On the Limitations of Sociodemographic Adaptation with Transformers

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Abstract

Sociodemographic factors (e.g., gender or age) shape our language. Previous work showed that incorporating specific sociodemographic factors can consistently improve performance for various NLP tasks in traditional NLP models. We investigate whether these previous findings still hold with state-of-the-art pre-trained Transformers. We use three common specialization methods proven effective for incorporating external knowledge into pre-trained Transformers (e.g., domain-specific or geographic knowledge). We adapt the language representations for the sociodemographic dimensions of gender and age, using continuous language modeling and dynamic multi-task learning for adaptation, where we couple language modeling with the prediction of a sociodemographic class. Our results when employing a multilingual model show substantial performance gains across four languages (English, German, French, and Danish). These findings are in line with the results of previous work and hold promise for successful sociodemographic specialization. However, controlling for confounding factors like domain and language shows that, while sociodemographic adaptation does improve downstream performance, the gains do not always solely stem from sociodemographic knowledge. Our results indicate that sociodemographic specialization, while very important, is still an unresolved problem in NLP.

1 Introduction

Sociodemographic factors like social class, education, income, age, or gender categorize people into specific groups or populations. At the same time, sociodemographic factors both shape and are reflected in our language (e.g., Trudgill, 2000; Eckert and McConnell-Ginet, 2013). For instance, people actively tailor their language to match what is acceptable in groups they identify with (e.g., age groups; cf. linguistic homophily). At the same time, many linguistic features are beyond people’s control, but mark them clearly as members of a certain group (e.g., dialect terms).

Various works in NLP have modeled sociodemographic variation, especially the correlations between words and sociodemographic factors (Bamman et al., 2014; Garimella et al., 2017; Welch et al., 2020, inter alia). In a similar vein, Volkova et al. (2013) and Hovy (2015) demonstrated that explicitly modeling demographic factors can consistently improve performance on various tasks. However, these observations were made for approaches that leveraged gender-specific lexica to specialize word embeddings and relied on text encoders (e.g., recurrent networks) that have not been pre-trained for language understanding. The benefits of demographic specialization have not been tested with Transformer-based (Vaswani et al., 2017) pre-trained language models (PLMs), which have (i) seen immense text corpora in pre-training and (ii) been shown to excel on most tasks and even sometimes outperform humans (Wang et al., 2018).

More recent studies focused mainly on monolingual English datasets and introduce (socio)demographic features in task-specific fine-tuning (Voigt et al., 2018; Buechel et al., 2018), which limits the benefits of (socio)demographic knowledge to tasks at hand. In this work, we investigate the (task-agnostic) sociodemographic specialization of PLMs, aiming to impart the associations between sociodemographic categories and linguistic phenomena into the PLMs parameters: if successful, such specialization would then benefit any downstream NLP task in which sociodemographic factors matter. For this, we adopt straightforward intermediate training paradigms that have been proven effective in specialization of PLMs.
for other types of knowledge, e.g., in domain, language, and geographic adaptation (Glavaš et al., 2020; Hung et al., 2022a; Hofmann et al., 2022).

Concretely, we encourage the PLMs to establish associations between linguistic phenomena and sociodemographic categories (gender and age groups, in our case). To this effect, we perform continuous language modeling on specialized corpora and in a dynamic multi-task learning setup (Kendall et al., 2018), combining language modeling with the prediction of demographic categories.

We evaluate the effectiveness of the proposed demographic specialization on three tasks – we combine demographic category prediction, as an intrinsic evaluation task, with sentiment classification and topic detection as extrinsic evaluation tasks – and across 4 languages: English, German, French, and Danish. For this, we utilize the multilingual corpus of reviews of Hovy et al. (2015), annotated with demographic information. In line with earlier findings (Hovy, 2015), our initial experiments based on a multilingual PLM, multilingual BERT (Devlin et al., 2019), render demographic specialization effective: we report gains in most tasks and settings. Our further analysis shows that, unfortunately, this is just a mirage. Through a set of controlled experiments, in which we (1) adapt with in-domain language modeling alone, without leveraging demographic information and (2) demographically specialize monolingual PLMs of evaluation languages, and (3) analyze the topology of the representation spaces of demographically specialized PLMs, we show that most of the original gains can be attributed to confounding effects of language and/or domain specialization.

