Locating Language-Specific Information in Contextualized Embeddings

Sheng Liang, Philipp Dufter, Hinrich Schütze
Center for Information and Language Processing (CIS)
LMU Munich, Germany
{shengliang, philipp}@cis.lmu.de

Abstract
Multilingual pretrained language models (MPLMs) exhibit multilinguality and are well suited for transfer across languages. Most MPLMs are trained in an unsupervised fashion and the relationship between their objective and multilinguality is unclear. More specifically, the question whether MPLM representations are language-agnostic or they simply interleave well with learned task prediction heads arises. In this work, we locate language-specific information in MPLMs and identify its dimensionality and the layers where this information occurs. We show that language-specific information is scattered across many dimensions, which can be projected into a linear subspace. Our study contributes to a better understanding of MPLM representations, going beyond treating them as unanalyzable blobs of information.

1 Introduction
Multilingual contextualized language models (e.g., Devlin et al., 2019; Conneau et al., 2020a) have been shown to exhibit a great degree of multilinguality as for example measured by zero-shot crosslingual transfer (Hu et al., 2020). Having multilingual models is useful as it is easier to deploy and maintain a single multilingual model rather than many monolingual ones. Further, low resource languages can benefit from transfer and less annotated data might be required. However, it is an active research question how current multilingual models work (Pires et al., 2019; Wu and Dredze, 2019) and whether the models are truly language agnostic (Gonen et al., 2020; Libovický et al., 2020; Zhao et al., 2020; Choenni and Shutova, 2020).

Most prior work such as (Libovický et al., 2020; Zhao et al., 2020) aims at creating language agnostic representations by subtracting the mean of language specific representations. Gonen et al. (2020) tries to extract word level translations from mBERT (Devlin et al., 2019).

We continue this line of research to decode interpretable language-specific information from multilingual representations, by analyzing the dimensionality of language-specific subspaces and how language-specific information evolves across different intermediate layers. To investigate this, we compare two linear projection methods, DensRay (Dufter and Schütze, 2019) and Linear Discriminant Analysis (LDA) (Fisher, 1936). Our experiments with three probing tasks, Language Identification, Linguistic Typology and Language Similarity, show that language-specific information is scattered across many dimensions. The dimensionality of the subspace is determined by the tasks. However, with our proposed methods there exists an upper bound on the dimensionality which is approximately equal to the number of languages in the model. We also find that languages are better separated in lower layers.

With this knowledge, we propose an activity regularization approach in Appendix B, which potentially encourages the model to preserve language-specific information during finetuning. We apply this approach when finetuning mBERT on NER and POS tagging tasks and show that it achieves small improvements on zero-shot cross-lingual transfer.

2 Related Work
Much recent work has examined how language information is stored in multilingual representations. Pires et al. (2019) construct a tree structure to describe language similarities via hierarchical clustering and CCA similarity scores. Libovický et al. (2020) assume that mBERT’s representations have a language-neutral component and a language-specific component. They remove the language-specific component by subtracting the language centroids. In a similar vein, Zhao et al. (2020)
induce language agnostic representations and explore batch normalization to decrease the distance between languages for better cross-lingual transfer, achieving improvement on XNLI and RFEval. Further, Gonen et al. (2020) extract an empirical language-identity subspace and language-neutral subspace in mBERT; to achieve this, they present a linear projection method based on null-space transformation yielded by iterative classification. This work mainly focuses on word translation and the dimensionality of the subspace is not well studied. Similarly, Choenni and Shutova (2020) investigate the language agnosticity using typological probing tasks. Huang et al. (2021) use a learning approach to achieve a linear syntax-subspace in mBERT, in which syntactic information is shared across languages. Researching a different aspect, Conneau et al. (2020b) show that sharing upper layers is essential for obtaining multilingual models. Related to this, Muller et al. (2021) show that the lower part of mBERT operates as a multilingual encoder which is critical for cross-lingual transfer, and a language-agnostic predictor which is less important in cross-lingual transfer.

