LEARNING INVARIANT REPRESENTATIONS ON MULTILINGUAL LANGUAGE MODELS FOR UNSUPERVISED CROSS-LINGUAL TRANSFER

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ABSTRACT

Recent advances in neural modeling have produced deep multilingual language models capable of extracting cross-lingual knowledge from unparallel texts, evidenced by their decent zero-shot transfer performance. While studies have attributed this success to cross-lingually shared representations, quantitative analyses are sparse. Towards a better understanding of the role of multilingual representations, in this work, we first make the following observations through empirical analysis: (1) invariance of the feature representations strongly correlates with transfer performance, and (2) distributional shift in class priors between data in the source and target languages negatively affects performance—an issue that is largely overlooked in prior work. Based on our findings, we propose an unsupervised cross-lingual learning method, called importance-weighted domain alignment (IWDA), that performs representation alignment, prior shift estimation, and correction. Experiment results demonstrate its superiority under large prior shifts. In addition, our method delivers further performance gains when combined with existing semi-supervised learning techniques.

1 INTRODUCTION

Many recent state-of-the-art results in natural language processing (NLP) have been achieved on Transformer-based deep neural language models (LMs) using the "pre-train then fine-tune" paradigm (Devlin et al., 2019; Conneau & Lample, 2019). Multilingual versions of these LMs are pre-trained on unannotated and unparallel texts from more than one language, such as multilingual BERT (mBERT) and XLM-R (Conneau et al., 2020a), and it is found that the learned representations are shared across languages. In particular, the cross-lingual knowledge acquired by these models has enabled *zero-shot* cross-lingual transfer, where after fine-tuned on data in a source language, not only do they work well when evaluated on the source, but also quite decently for the same task on almost all languages they have seen during pre-training (Wu & Dredze, 2019).

Their success on zero-shot cross-lingual transfer has prompted numerous studies on their multilingual abilities. Among the many explanations, a recent hypothesis suggests that the deep representation combined with parameter sharing induced intermediate feature representations that are shared across languages (K et al., 2019; Conneau et al., 2020b; Muller et al., 2021). Following this, we begin by studying the following question for mutilingual neural LMs:

What is the role of shared representations in unsupervised cross-lingual learning?

In an effort to answer this question in a quantitative manner, through empirical analysis on mBERT, we find that (1) its cross-lingual transfer performance strongly correlates with the alignment of feature representations for the NLP task at hand between the source and target languages (Section 2.1). In addition, (2) distributional shift in class priors between data in the source and target languages negatively affects transfer performance (sections 2.2 and 4.2). Despite being a common issue with real-world data under unsupervised settings, it has been largely overlooked in prior work.

Based on these findings on the cross-lingual transfer of mutilingual neural LMs, towards a principled approach for the unsupervised setting where access to *unlabeled* data in the target language for the downstream task at hand is available in addition to labeled ones in the source (hereafter referred

to as UCL[1]), we propose importance-weighted domain alignment (IWDA). This method performs representation alignment, class prior shift estimation, and correction (Section 3). Experiment results show that IWDA outperforms the more popular semi-supervised learning methods under large prior shifts, and can be additionally combined with them for further performance gains (Section 4).

1.1 Related Work

Our proposed method is heavily inspired by Tachet des Combes et al. (2020), which studied the issues with alignment-based domain adaptation (DA) under the presence of class prior shifts, and proposed the inclusion of prior shifts estimation and correction procedures in DA. Our method also shares similar components with the DA-based UCL method by Keung et al. (2019), while highlighting its limitations discovered in the present work (Section 2.2).

Analyzing Multilingual Neural LMs. Most studies analyze mBERT's cross-lingual ability via probing experiments, and identified influencing factors including but not limited to linguistic similarity, size of pretraining corpus, domain similarity, parameter sharing and model depth (Pires et al., 2019; K et al., 2019; Lauscher et al., 2020; Conneau et al., 2020b; Dufter & Schütze, 2020). Another line of research analyze intermediate representations and observed that mBERT learns cross-lingually shared representations (Wu & Dredze, 2019; Conneau et al., 2020b; Muller et al., 2021).