These findings suggest that specialization approaches proven effective for other types of knowledge fail to adequately instill demographic knowledge into PLMs, making demographic specialization of NLP models an open problem in the age of large pre-trained Transformers.

2 Sociodemographic Adaptation

Our goal is to inject sociodemographic knowledge through intermediate model training in a task-agnostic manner. To achieve this goal, we train the PLM (1) via Masked Language Modeling and (2) in a dynamic multi-task learning setup (Kendall et al., 2018) where we couple language modeling with the prediction of a sociodemographic factor. This setup pushes the PLM to learn an association (i.e., joint representation) of the contextual information and the sociodemographic factors.

2.1 Masked Language Modeling (MLM)

Following successful work on pretraining via language modeling for domain-adaptation (Gururangan et al., 2020; Hung et al., 2022a), we investigate the effect of running standard MLM on the data. The MLM loss $L_{mlm}$ is computed as the negative log-likelihood of the true token probability:

$$L_{mlm} = -\sum_{m=1}^{M} \log P(t_m),$$

where $M$ is the total number of masked tokens of the given text and $P(t_m)$ is the predicted probability of the token $t_m$ over the vocabulary size.

2.2 Sociodemographic Factor Prediction

In the multi-task learning setup, the representation of the input texts is additionally fed into a classification head that predicts the sub-group of sociodemographic factors: age (under 35 and over 45 – to avoid fuzzy age boundaries following the setup from Hovy (2015)), and gender (female and male). The sociodemographic prediction loss $L_{socio}$ is computed as the binary cross-entropy loss:

$$L_{socio} = -\sum_{c \in C} y(c) \log P(c),$$

where for each class $c$, we use its predicted probability $P(c)$, and the true class probability $y(c)$.

We investigate the effectiveness of the input text representation for two variants: (i) using the [CLS] token representation and (ii) using the contextualized representation of the masked tokens. The [CLS] token represents the whole sequence, while the contextualized representation of the masked tokens focuses on the token-level relationships. Thus, in the first setup, we seek to strengthen the sociodemographic link for a higher-level, wider context, while the token-level setup intuitively enforces a narrower, lower-level specialization.

2.3 Multi-Task Learning

The multi-task objective forces the model to recognize the sociodemographic aspect while obtaining the linguistic knowledge via masked language modeling. In joint multi-task training, we could simply sum the task-specific losses as a naive way of computing a joint loss. However, the summation approach is based on the assumption that all tasks have equal weights of losses (i.e., an equal
Table 1: Statistics for the Trustpilot dataset (Hovy et al., 2015) we use in our experiments. For each country (Denmark, France, Germany, UK, and US), we report the language, the size of the specialization portions, and the total number of fine-tuning review texts for each task (sentiment analysis (SA), topic detection (TD), as well as attribute classification on the SA and TD portions (AC-SA and AC-TD, respectively)) for gender and age. Following Hovy (2015), we split the fine-tuning data randomly into train/dev/test portions with the ratio: 60/20/20.

3 Experimental Setup

We describe our setup for assessing the effectiveness of the approaches for intermediate injection of sociodemographic knowledge.

3.1 Evaluation Tasks and Measure

We evaluate the effect of the sociodemographic specialization across the three text-classification tasks from Hovy et al. (2015). Two of these tasks focus on extrinsic classification and represent a downstream scenario: Sentiment Analysis (SA) and Topic Detection (TD). Additionally, Attribute Classification (AC) is designed to directly, i.e., intrinsically, evaluate knowledge about sociodemos by asking the models to predict the sociodemographic class of an author of a text.

Sentiment Analysis (SA) is the task of determining the polarity of a given text. We consider SA in product reviews, in which the dataset label is collected based on the 1-, 3-, or 5-star ratings from the review text, which corresponds to a negative, neutral, and positive sentiment, respectively.

Topic Detection (TD) is the task of assigning the topic to a given text. We frame TD as a multi-class classification problem on review texts, as before for SA. We consider 5 classes based on the labels provided by the dataset we use.

Attribute Classification (AC) is the intrinsic classification task of identifying the sociodemographic sub-groups based on linguistic features of a text (e.g., the text is written by a man or woman; Ciot et al., 2013; Preoţiuc-Pietro et al., 2015). We consider a binary classification formulation given two sociodemographic classes (i.e., predict the correct gender/age sub-group).
We report the F1-measure for each task.