Overall, we follow this line of research, but we set the focus on locating the language-specific information both in terms of dimensionality of the subspace and in which intermediate layers this information is contained. In addition, we propose an activity regularization approach based on our findings.

3 Methods

3.1 Locating Language-Specific Information

We aim at locating language-specific linear subspaces. Therefore, we compare two linear projection methods, DensRay (Dufter and Schütze, 2019) and LDA (Fisher, 1936). DensRay learns an orthogonal transformation of an embedding space to find a subspace of certain linguistic features. It maximizes the distances of embeddings between different languages and minimizes them within each language. Similarly, LDA identifies directions in the space that separate classes (languages).

The methods require representations from different classes. More specifically, we obtain vectors \((x^l_i)_{i \in 1,2,...}, (x^i_l)_{i \in 1,2,...} \in \mathbb{R}^d\), ...for languages \(l_1, l_2, \ldots\). When we feed these vectors together with the language information to the algorithms we obtain projection matrices \(Q \in \mathbb{R}^{d \times d}\) where the n-th dimension contains the n-th most language information. Please consult the references for more details on how the matrices are computed.

Both methods are computable with analytical solutions. The upper bound of the subspace dimensionality is characterized by the matrix rank in their objective function (see A). There are two main differences between DensRay and LDA: 1) DensRay yields an orthogonal transformation matrix, while orthogonality is not guaranteed for LDA (Ye et al., 2006). 2) DensRay only considers the centroids of each language, while LDA additionally utilizes the centroid of the entire space. We choose both methods as LDA is a canonical choice and DensRay is an analytical version of Densifier (Rothe et al., 2016), which is an established method in natural language processing.

4 Experiments

4.1 Computing Language Specific Subspaces

We download text data for 104 languages of mBERT (Devlin et al., 2019) from Wikipedia, and for 100 languages of XLM-R from the CC-100 corpus (Conneau et al., 2020a). For each language we sample 10,000 random token embeddings to compute the projection matrix for each layer, and project the multilingual representation space into a linear subspace shared by all languages, in which all languages are well separated. Thus the language-specific subspace contains interpretable
Figure 2: Probing tasks LI, LT and LS when considering 10 dimensions. For 50 on the x-axis, we report the difference between the accuracy when using dimensions 41–50 vs. 10 random dimensions.

information that can identify different languages.

4.2 Probing Tasks
After projecting the representations, we use probing tasks to analyze how much language-specific information is contained.

In language-specific subspaces, it should be easy to determine what language the token/sentence is written in. We randomly select language pairs to train binary Logistic Regression classifiers for Language Identification (LI) on the subspaces and evaluate the average pairwise accuracy. That is, we train and evaluate in a one-vs-one fashion.

To investigate Linguistic Typology (LT), we use WALS (Dryer and Haspelmath, 2013). To predict each of WALS’s 192 typological features, we train a logistic regression on the subspaces in a one-vs-rest fashion, and report the micro average $F_1$ score.

Following (Libovický et al., 2020), we quantify the Language Similarity (LS) in the subspaces by V-measure. We apply hierarchical clustering to the subspaces’ centroids of languages and compare the clusters with language families.

4.3 Token Classification
To analyze the cross-lingual transfer ability of the subspaces for downstream tasks, we use the Wikiann dataset (Pan et al., 2017) for named entity recognition (NER) and Universal Dependencies treebanks (Nivre and Abrams, 2018) for Part-of-Speech (PoS) tagging. Somewhat in between a probing task and a downstream task, we train a linear classifier with different subspace dimensions on mBERT representations to predict NER/PoS, and evaluate the zero-shot transfer performance by average $F_1$ score on all languages.

4.4 Setup
Multilingual Language Models For mBERT and XLM-R, we use the models "bert-base-multilingual cased" and "xlm-roberta-base" from the Transformers library (Wolf et al., 2020).

Probing Tasks For each task, we sample 8,000 token embeddings for training and 2,000 for evaluation. We run each experiment with five different seeds and report the mean. We use Logistic Regression from the Scikit-learn library (Pedregosa et al., 2011) and Hierarchical Clustering from the Scipy library (Virtanen et al., 2020) with their default setting.