Cross-Lingual Representation Alignment. The idea of learning invariant representations has powered a long history of approaches for cross-lingual transfer on neural models. Under zero-shot settings, it is achieved by aligning word embeddings on bilingual dictionaries that could be induced via adversarial training (Mikolov et al., 2013; Smith et al., 2017; Zhang et al., 2017; Artetxe & Schwenk, 2019; Cao et al., 2019), a method that has powered many machine translation techniques (Artetxe et al., 2018; Lample et al., 2018; Arivazhagan et al., 2019; Pham et al., 2019; Hu et al., 2021) It is found on static embedding models that the goodness of alignment affects transfer performance (Patra et al., 2019; Dubossarsky et al., 2020). On deep models such as mBERT, it could also take the form of shared feature representations in the Transformer body (Artetxe et al., 2020b; Pfeiffer et al., 2020). Under UCL and supervised settings, techniques based on representation alignment were proposed for models ranging from distributed word embeddings (Joty et al., 2017; Chen et al., 2018), RNN (Kim et al., 2017; Huang et al., 2019), to mBERT (Keung et al., 2019; Zheng & Lapata, 2019; Xia et al., 2021). For a survey, see Ruder et al. (2019) and Ruder (2019).

Connection to Domain Adaptation. Domain adaptation is a popular framework for handling domain shifts between training and test data, e.g. learning a POS tagger on news articles but to be deployed on biomedical papers with a significantly different word distribution (Ben-David et al., 2007). The concept of domain is extended naturally to cross-lingual learning by treating the distributions of sentence and document pertaining to the same task in each language as separate domains[2] (Ruder, 2019). Thereby, adaptation techniques proposed for domain shift can be applied to UCL. Besides methods aiming at extracting shared representations (Li et al., 2020; Vernikos et al., 2020), another family of successful approaches is semi-supervised learning, which include self-training (Dong & de Melo, 2019), tri-training (Ruder & Plank, 2018), knowledge distillation (Wu et al., 2020), and data augmentation (Wang et al., 2018; Maharana & Bansal, 2020; Bari et al., 2021).

2 Factors Affecting Cross-Lingual Transfer

To develop and provide evidence to the hypothesis that attributes the cross-lingual transfer success of multilingual neural LMs to shared representations, as well as to understand its implications on the design of unsupervised transfer algorithms, we attempt to quantify the relation between representation invariance and transfer performance in this section.

We briefly summarize the "pre-train then fine-tune" training paradigm and introduce notation along the way. Let $g : \mathcal{X} \to \mathcal{Z}$ denote the feature mapping provided by the pre-trained multilingual LM,

[1]With an abuse of notation. In this work, the acronym UCL refers to the learning setting considered, and is meant to distinguish from the umbrella term "unsupervised cross-lingual learning", which also includes the study of the zero-shot setting where no target language task data is given.

[2]Hence the terms *domain* and *language* are used interchangeably in this work.

and $z = g(x) \in \mathcal{Z} \subseteq \mathbb{R}^d$ the feature vector computed on an input sentence or token $x \in \mathcal{X}$. On BERT-Base models, $d = 768$. In practice as well as in our studies and experiments, the feature is the last-layer wordpiece embeddings for token classification tasks, and the embedding of a special start-of-sentence marker (symbolized as `[CLS]`) for sequence classification tasks. Let $h : \mathcal{Z} \to \mathcal{Y}$ denote the output layer(s) added on top of g with an appropriate activation, usually just a single linear layer with Softmax activation for classification tasks in practice. Hence, an end-to-end model is obtained, which computes predictions via $\hat{y} = h(g(x))$. By fine-tuning both g, h on labeled task data (x, y) sampled from the source language domain p_S only, we get a zero-shot transfer model for the downstream task at hand, where the term zero-shot points to the fact that the model does not use any task data from the target language $(x', y') \sim p_T$ during training.