3.2 Data

We use the dataset introduced by Hovy et al. (2015) obtained from the international user review website Trustpilot.¹ For investigating the effectiveness of our sociodemographic specialization methods, we follow the preprocessing and selection criteria from Hovy (2015). This process results in two collections of text for gender and age, with two sub-groups each: female vs. male, and under 35 vs. over 45,² across 5 countries: the United States (US), Denmark, Germany, France, and United Kingdom (UK). Thus, our data covers 4 different languages (English, Danish, German, and French).

To avoid any information leak, we split the collection into task-specific portions (for SA, TD, and AC, respectively), and portions from which we sample data for model specialization (Specialization). For TD, we avoid topic bias based on sociodemographic groups and eliminate the topic frequency as a confounding factor by restricting the data to the 5 most frequent topics that occur across the sub-groups for each country. For AC, the task-specific texts correspond to the data used for SA and TD, where the class labels are balanced to minimize the effect of any confounding factors (i.e., we have two AC portions for each sociodemographic factor: AC-SA and AC-TD). Table 1 shows the final number of review texts per country, sociodemographic aspect, and portion in the dataset.

For intermediate specialization of the multilingual model, we randomly sample 100K instances per sociodemographic group from the gender specialization portion and 50K instances each from the texts reserved for age specialization concatenated across all 5 countries. For the specialization of monolingual PLMs, we randomly sample the same number of instances but from the specialization portions of a single country. Following the established procedure (e.g., Devlin et al., 2019), we dynamically mask 15% of the tokens in the sociodemographic specialization portions for MLM.

3.3 Models and Baselines

In our first experiment, we employ mBERT (Devlin et al., 2019), a multilingual PLM. We do so for efficiency reasons: the specialization procedure needs to be conducted only once on the multilingual intermediate training set and the resulting specialized model can then be applied to each of our country-specific fine-tuning portions. To validate our results and to control for the confounding factor of the multilingual representations, we later run additional experiments in which we resort to monolingual BERT variants for English, French, German and Danish.³ As baselines, we report the performance of the non-specialized counterparts (i.e., we only fine-tune the PLMs on the training sets of the downstream tasks) and compare them against our sociodemographic-specialized PLM variants, obtained after intermediate training on the mixed-gender or -age corpora (§2): (1) MLM: continual masked language modeling, (2) MTL-W (CLS): dynamic multi-task learning in which we couple the MLM objective and the sociodemographic class prediction on the [CLS] token representation, and (3) MTL-W (CTX): dynamic multi-task learning, in which we predict the sociodemographic class based on the representation of the averaged contextualized masked tokens.

3.4 Hyperparameters and Optimization

During specialization, we fix the maximum sequence length to 128 subword tokens. We train for 30 epochs, in batches of 32 instances and search for the optimal learning rate among the following values: \{5 \cdot 10^{-5}, 1 \cdot 10^{-5}, 1 \cdot 10^{-6}\}. We apply early stopping based on development set performance (patience: 3 epochs). For downstream task evaluation, we train for maximum 20 epochs in batches of 32 with the learning rate among the following values: \{5 \cdot 10^{-5}, 1 \cdot 10^{-5}, 5 \cdot 10^{-6}, 1 \cdot 10^{-6}\}. We also apply dev-set-based early stopping (patience: 5 epochs). In all experiments, we use Adam (Kingma and Ba, 2015) as the optimization algorithm.

4 Results and Discussion

We first discuss the results of the multilingual model (with and without specialization) across the five countries and the two sociodemographic factors for our three evaluation tasks (§4.1). We then thoroughly examine the effectiveness of the proposed sociodemographic specialization methods through a set of control experiments (§4.2).