Token Classification We use the script from Xtreme (Hu et al., 2020) and switch the dimension of the output layer and connect to the corresponding subspaces.

5 Results
5.1 Probing Tasks
Figure 1 shows the scores of the probing classifier for the different dimensions. For LI one can see
nicely that the curves for using dimensions \([0:x]\) consistently increase. Similarly, when using the dimensions \([x:2x]\) the scores go up, but then decrease. This is the point where language information becomes less prevalent. The curve meets the dotted line that indicates the accuracy when choosing \(x\) random dimensions at roughly \(x=100\). This is an indication that up to 100 dimensions contain all language-specific information, which matches our proof in Appendix A.

For LT one can see a similar effect, yet not so pronounced. Most probably because classifying linguistic features is a more challenging task and many languages can share the same features. For LS, the solid line decreases as here we use an unsupervised clustering approach rather than training classifiers. So adding more dimensions results in more noise.

Thus we provide a different view in Figure 2 for the same tasks, where the main difference is, Figure 1 shows the dimensionality to cover all language information is roughly equal to the number of languages, while Figure 2 shows the dimensionality to cover sufficient language information is different for each task.

Figure 2 directly plots the difference between accuracy when using dimensions \([x-10:x]\) compared to 10 random dimensions. We see that the dimensionality of the language specific subspace is different in each task, e.g., in LI, language-specific subspace on the 12th layer in mBERT has dimensionality\(\approx 100\), while for LT/LS, it is 70 and 30. Clearly, a one-dimensional language-specific subspace (as often assumed in some prior work) is not valid.

In Figure 3 we demonstrate the probing results with subspaces \([0:x]\) on different layers. We select \(x=1\) in LI while \(x=20\) in other two tasks for better visualization, since LI is a simple task, the differences between layers will be less obvious with larger \(x\). Results show that lower layers show strong LI and LT capabilities, which may indicate that lower layers store more language-specific information. Although the LI curves go up at the last layers, this also happens in LT while not so significant, the reason may be the learned parameters in the classifier also contribute to the results. Our findings are in line with prior work that finds that lower layers are more language specific (Muller et al., 2021). Overall, the two methods, DensRay and LDA, show similar trends.

5.2 Token Classification
In Figure 4 we demonstrate performance gap between using the entire space and the subspace \([x:768]\), which mainly stores language-agnostic information for NER and PoS. We see that the curves are to zero initially, rising gradually. Omitting the first 100 dimensions only marginally affects the crosslingual performance. Then, the difference grows close to linearly. This might indicate that downstream tasks would be more sensitive to the semantic information in language-agnostic subspace, and less sensitive to the language identity information in the language-specific subspace, which would insight our proposed regularization approach in Appendix B.

6 Conclusion
This work follow the line of research to analyze how interpretable language information is stored in multilingual representations. We applied DensRay and LDA to locate language-specific information in linear subspaces from mBERT and XLM-R’s representations. Our probing results show that language-specific information can be well decoded by the method we proposed. The dimensionality of the subspace we extracted is determined by the task, while there exists an upper bound roughly equal to the number of languages. We also found that languages are well separated in lower layers, which may indicate that lower layers store more language-specific information.

For future work, we are interested in continuing the research for better utilizing language-specific information to achieve better zero-shot cross-lingual transfer performance.
References

Rochelle Choenni and Ekaterina Shutova. 2020. What does it mean to be language-agnostic? probing multilingual sentence encoders for typological properties. arXiv preprint arXiv:2009.12862.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Édouard Grave, Luke Zettlemoyer, and Veselin Stoyanov. 2020a. Unsupervised cross-lingual representation learning at scale. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8440–8451, Online. Association for Computational Linguistics.

Alexis Conneau, Shijie Wu, Haoran Li, Luke Zettlemoyer, and Veselin Stoyanov. 2020b. Emerging cross-lingual structure in pretrained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6022–6034, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Matthew S. Dryer and Martin Haspelmath, editors. 2013. WALS Online. Max Planck Institute for Evolutionary Anthropology, Leipzig.