Based on the following decomposition of the joint feature-label distribution into the product of class-conditional feature distribution and marginal prior distribution,

$$p(z, y) = p(z|y)p(y) := p(\{x \in \mathcal{X} : g(x) = z\}|y)p(y),$$

we examine how cross-lingual transfer performance is influenced by (1) invariance of the feature representation of data between the source and target languages, with perfect invariance being $p_S(z|y = j) = p_T(z|y = j)$ for all $j \in \mathcal{Y}$, and (2) the distributional shift in the class priors, with no shift being $p_S(y = j) = p_T(y = j)$ for all $j \in \mathcal{Y}$. On classification tasks, $\mathcal{Y} = \{1, 2, \cdots, k\}$ is discrete. For legibility in later sections, we use the shorthands to denote the class-conditional feature distribution and the marginal prior distribution: $p^{Z|Y}$ and p^Y.

Setup. Our empirical analysis is performed on the representations learned by mBERT zero-shot fine-tuned on English for two multilingual tasks: sentiment analysis on the Multilingual Amazon Reviews Corpus (MARC), and named-entity recognition (NER) on the WikiANN dataset (see descriptions in Section 4). To simulate the effects of varying amount of representation misalignment and class prior difference, evaluation is performed on 500 smaller datasets randomly subsampled from the original MARC according to different class priors, and roughly 700 datasets from WikiANN. MARC covers five high-resource languages (excluding English), and (our selected subset of) WikiANN covers 39 languages of distinct linguistic properties and varying resourcefulness.

2.1 Invariance of Feature Representations

For studying the effects of representation invariance, we compare model performance to the discrepancy between the class-conditional feature distributions on the source and target domains, $p_S^{Z|Y}$ and $p_T^{Z|Y}$. We take the average to aggregate the discrepancies computed when conditioned on each class, $\frac{1}{k}\sum_{j=1}^{k} D(p_S^{Z|Y=j}, p_T^{Z|Y=j})$, and refer to this quantity by *conditional feature shift*.

The discrepancy measure we use computes the ℓ_1-distance between the mean feature vectors[3],

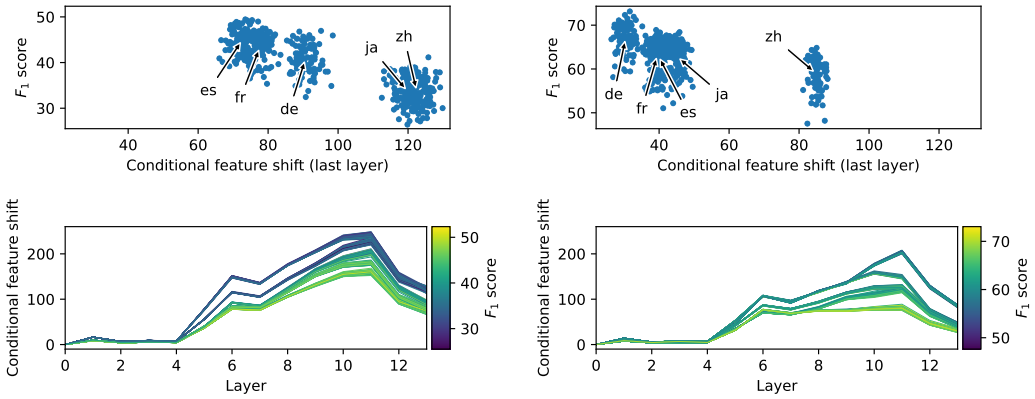
$$D(p, q) := \left\| \mathbb{E}_{x\sim p}[x] - \mathbb{E}_{x'\sim q}[x'] \right\|_1 = \sum_{i=1}^{d} \left| \mathbb{E}_{x\sim p}[x_i] - \mathbb{E}_{x'\sim q}[x'_i] \right|.$$

Measuring the distance between the means of representations for the purpose of analyzing mBERT has appeared in prior work. A similar quantity is referred to as *language centroids* by Libovický et al. (2020). The important distinction here is that we explicitly remove the effects of class prior shift by conditioning on the class labels, which we argue is an artifact of the dataset since arbitrary amounts of *unconditioned* feature shift can be generated by altering the class priors.