¹https://www.trustpilot.com/
²As suggested by Hovy (2015) the split for the age ranges result in roughly equally-sized data sets for each sub-group and is non-contiguous, avoiding fuzzy boundaries.
³We use the multilingual and monolingual PLM from Huggingface: bert-base-multilingual-cased (multilingual), bert-base-cased (English), bert-base-german-cased (German), dbmdz/bert-base-french-europeana-cased (French) and Maltehb/danish-bert-botxo (Danish).
Table 2: Intrinsic evaluation results for gender and age on Attribute Classification (AC-SA, AC-TD). We report the F1-score and compare the specialized models (MLM, MTL-W (CLS), MTL-W (CTX)) with vanilla mBERT.

| Model       | w/o specialization | with specialization |
|-------------|--------------------|---------------------|
|             | US                | Denmark             | Germany             | France             | UK     | Avg.  | US    | Denmark | Germany | France | UK     | Avg.  |
| mBERT       | 62.6              | 64.0                | 59.5                | 63.9                | 61.9   | 62.4  | 58.1  | 61.8    | 57.9    | 61.2   | 63.1   | 60.4  |
| **gender**  | **w/o specialization** | **mBERT**           | **63.3**            | **65.2**            | **61.2**| **64.6** | **63.0** | **63.4** | **59.6** | **63.4** | **60.1** | **62.1**|
| MLM         | 63.8              | 64.9                | 60.1                | 64.1                | 63.4   | 63.3  | 59.2  | 63.5    | 60.3    | 63.1   | 64.9   | 62.2  |
| MTL-W (CLS) | 62.2              | 65.0                | 62.9                | 65.0                | 63.5   | 63.7  | 58.8  | 63.5    | 58.3    | 62.9   | 65.6   | 61.8  |
| **gender**  | **w/o specialization** | **mBERT**           | **62.9**            | **57.2**            | **58.0**| **55.7** | **65.1** | **59.8** | **60.7** | **64.5** | **56.9** | **56.6**| **65.2**| **60.8**|
| MLM         | 63.6              | 65.5                | 61.1                | 56.8                | 65.4   | 62.5  | 61.9  | 65.1    | 58.9    | 57.2   | 65.6   | 61.7  |
| MTL-W (CLS) | 60.7              | 65.2                | 56.4                | 55.1                | 65.3   | 60.5  | 61.5  | 65.2    | 58.2    | 55.5   | 62.8   | 60.6  |
| MTL-W (CTX) | 59.7              | 65.3                | 56.6                | 54.4                | 64.0   | 60.0  | 61.2  | 64.6    | 57.4    | 55.9   | 62.8   | 60.4  |

4.1 Overall Results

We report the intrinsic performance on predicting the sociodemographic groups (AC-SA/-TD, Table 2) as well as the extrinsic performance on Sentiment Analysis (SA) and Topic Detection (TD) on the group-specific test portions of the two sociodemographic factors (gender: Table 3; age: Table 4).

The rows for each task are segmented into two parts: at the top we show the baseline results, mBERT without any sociodemographic specialization, and the following rows contain results for our proposed adaptation methods (§2), continual mask language modeling (MLM), or dynamic multi-task learning (using the sequence representation token (MTL-W (CLS)) or the average masked token representation (MTL-W (CTX))).

Gender. Across all specialization methods, we see gains on the intrinsic task of predicting the gender of an author (for both AC-SA and AC-TD portions, Table 2) with average improvements of up to 1.8 percentage points compared to vanilla mBERT. The highest gains come from our multi-task learning methods, MTL-W (CLS) and MTL-W (CTX), where the association between linguistic factors and sociodemographics is directly enforced.

Also, the results for the extrinsic evaluation on SA and TD (Table 3) hold promise for successful task-agnostic gender specialization: on average, across the 5 countries with gender-specific (F, M) and gender-agnostic (X) fine-tuning and testing portions, we observe gains for all specialization methods of up to 1.3 percentage points for SA and 0.9 percentage points for TD.

Age. We observe similar improvements when studying age: in the intrinsic evaluation, i.e., predicting the age group of an author, our specialized models perform on average up to 2.7 percentage points better than their non-specialized counterpart.
Table 4: Results of the extrinsic evaluation on age data for age-specialized and non-specialized models for Sentiment Analysis (SA) and Topic Detection (TD). We report the F1-score.

Table 2). Similarly, when fine-tuning and testing on the age-specific (<35, >45) and mixed (X) fine-tuning portions, the specialized models excel with 1.3 percentage points improvement for SA and 0.9 percentage points improvement for TD (Table 4).

Again, this points to the effectiveness of sociodemographic specialization through intermediate training. Surprisingly, the multi-task learning methods do not help for age classification (AC-SA and AC-TD age) but always lead to improvements for SA and TD tasks. Thus, the injected knowledge of age offers less discriminative power than knowledge of gender. Our intuition is that age affects the texts less than gender and is rather expressed in non-lexical ways (i.e., sentence structure).