Philipp Dufter and Hinrich Schütze. 2019. Analytical methods for interpretable ultradense word embeddings. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1185–1191, Hong Kong, China. Association for Computational Linguistics.

Ronald A Fisher. 1936. The use of multiple measurements in taxonomic problems. Annals of eugenics, 7(2):179–188.

Hila Gonen, Shauli Ravfogel, Yanai Elazar, and Yoav Goldberg. 2020. It’s not greek to mbert: Inducing word-level translations from multilingual bert. In Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP, pages 45–56.

Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. 2020. XTREME: A massively multilingual multitask benchmark for evaluating cross-lingual generalisation. In Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event, volume 119 of Proceedings of Machine Learning Research, pages 4411–4421. PMLR.

James Y Huang, Kuan-Hao Huang, and Kai-Wei Chang. 2021. Disentangling semantics and syntax in sentence embeddings with pre-trained language models. arXiv preprint arXiv:2104.05115.

Jindřich Libovický, Rudolf Rosa, and Alexander Fraser. 2020. On the language neutrality of pre-trained multilingual representations. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1663–1674, Online. Association for Computational Linguistics.

Benjamin Muller, Yanai Elazar, Benoît Sagot, and Djamé Seddah. 2021. First align, then predict: Understanding the cross-lingual ability of multilingual BERT. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 2214–2231, Online. Association for Computational Linguistics.

Joakim Nivre and Mitchell et al. Abrams. 2018. Universal Dependencies 2.2. LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics (UFAL), Faculty of Mathematics and Physics, Charles University.

Xiaoman Pan, Boliang Zhang, Jonathan May, Joel Nothman, Kevin Knight, and Heng Ji. 2017. Cross-lingual name tagging and linking for 282 languages. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1946–1958, Vancouver, Canada. Association for Computational Linguistics.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830.

Telmo Pires, Eva Schlinger, and Dan Garrette. 2019. How multilingual is multilingual BERT? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4996–5001, Florence, Italy. Association for Computational Linguistics.

Sascha Rothe, Sebastian Ebert, and Hinrich Schütze. 2016. Ultradense word embeddings by orthogonal transformation. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 767–777, San Diego, California. Association for Computational Linguistics.

Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovskiy, Pearu Peterson, Warren
Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C J Carey, Illhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, Paul van Mulbregt, and SciPy 1.0 Contributors. 2020. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17:261272.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Shijie Wu and Mark Dredze. 2019. Beto, bentz, becas: The surprising cross-lingual effectiveness of BERT. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 833–844, Hong Kong, China. Association for Computational Linguistics.

Jieping Ye, Tao Xiong, and David Madigan. 2006. Computational and theoretical analysis of null space and orthogonal linear discriminant analysis. *Journal of Machine Learning Research*, 7(7).

Wei Zhao, Steffen Eger, Johannes Bjerva, and Isabelle Augenstein. 2020. Inducing language-agnostic multilingual representations. *arXiv preprint arXiv:2008.09112*. 
A The Upper bound of Dimensionality

Assume that we have \( n \) classes of embeddings \( C_1, ..., C_n \), which stand for \( n \) languages in this work, \( C_i \in \mathbb{R}^{l_x \times d} \). Fisher (1936) proved the rank of LDA objective limits the upper bound of subspace dimensionality to \( n-1 \). Follow the same idea, here we prove the dimensionality of subspace yields by DensRay has a upper bound \( n+1 \).