First, we consider zero-shot transfer. In Fig. 1a, we plot the F_1 score[4] attained by the zero-shot model against conditional feature shift between English features and those of the target language, and observe that better representation alignment is indicative of better transfer performance. Findings in prior work on the cross-lingual ability of mBERT are reflected. For instance, linguistic similarity, a factor commonly argued to be important for cross-lingual transfer, could be related to the alignment

[3]Comparisons to more sophisticated metrics such as RBF-kernel MMD and linear CKA were made in our preliminary studies (Gretton et al., 2012; Kornblith et al., 2019), and we found that they correlate tightly with our first-moment discrepancy measure for analyzing conditional feature shift.

[4]To study the effects of class prior shift, we use macro-averaged F_1 as the performance metric in this section, because classification accuracy could be inflated on datasets with skewed priors (Azizzadenesheli et al., 2018).



(a) Zero-shot (trained on English only)

(b) Bilingually supervised (English and target)

Figure 1: Cross-lingual transfer performance of mBERT on MARC sentiment analysis under two learning settings, compared to the (class-conditional) (mis)alignment of feature representations between English and target languages (lower shift means more aligned). **Top panels:** Performance (y-axis; higher the better) against alignment of last-layer features (x-axis). Average F_1 scores and feature shifts are marked by language. **Bottom panels:** Performance (now indicated by color; lighter means better) against alignment of features (y-axis) on all Transformer layers (x-axis). It is observed that performance correlates with representation alignment on all later layers. Note that the near-perfect alignment in lower layers is an artifact of using `[CLS]` embeddings as features, which are not informative until contextualized in later layers; see Fig. 5a for results on word embeddings.

of features: Spanish, French and German are more linguistically similar to English than Japanese and Chinese, whose features are less aligned with those of English. These results also reflects the successes of zero-shot learning approaches on mBERT that aim to achieve representation invariance.

While the above finding shows that representation alignment is desirable for zero-shot transfer, is it also suitable for UCL settings where task data from the target language are available? We start by recognizing that the objective function of most unsupervised transfer algorithms consists of two parts: loss on labeled source data, and terms involving unlabeled data that in theory are linked to the loss on target domain. Based on this, we compared against conditional feature shift the performance of the model fine-tuned supervisedly on labeled data from source and target languages, as it would be the ideal objective for unsupervised algorithms. The results are plotted in Fig. 1b. Instead of observing increases in conditional feature shifts, which would have implied that language-specific features are preferred by over shared ones for good performance on each language, we observe much-improved representation alignments between English and each of the target languages. This means that achieving representation invariance is also appropriate under UCL settings.

To demonstrate that the correlation between last-layer class-conditional alignment and performance is not an artifact of the linear classification head, we show that model performance is also correlated with (1) conditional feature shift in intermediate layers, plotted on the bottom panels of Fig. 1, and (2) *class-balanced* feature shift, plotted in Fig. 8 in the appendix, where the removal of prior shift effects is achieved by reweighting the class priors to be uniform (eq. 1). Furthermore, we include results on the XNLI dataset, a higher-level semantic task (Fig. 6), and results on MARC with the more powerful XLM-R Large model (Fig. 7).