Overall, the results are in line with the findings from previous work (Hovy, 2015): specialization for gender and age factors injects sociodemographic knowledge into multilingual PLMs. This knowledge consistently improves downstream task performance. This effect is especially pronounced in multi-task learning, which encourages the model to establish an explicit connection between the linguistic elements (i.e., a sequence or a token) and the sociodemographic factors. This approach is also efficient: we only need to refine the PLM once (i.e., the knowledge is shared across the different languages) before fine-tuning on specific tasks.

4.2 Control Experiments

To validate our results, we pose four additional questions: (1) Will we get similar gains when using monolingual PLMs? Monolingual PLMs do not suffer from the curse of multilinguality (Conneau et al., 2020) – thus, intuitively, they have less potential for further improvement. (2) Will we still see gains when specializing our models on data that contains knowledge about the sociodemographic factors but no knowledge about our domain at hand, i.e., product reviews? (3) Can we quantitatively assess the impact of sociodemographics, domain, language, and injection method on the results? (4) Do the internal representations of the PLMs reflect the sociodemographic specialization?

Monolingual vs Multilingual PLMs. We compare the results across five countries when leveraging monolingual vs. multilingual BERT (Devlin et al., 2019), respectively (Table 5). Unsurprisingly, the monolingual PLMs outperform their multilingual counterpart on all three tasks in most cases with gains of up to 2.5 percentage points for AC-SA gender. Further, we note that the performance improvement from before, which we attribute to our sociodemographic specialization, vanishes (i.e., < +0.5% across the board). This finding challenges our previous hypothesis: are the performance gains we observed for the multilingual PLM obtained from injecting the sociodemographic knowledge?

In-domain vs Out-of-domain. To further investigate to what extent domain knowledge (i.e., knowledge about product reviews) is driving the performance improvements, we conduct additional experiments in which we control for this factor. Concretely, we select two out-of-domain corpora, which should still contain the sociodemographic knowledge we seek to specialize for: RtGender (Voigt et al., 2018) for gender and Blog Authorship Corpus (BAC; Schler et al., 2006) for age. RtGender consists of texts from online social
Table 5: Results of the monolingual PLMs (BERT, germanBERT, danishBERT, frenchBERT) on Sentiment Analysis (SA), Topic Detection (TD), and Attribute Classification (AC-SA, AC-TD) with and without intermediate specialization for gender and age on the country-specific specialization portions of Trustpilot. We report the deltas in F1-score compared to the original results of the multilingual PLM (mBERT).

| Model               | US            | Denmark       | Germany       | France        | UK            |
|---------------------|---------------|---------------|---------------|---------------|---------------|
|                     | w/o specialization | w/o specialization | w/o specialization | w/o specialization | w/o specialization |
|                     | with specialization | with specialization | with specialization | with specialization | with specialization |
| w/o specialization | BERT | 1.7 | 2.1 | 0.3 | 0.1 | 1.3 |
| BERT                | 0.5 | 2.0 | 1.0 | 1.9 | 1.9 | 1.9 |
| MLM                 | 1.3 | 0.9 | 0.8 | 1.2 | 1.2 | 1.2 |
| MLM (CTX)           | 2.5 | 0.6 | 3.3 | 2.8 | 2.8 | 2.8 |
| w/o specialization | BERT | 2.3 | 3.1 | 0.4 | 0.8 | 2.4 |
| BERT                | 2.3 | 3.2 | 1.0 | 0.4 | 2.5 | 2.5 |
| MLM                 | 1.6 | 1.0 | 1.2 | 0.8 | 1.4 | 1.4 |
| MLM (CTX)           | 6.0 | 0.2 | 1.5 | 0.6 | 0.2 | 0.1 |
| w/o specialization | BERT | 0.8 | 0.7 | 0.6 | 0.4 | 1.3 |
| BERT                | 0.7 | 0.8 | 0.7 | 0.8 | 0.6 | 0.4 |
| MLM                 | 0.9 | 1.0 | 0.6 | 1.4 | 1.5 | 1.5 |
| MLM (CTX)           | 1.0 | 1.3 | 1.0 | 1.4 | 1.1 | 1.1 |
| w/o specialization | BERT | 2.0 | 0.9 | -0.2 | 0.5 | 2.4 |
| BERT                | 2.0 | 1.4 | 0.6 | 0.9 | 1.8 | 1.8 |
| MLM                 | 1.0 | 1.2 | 0.2 | 0.4 | 1.4 | 1.4 |
| MLM (CTX)           | 2.0 | 0.4 | 0.7 | 0.9 | 1.8 | 1.8 |