With DensRay objective (Dufter and Schütze, 2019), we get \( C(n, 1) = n \) pairs of languages for \( L_1 \), and \( C(n, 2) = n(n-1)/2 \) pairs for \( L_2 \). Note \( c_i \) as the mean of and \( C_i \), one can simply rewrite the objective into matrix form, so for each pair \((C_i, C_j)\) and \( v \in C_i, w \in C_j \) we have:

\[
\sum_{v,w} d_{vw}^2 = -l_i l_j (c_i c_j^T + c_j c_i^T) + l_i C_i c_j^T + l_j C_j c_i^T
\]

When all classes have the same number of samples \( l_i = m \), it becomes:

\[
\sum_{v,w} d_{vw}^2 = -m^2 c_i c_j^T - m^2 c_j c_i^T + m C_i c_j^T + m C_j c_i^T
\]

Set weights \( \alpha_m = 1/n \) and \( \alpha_n = 2/(n-1) \), then for \( v, w \in L_2 \):

\[
\alpha_m = \frac{2m^2}{n(n-1)} \sum_{i,j=1}^{n} c_i c_j^T + \frac{2m}{n} \sum_{i=1}^{n} C_i c_i^T
\]

And for \( v, w \in L_2, \alpha_n \sum_{v,w} d_{vw}^2 =
\]

\[
\frac{2m^2}{n(n-1)} \sum_{i,j=1}^{n} c_i c_j^T + \frac{n-1}{m} \sum_{i=1}^{n} C_i c_i^T
\]

Let \( A_1 = \sum_{i=1}^{n} c_i c_i^T, A_2 = (\sum_{i=1}^{n} c_i) (\sum_{i=1}^{n} c_i)^T \), then:

\[
A = \frac{2m^2}{n-1} (A_1 - \frac{1}{n} A_2)
\]

Obviously the rank \( R(A_1) \leq n \) reaches its upper bound \( n \) when all the classes are completely independent, also we have \( R(A_2) = 1 \) since \( \sum_{i=1}^{n} c_i \) is a vector. Thus:

\[
R(A) \leq R(A_1) + R(A_2) \leq n + 1
\]

This formula indicates that \( n+1 \) is the upper bound of dimensionality to cover all the information needed for DensRay. Specially, when \( n = 2 \), we have \( A = m^2/2 (c_1 - c_2) (c_1 - c_2)^T \) and \( R(A) = 1 \). Also, when languages are similar, \( R(A_1) \) will be less than \( n \), which would lead to a smaller subspace.

Figure 5: LI with every 2 dimensions on mBERT embeddings, projected by DensRay, we demonstrate the performance gap with 2 random dimensions.

B Activity Regularization

B.1 Methodology

Primarily we locate the language-specific information via linear projections. However, we attempt to use gained insights for better zero-shot transfer and propose an activity regularization approach. The regularizer aim to encourage the model to keep the language-specific information close to the representations in PLM and to change only the language-agnostic information. This assumes that the PLM is multilingual and finetuning on a downstream task using only a single language would destroy this multilinguality to some degree.

Let \( E \in \mathbb{R}^{n \times d} \) be the original representation obtained from a pretrained multilingual encoder, \( E \in \mathbb{R}^{n \times d} \) be the representation during finetuning in a downstream task. With a DensRay transformation matrix \( Q \in \mathbb{R}^{d \times d^*} \) where \( d^* \) is the dimensionality of language-specific subspace, we propose L-DAR (Language subspace - DensRay Activity Regularization), a regularizer to improve the performance on zero-shot cross-lingual transfer. More specifically, we add the following regularization term to the training objective during finetuning:

\[
L_{DAR} = \alpha \| W (EQ - EQ) \| \text{ where } \alpha \text{ is a weight to allow for a balance between this regularizer and the cross entropy loss, and } W \in \mathbb{R}^{d^*} \text{ is the explained variance ratio of the dimensions in } Q. \text{ As}
\]
Table 1: Results of Zero-shot transfer.

|                | PoS Train | Zero-S. | All | NER Train | Zero-S. | All |
|----------------|-----------|---------|-----|-----------|---------|-----|
| Single-Src. mBERT | 95.3      | 71.0    | 71.8| 84.1      | 61.2    | 61.8|
| L-DAR          | 95.4      | 71.3    | 72.1| 84.6      | 61.5    | 62.1|
| Multi-Src. mBERT | 93.8      | 72.1    | 74.1| 82.5      | 67.4    | 68.6|
| L-DAR          | 94.1      | 72.6    | 74.6| 82.6      | 66.7    | 68.0|

Table 1: Results of Zero-shot transfer.