2.2 Distributional Shift in Class Priors

Most benchmarks for evaluating cross-lingual transfer are constructed so that the class prior distributions between data in the source and target languages are the same. This is desired for assessing zero-shot learning approaches, as the focus should not be on "'tricks' for how to best handle the class imbalance" (Schwenk & Li, 2018). However, for UCL settings with unlabeled target data, we argue that making the best use of the additional data involves the detection and correction of prior shift. Otherwise, as we show in this and later sections, negative transfer could occur.

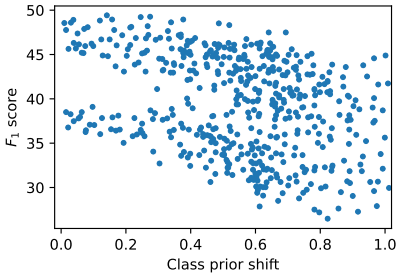


Figure 2: Distributional shifts in class priors between English and target datasets vs. zero-shot performance on MARC. Performance negatively correlates with prior shift.

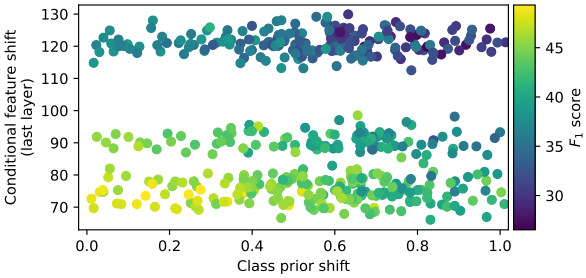


Figure 3: Conditional feature representation alignment and class prior shift vs. zero-shot performance (indicated by scatter color; lighter means better) on MARC. Stronger correlations of each factor with performance than those in figs. 1 and 2 are revealed.

To examine the effects of class prior shift on cross-lingual transfer, we compare zero-shot transfer performance to the difference in prior distributions, $D(p_S^Y, p_T^Y)$, equivalent to total variation (TV). The results are presented in Fig. 2. We also plot the effects of representation alignment and prior shift jointly in Fig. 3, where stronger correlations are revealed: (1) transfer performance generally takes a hit when prior shifts are large, regardless of how well the features are aligned, and (2) on target domains of the same amount of prior shift, performance decreases when features are less aligned. The findings suggest that in addition to achieving representation invariance, good transfer performance also requires the detection and handling of potential prior shifts. While this is not possible under zero-shot settings without any data from the target domain, the unlabeled target task data provided under UCL settings could be leveraged toward this goal.

We examined existing approaches proposed for multilingual neural LMs for the UCL settings, but did not find procedures for prior shift correction, and moreover, there is a lack of attention to the potential issues and effects of class prior shift to the algorithms. Specifically, for alignment-based methods, Zhao et al. (2019) and Tachet des Combes et al. (2020) showed that adaptation could lead to negative transfer when prior shifts are not accounted for due to erroneous alignment. For methods based on semi-supervised learning, negative transfer is observed empirically under large shifts in our studies (Section 4.2). These cases of negative transfer call for more considerations to the effects of class prior shift in future work on cross-lingual transfer that leverage target data.

Interestingly, although the alignment-based method proposed by Keung et al. (2019) did not account for prior shift, it avoided negative transfer on the CoNLL NER task (which exhibits shifts) by performing feature alignment on the `[CLS]` sentence embeddings instead of the word embeddings (recall that predictions are made on word embeddings on token classification tasks). Since sentence embeddings on Transformer-based models could be loosely related to a weighted sum of the word embeddings, the procedure of Keung et al. (2019) is performing coarse-grained representation alignment, which avoids negative transfer while providing decent performance gain. However, as we compare in Table 1, this misses out opportunities for larger gains from word embedding alignment. If alignment were performed on word embeddings without prior shift correction, deteriorating performance would have been observed (Fig. 10).