Table 5: Results of the monolingual PLMs (BERT, germanBERT, danishBERT, frenchBERT) on Sentiment Analysis (SA), Topic Detection (TD), and Attribute Classification (AC-SA, AC-TD) with and without intermediate specialization for gender and age on the country-specific specialization portions of Trustpilot. We report the deltas in F1-score compared to the original results of the multilingual PLM (mBERT).

media platforms\(^4\) where the author profiles indicate the gender. Similarly, BAC consists of texts from a blogging website (blogger.com). In case we still see improvements after specializing the models on these out-of-domain corpora, the gains should solely stem from the sociodemographic knowledge – and thus prove the injection effective. To test this, we sample 100K and 50K instances each from the corpora and then specialize BERT via MLM and MTL-W (CTX). Since texts from both corpora are in English and to eliminate the confounding multilingual dimension, we evaluate on the Trustpilot fine-tuning data from English-speaking countries (UK and US) only and use the English monolingual PLM (original BERT). As expected, the out-of-domain specialization deteriorates the downstream task performance in most cases (Figure 1). Especially explicitly coupling linguistic aspects with the sociodemographics through MTL-W (CTX) seems to hurt the performance. The observation once again leads us to question whether the performance gains we observe in the multilingual scenario can be attributed to sociodemographic adaptation.

Meta-regression Analysis. Next, we quantitatively assess the impact of each of the factors involved in our study: the country of the fine-tuning texts (e.g., France), the method used (e.g., MLM), whether we run the specialization in-domain or out-of-domain, whether we use a monolingual or multilingual PLM, and the sociodemographic group the fine-tuning texts belong to (e.g., F, M, or X). To do so, we treat these factors as individual features and fit a linear regression to predict the final F1-scores obtained for each task (in all previously discussed Tables). We study the feature weights when includ-
Figure 1: Results on Trustpilot for Sentiment Analysis (SA) and Topic Detection (TD) when running the intermediate specialization on out-of-domain data (RtGender (Voigt et al., 2018) for gender and BAC (Schler et al., 2006) for age). We report the delta in F1-score in comparison to the specialization on Trustpilot in-domain data.

Table 6: Results of our meta-regression analysis. We report the performance of predicting the results of our previous experiments on Sentiment Analysis (SA), Topic Detection (TD), and Attribute Classification (AC-SA and AC-TD) for gender and age when including all features (in) and excluding (ex) individual features: domain (ex-D), monolingual / multilingual (ex-M), sociodemographic factor (ex-S), country (ex-C). For each task, when including all features (column: in), we list the features with weights $\geq 0.2$ (selected features) and provide their assigned weights in parenthesis. RMSE=Root Mean Square Error; MAE=Mean Absolute Error.
Figure 2: Results of our multilingual qualitative analysis. We show a tSNE visualization of review texts embedded with a non-specialized (mBERT) and specialized (MTL-W (CTX)) model. We plot 2K instances for (a) gender and (b) age. Colors indicate the sociodemographic subgroup (upper figures) and countries (lower figures), respectively.

Qualitative Analysis. Finally, we visualize the [CLS] representations obtained when feeding the reviews through the encoder of the monolingual and multilingual BERTs before and after sociodemographic specialization with MTL-W (CTX). We randomly sample 2K instances from the development set of the specialization corpora.\(^5\) For plotting, we reduce the dimension with the t-distributed stochastic neighbor embedding (tSNE; Maaten and Hinton, 2008) and color the points representing texts according to the sociodemographic group of the author. As illustrated in Figure 2, representations obtained from the MTL-W (CTX)-specialized model arrange more clearly in clusters than the original mBERT. However, sociodemographic groups in gender and age do not cluster at all. In contrast, when coloring according to country, clear boundaries emerge. To further disentangle the situation, we also visualize the embeddings of the monolingual variants in Figure 3. Although MTL-W (CTX) shows more assembly than the original BERTs, there is no significant clustering phenomenon for sociodemographic subgroups. We conclude: although our sociodemographic adaptation methods help improve the downstream performance, the gains do not stem from the sociodemographic knowledge itself, but more from distinguishing the diversified languages and other associated effects needed for the downstream tasks.