DensRay is computed using an eigendecomposition we can interpret eigenvalues as explained variance. $W$ weighs individual dimensions with their contributions.

### B.2 Setup

We evaluate L-DAR on the Xtreme setup (Hu et al., 2020) working with mBERT for PoS and NER, which finetuned mBERT for 2 epochs, with a training batch size of 4, a gradient accumulation step of 8, and a learning rate of 2e-5. For L-DAR, we turn off the dropout and set dimensionality $d^*$ to 105, and set $\alpha$ to 5e-3. We apply the regularizer for representations on all hidden layers. All experiments are executed on GeForce RTX 2080 Ti, which would take around 6 minutes for each epoch.

Besides using only English training data, we also work with a multisource transfer where we use training data from English, German and Chinese. This allows the model to learn and preserve language differences more effectively because it sees multiple languages during finetuning. We evaluate zero-shot transfer with $F_1$.

### B.3 Results

Table 1 shows that with English training data, L-DAR achieves a small improvement around 0.3% on both tasks. Thus, preserving language specific information from pretraining seems a promising research approach for future work. In multisource training with English, German and Chinese, L-DAR outperforms the baseline with 0.5% on POS tagging while the average $F_1$ score drops by 0.6% on NER task. Detailed results for each language are shown in Table 2~Table 5.

### B.4 Analysis

As an additional analysis we apply the regularizer for representations from every 4 layers e.g. $\Delta 1 - 4$. Here we set $\alpha$ to 2e-2. Table 6 shows that L-DAR achieves better performance on upper layers, especially, on both single source task and multisource PoS, L-DAR shows comparable $F_1$ with the baseline. However this behaviour is not shown on multilingual NER, which leads to the drop in this task, we left this problem for further research.
| Lang.       | en | af | ar | bg | de | el | es | et | eu | fa | fi | fr | he | hi | hu | id | it |
|------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| mBERT      | 95.3 | 86.7 | 55.7 | 84.7 | 85.5 | 81.2 | 86.7 | 79.5 | 60.8 | 66.4 | 79.3 | 83.0 | 55.7 | 66.9 | 78.9 | 71.3 | 88.4 |
| L-DAR      | 95.4 | 86.0 | 54.9 | 86.5 | 86.7 | 82.6 | 87.5 | 80.3 | 59.3 | 67.8 | 79.8 | 84.0 | 56.2 | 63.1 | 79.7 | 71.6 | 88.2 |
| ja         | 50.9 | 70.8 | 50.2 | 69.0 | 88.7 | 86.2 | 85.5 | 58.9 | 75.5 | 41.7 | 82.1 | 68.9 | 57.8 | 55.5 | 58.8 | 62.2 | 71.8 |
| L-DAR      | 48.4 | 71.1 | 51.1 | 74.4 | 88.7 | 86.7 | 86.4 | 60.1 | 76.7 | 40.0 | 83.2 | 69.1 | 56.8 | 55.0 | 57.7 | 63.1 | 72.1 |
| Table 2: Zero-shot (en) Transfer on POS tagging. |

| Lang.       | en | de | zh | af | ar | bg | el | es | et | eu | fa | fi | fr | he | hi | hu | id | it |
|------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| mBERT      | 94.9 | 96.2 | 90.3 | 87.1 | 53.7 | 86.7 | 86.8 | 86.7 | 81.2 | 66.3 | 66.2 | 80.9 | 84.3 | 56.8 | 66.7 | 80.9 | 72.6 |
| L-DAR      | 95.1 | 97.1 | 90.2 | 86.4 | 54.8 | 87.8 | 87.1 | 87.3 | 80.9 | 62.0 | 68.3 | 81.7 | 84.5 | 56.7 | 67.9 | 81.1 | 72.7 |
| it | ja | kk | ko | mr | nl | pt | ru | ta | te | th | tl | tr | ur | vi | yo | zh | avg |
| mBERT      | 86.1 | 46.3 | 73.0 | 52.1 | 76.3 | 90.1 | 84.0 | 86.3 | 62.9 | 75.5 | 48.8 | 82.9 | 72.1 | 57.7 | 55.4 | 57.9 | 74.1 |
| L-DAR      | 86.5 | 46.5 | 73.6 | 52.5 | 76.3 | 89.6 | 84.4 | 86.7 | 62.4 | 75.4 | 49.8 | 86.7 | 72.6 | 59.7 | 56.9 | 60.5 | 74.6 |
| Table 3: Zero-shot (Multisource) Transfer on POS tagging. |