3 Importance-Weighted Domain Alignment

For unsupervised cross-lingual learning on multilingual neural LMs with access to *unlabeled* target language data (which we refer to as the UCL setting), the findings in Section 2 suggest that good performance can be achieved via aligning representations and correcting class prior shifts. Based on these principles, we propose class-importance-weighted domain alignment (IWDA) for UCL, following closely the work by Tachet des Combes et al. (2020). In this section, we provide a high-level description of the algorithm and its connection to the findings above, and refer interested readers to the aforementioned work and Appendix C for further implementation details.

We have seen that class-conditional feature alignment is desired for cross-lingual transfer, however, this is not possible to achieve under the UCL setting since the target labels are unknown. Assume for now that the target class prior distribution is known, then we can compute the true ratio of the class priors, $w_j^* := p_T(y=j)/p_S(y=j)$, also known as the importance weights (IWs), and aim for a weaker *importance-weighted* feature alignment, $p_S^{w^*,Z} = p_T^Z$, where

$$p_S^{w^*}(x, y=j) = p_S(x|y=j)p_S(y=j)w_j^* = p_S(x|y=j)p_T(y=j). \tag{1}$$

Besides as shown in Fig. 8 that importance-weighted feature alignment also correlates with transfer performance, it is also a necessary condition for the ideal goal of class-conditional alignment (Tachet des Combes et al., 2020).

Since the true w^* are unknown under UCL, they are estimated by matching first-moment statistics using the confusion matrix (Saerens et al., 2002; Lipton et al., 2018). Assume now that the features are conditionally aligned, $p_S^{Z|Y=j} = p_T^{Z|Y=j}$ for all $j \in \mathcal{Y}$ (known as the *label shift* assumption), and the label space is discrete, $\mathcal{Y} = \{1, \cdots, k\}$. Then for each class $i \in [k]$, we have the following relation between *predicted* target prior distribution, the source confusion matrix, and w^*:

$$p_T(\hat{y}=i) = \sum_{j=1}^{k} p_T(\hat{y}=i|y=j)p_T(y=j) = \sum_{j=1}^{k} p_S(\hat{y}=i|y=j)p_T(y=j) = \sum_{j=1}^{k} p_S(\hat{y}=i, y=j)w_j^*, \tag{2}$$

where $\hat{y} = h(g(x))$ are predicted labels. Since we have the same number of equations as unknowns, w^* could be recovered under mild assumptions (Lipton et al., 2018).

Careful readers may have noticed that achieving either goal above requires having the other as an assumption. Indeed, attempting to estimate IW without conditional alignment could fail, as well as alignment without accurate IWs. The hope is that the optimization will be predominantly guided by the implicit bias of the pre-trained multilingual LM for selecting largely invariant features (hence conditionally aligned), so that small improvements to feature alignment and updates to prior shift estimates could bring incremental improvements to both components.

Optimization. The two goals above define an optimization problem over g, h and w,

$$\min_{g,h} \Big(\mathbb{E}_{(x,y)\sim p_S}[\ell(h(g(x)), y)] + \lambda D(p_S^{w,Z}, p_T^Z) \Big), \quad \min_{w} \sum_{\hat{y}\in[k]} \Big(p_T(\hat{y}) - \sum_{y} p_S(\hat{y}, y) w_y \Big)^2,$$

where alignment objective minimizes source task loss and the discrepancy of w-importance-weighted feature distributions (the metric should be more fine-grained than the first-moment metric used in our analysis), and the IW estimation objective solves eq. 2 using current statistics based on h, g with the constraints $w \geq 0$ and $w^\top p_S^Y = 1$.

In our implementation, we use the minimax formulation of the alignment objective optimized with adversarial training, where D is replaced by a shallow ReLU network Wasserstein-1 critic and zero-centered gradient penalty (Arjovsky et al., 2017; Thanh-Tung et al., 2019). We found the Wasserstein-1 adversarial loss to be more responsive to importance weighting than cross-entropy loss (Ganin et al., 2016).