5 Related Work

Intermediate Training (Adaptation). Intermediate language modeling on texts from the same or similar distribution as the downstream data has been shown to lead to improvements on var-

\(^5\)Note that the dev set was originally kept for evaluating MLM training performance. The instances are equally distributed over 5 countries and 2 sub-groups of each sociodemographic factor.
ious NLP tasks (e.g., Gururangan et al., 2020). During this process, the goal is to inject additional information into the PLM and thus specialize the model for a particular domain (e.g., Aharoni and Goldberg, 2020; Hung et al., 2022a) or language (e.g., Glavaš et al., 2020) or to encode other types of knowledge such as common sense knowledge (e.g., Lauscher et al., 2020), argumentation knowledge (e.g., Holtermann et al., 2022), or geographic knowledge (e.g., Hofmann et al., 2022).

For instance, Glavaš et al. (2020) and Hung et al. (2022b) perform language adaptation through intermediate MLM in the target languages with filtered text corpora, demonstrating substantial gains in downstream zero-shot cross-lingual transfer for abusive language detection and for dialog tasks, respectively. Hung et al. (2022a) propose a computationally efficient approach by employing domain-specific adapter modules. They show that their domain adaptation approach leads to improvements in task-oriented dialog. These specialization approaches mostly rely on a single objective (e.g., masked language modeling on “plain” text data). Instead, Hofmann et al. (2022) conduct geoadaptation by coupling MLM with a token-level geolocation prediction in a dynamic multi-task learning setup. In this work, we adopt a similar approach.

**Sociodemographic Specialization.** Language preferences vary with user demographics (Loveys et al., 2018), and accordingly, several studies have leveraged sociodemographic information (e.g., gender, age, education) to obtain better language representations for various NLP tasks (Volkova et al., 2013; Garimella et al., 2017). Recent research studies on sociodemographic adaptation mainly focus on (1) learning sociodemographic-aware word embeddings and do not work with large PLMs (Hovy, 2015) or (2) leveraging demographic information with special PLM architectures specifically designed for certain downstream tasks (e.g., empathy prediction (Guda et al., 2021)). The latter, however, do not consider a task-agnostic approach to injecting sociodemographic knowledge into language models, and also focus on a monolingual setup only. Further, what roles the different factors (i.e., domain, language, sociodemographic aspect) in the specialization really play remains unexplored.

6 Reproducibility

To ensure full reproducibility of our results and fuel further research on sociodemographic adaptation in NLP, we release our code and data, which make our approach completely transparent: [https://github.com/umanlp/SocioAdapt](https://github.com/umanlp/SocioAdapt).

7 Conclusion

In this work, we thoroughly examined the effects of sociodemographic specialization of Transformers via straight-forward injection methods that have been proven effective for other types of knowledge. Initial results on extrinsic and intrinsic evaluation tasks using a multilingual PLM indicated the usefulness of our approach. However, running a series of additional experiments in which we controlled for potentially confounding factors (language and domain) as well as a meta-analysis indicate that the sociodemographic aspects only have a negligible impact on the downstream performance. This observation is supported by an additional qualitative analysis. Overall, our findings point to the difficulty of injecting sociodemographic knowledge into Transformers and warrant future research on the topic for truly human-centered NLP.
Limitations

In this work, we have focused on the sociodemographic adaptation of PLMs. We conducted our experiments with review texts covering five countries and four languages (Hovy, 2015). It is worth pointing out that this data does not reflect the wide spectrum of (gender) identities (Dev et al., 2021; Lauscher et al., 2022) and is also limited with respect to its cultural variety (Joshi et al., 2020). Furthermore, while the criteria for selecting the data lead to balanced groups and potentially confounding factors have been monitored during the sampling process, potential harms might arise from unfair stereotypical biases in the data (Blodgett et al., 2020). We hope that future research builds on top of our findings and explores other sociodemographic factors, other groups within these factors, and also other languages and countries.

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