 | -0.18 | 0.0 | -0.28 | 0.0 |
| 79A   | -0.24     | 0.05    | -        | -0.72   | 0.07   | -        | -        | -0.35 | 0.01 | -0.44 | 0.13 | 0.02 | 0.0 |
| 79B   | 0.52      | -0.03   | -        | -0.22   | 0.03   | -        | -        | -0.44 | 0.13 | 0.02 | 0.0 |
| 81A   | -0.09     | 0.0     | -0.81  | 0.0     | -0.42   | 0.0       | -0.51  | 0.0   | -0.57 | 0.0  | -0.52 | 0.0 |
| 82A   | -0.52     | 0.7     | -0.72  | 0.73    | 0.29    | -0.25     | 0.25   | -0.24 | 0.48 | 0.63 | 0.0 | -0.13 | 0.0 | -0.08 | 0.02 |
| 83A   | -0.14     | 0.0     | -0.81  | 0.0     | -0.41   | 0.0       | -0.52  | 0.0   | -0.48 | 0.0  | -0.52 | 0.0 |
| 85A   | -0.19     | 0.0     | -0.84  | 0.0     | -0.32   | 0.0       | -0.49  | 0.0   | -0.49 | 0.0  | -0.55 | 0.0 |
| 86A   | -        | -0.58   | 0.1    | 0.09   | -0.02   | 0.0       | -0.56  | 0.0   | -0.8 | -0.02 | 0.0 | -0.18 | 0.0 | -0.28 | 0.0 |
| 87A   | -0.88     | 0.01    | -0.28  | 0.01    | -0.19   | 0.01      | -0.75  | 0.0   | -0.58 | 0.01 | -0.44 | 0.01 | -0.28 | 0.0 |
| 92A   | 0.7       | -0.26   | -0.38  | 0.26    | 0.4     | -0.12     | 0.13   | 0.0   | -        | -0.1 | -0.08 | 0.0 |
| 93A   | -        | -0.26   | 0.0    | 0.22   | 0.0     | -        | -0.49   | 0.5   | -        | -0.1 | -0.08 | 0.0 |
| 95A   | -0.13     | 0.01    | -0.83  | 0.01    | -0.43   | 0.01      | -0.52  | 0.0   | -0.56 | 0.01 | -0.52 | 0.0 |
| 97A   | -0.89     | 0.03    | -0.69  | 0.03    | -0.22   | 0.03      | -0.7   | 0.01 | -0.72 | 0.0  | -0.64 | 0.03 | -0.26 | 0.01 |
| 115A  | -        | -        | -0.6   | 0.0    | -0.51   | 0.0       | -        | -0.32 | 0.0 |
| 116A  | -0.14     | 0.02    | -0.26  | 0.23    | 0.11    | -0.02     | 0.22   | -0.32 | 0.56 | 0.49 | -0.45 | 0.45 | -0.13 | 0.0 |
| 143F  | -0.13     | 0.0    | -0.19  | 0.0    | -0.3    | 0.29       | -0.67  | 0.34 | 0.48 | -0.97 | 0.74 | 0.34 | 0.14 | -0.09 |
| 144D  | -0.16     | 0.0    | -0.52  | 0.0    | -        | -0.53   | 0.0       | -0.75  | 0.0 |
| 144J  | -0.14     | 0.0    | -0.58  | 0.0    | -0.36   | 0.0       | -0.55   | 0.0   | -0.81 | 0.0 |

Table 3: The average change in performance per task τ and cross-neutralizing language x for XLM-R categorized by languages that have the same and those that have a different feature value from language x. Note, the blank spaces indicate the cases in which x was omitted from the task due to a lack of coverage in WALS.
C Cross-neutralising results for M-BERT across layers

Figure 3: The change in performance for all test languages when cross-neutralising M-BERT representations with a language-centroid computed from the Spanish sentences. Languages are categorized by whether they had the same or a different feature value from that of Spanish for the respective tasks.
## D WALS codes, categories and feature names

| Code  | Category       | Feature name                                                      |
|-------|----------------|------------------------------------------------------------------|
| 37A   | Nominal Category | Definite articles                                                 |
| 38A*  | Nominal Category | Indefinite articles                                               |
| 45A†  | Nominal Category | Politeness distinctions in pronouns                               |
| 47A‡  | Nominal Category | Intensifiers and reflexive pronouns                               |
| 51A§  | Nominal Category | Position of case affixes                                          |
| 70A   | Verbal Category  | The morphological imperative                                      |
| 71A   | Verbal Category  | The prohibitive                                                   |
| 72A   | Verbal Category  | Imperative-hortative systems                                      |
| 79A§  | Verbal Category  | Suppletion according to tense and aspect                           |
| 79B‡  | Verbal Category  | Suppletion in imperatives and hortatives                           |
| 81A   | Word Order      | Order of Subject, Object and Verb (SOV)                           |
| 82A   | Word Order      | Order of Subject and Verb (SV)                                    |
| 83A   | Word Order      | Order of Object and Verb (OV)                                     |
| 85A†  | Word Order      | Order of adposition and noun phrase                               |
| 86A‡  | Word Order      | Order of genitive and noun                                        |
| 87A   | Word Order      | Order of adjective and noun                                       |
| 92A   | Word Order      | Position of polar question particles                              |
| 93A§  | Word Order      | Position of interrogative phrases in content questions            |
| 95A   | Word Order      | Relationship between OV and adposition and noun phrase order      |
| 97A   | Word Order      | Relationship between OV and adjective and noun order              |
| 115A# | Simple Clauses  | Negative indefinite pronouns and predicate negation               |
| 116A♦ | Simple Clauses  | Polar questions                                                    |
| 143F  | Word Order      | Postverbal negative morphemes                                     |
| 144Dδ | Word Order      | Position of negative morphemes                                    |
| 144Jδ | Word Order      | Order of Subject, Verb, Negative word, and Object (SVNegO)        |

Table 4: The 25 WALS features used for probing along with their corresponding WALS codes and categories. The multilingual sentence representations for each of these features are probed for in separate tasks. Unless indicated otherwise, all language pairs were covered. Excluded pairs: *:(1), †:(1, 3 and 6), ‡:(6 and 7), §:(2, 4, 5 and 7), |:(5 and 6), ¶:(1, 4, 6, 7), #:(1-3 and 6), §:(7), †:(3, 5 and 7), δ:(5 and 7)