| Lang.       | en | de | zh | af | ar | bg | bn | de | el | es | et | eu | fa | fi | fr | he | hi | hu | id | it | ja | jv |
|------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| mBERT      | 84.1 | 76.5 | 43.0 | 76.7 | 67.9 | 77.2 | 72.5 | 71.2 | 75.2 | 64.7 | 36.2 | 76.8 | 79.2 | 57.0 | 65.9 | 76.0 | 67.4 | 80.8 | 29.9 | 64.7 |
| L-DAR      | 84.6 | 77.3 | 41.6 | 77.2 | 68.0 | 79.1 | 74.1 | 77.0 | 76.9 | 60.6 | 38.8 | 77.6 | 80.2 | 56.6 | 65.2 | 76.6 | 57.7 | 81.9 | 29.4 | 65.3 |
| ka | kk | ko | ml | mr | ms | my | nl | pt | ru | sw | ta | te | th | tl | tr | ur | vi | yo | zh | avg |
| mBERT      | 64.8 | 48.8 | 59.7 | 51.8 | 56.7 | 71.3 | 50.2 | 82.0 | 79.3 | 61.7 | 71.1 | 50.9 | 47.9 | 0.64 | 73.5 | 73.8 | 33.3 | 35.1 | 72.9 | 43.3 | 61.8 |
| L-DAR      | 65.7 | 46.7 | 58.3 | 53.8 | 57.6 | 66.9 | 51.2 | 82.4 | 81.4 | 64.1 | 67.1 | 49.8 | 47.5 | 0.60 | 74.5 | 76.7 | 33.9 | 43.2 | 71.8 | 43.2 | 62.1 |
| Table 4: Zero-shot (en) Transfer on NER. |

| Lang.       | en | de | zh | af | ar | bg | bn | el | es | et | eu | fa | fi | fr | he | hi | hu | id | it | ja | jv |
|------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| mBERT      | 82.3 | 87.6 | 77.5 | 80.8 | 51.6 | 82.0 | 69.8 | 78.4 | 83.6 | 81.0 | 69.9 | 48.5 | 80.5 | 85.4 | 58.9 | 70.0 | 83.5 | 65.0 | 81.6 | 42.7 |
| L-DAR      | 82.2 | 87.6 | 77.9 | 80.6 | 47.5 | 82.0 | 71.9 | 79.2 | 82.8 | 80.0 | 74.3 | 43.4 | 81.9 | 84.5 | 57.6 | 68.3 | 82.2 | 71.2 | 85.1 | 46.1 |
| jv | ka | kk | ko | ml | mr | ms | my | nl | pt | ru | sw | ta | te | th | tl | tr | ur | vi | yo | zh | avg |
| mBERT      | 65.9 | 73.1 | 57.6 | 67.4 | 64.8 | 64.6 | 74.1 | 55.2 | 84.4 | 83.3 | 70.6 | 64.6 | 54.8 | 56.6 | 6.1 | 74.7 | 82.5 | 47.0 | 59.3 | 75.8 | 68.6 |
| L-DAR      | 65.2 | 71.4 | 52.6 | 67.9 | 62.6 | 65.2 | 73.5 | 53.8 | 85.9 | 83.5 | 69.0 | 61.4 | 57.3 | 60.4 | 9.1 | 74.5 | 78.8 | 37.6 | 51.9 | 69.1 | 68.0 |
| Table 5: Zero-shot (Multisource) Transfer on NER. |