Improving Stability of IW Estimates. In Tachet des Combes et al. (2020), the IWs estimation objective is solved by quadratic programming (QP), and updated once every epoch of training in their implementation. Since accurate IWs estimates are integral to successful adaptation, we (1) update w using projected gradient descent at every training step so to maintain their optimality. This, however, led to the discovery of previously unexplored practical issues with the IW estimator. In our preliminary experiments, we observed that w tends overestimate the majority class on the target domain, and diverges during longer training episodes.

These issues are unique to unsupervised adaptation settings, and are due to inefficiencies of the critic and noises introduced by the alignment objective. They could also be reproduced with the previous QP procedure. We address these issues by (2) ℓ_2-regularizing w (Azizzadenesheli et al., 2018), and (3) using a decaying learning rate schedule for w. These modifications are necessary for achieving best performance, as long training episodes are required for fine-tuning on many NLP tasks, and also needed to maintain the critic near optimality for guiding properly the alignment.

Table 1: CoNLL NER (macro-averaged F_1).

	en	de	es	nl
Supervised results (in-language)				
mBERT	91.97	82.82	87.38	90.94
XLM-R	92.92	85.81	89.72	92.53
Zero-shot baselines				
mBERT	90.57	69.77	74.14	78.28
XLM-R	92.49	72.37	77.06	82.03
Unsupervised learning				
Keung et al. (2019)	-	71.9	74.3	77.6
Wu et al. (2020)	-	73.22	76.94	**80.89**
mBERT IWDA	90.77	72.56	76.11	78.63
+ KD	90.89	**73.71**	**77.14**	79.72
mBERT IWDA (oracle)	90.75	72.58	76.48	79.17
Bari et al. (2021)	-	**80.99**	**83.24**	**85.32**
XLM-R IWDA	92.55	75.42	79.08	81.79
XLM-R IWDA (oracle)	92.42	75.32	78.94	81.82

Table 2: WikiANN NER (macro-averaged F_1).

	en	bn	my	ur
Supervised results (in-language)				
mBERT	83.73	92.69	69.08	93.29
XLM-R (Hu et al., 2020)	84.7	97.8	76.8	97.1
Zero-shot baselines				
mBERT	83.73	68.55	50.16	35.78
XLM-R	83.55	76.24	58.12	62.66
Unsupervised learning				
Wu et al. (2020)	-	71.78	46.32	44.52
mBERT IWDA	83.93	71.05	55.86	75.79
+ KD	83.07	**73.15**	56.05	**77.58**
mBERT IWDA (oracle)	83.93	72.19	**60.22**	74.98
Bari et al. (2021)	-	**82.68**	**70.61**	**84.99**
XLM-R IWDA	83.43	78.03	57.10	78.89
XLM-R IWDA (oracle)	83.35	78.81	57.37	79.21

4 EXPERIMENTS

In our experiments, we compare importance-weighted domain alignment (IWDA) to two baseline methods for cross-lingual transfer on three NLP tasks, under the unsupervised setting where access to *unlabeled* task data from the target language is provided (UCL setting). Besides supporting our findings and our motivated algorithm, these experiments are aimed at investigating the limitations of existing approaches under distributional shifts in prior distributions between source and target. We also illustrate the potential benefits of IWDA in light of stronger cross-lingual learning methods.

Datasets. The tasks considered are named-entity recognition (NER), sentiment analysis, and textual entailment. **NER:** Two benchmark multilingual datasets are used, CoNLL (Tjong Kim Sang, 2002; Tjong Kim Sang & De Meulder, 2003) and WikiANN (Pan et al., 2017; Rahimi et al., 2019). The former includes English, German, Spanish and Dutch, and the latter covers over 200 languages, from which we select a subset of 40 according to the XTREME benchmark (Hu et al., 2020). **Sentiment analysis:** Multilingual Amazon Reviews Corpus (MARC) is used (Keung et al., 2020), a *balanced* dataset with product reviews in English, German, Spanish, French, Japanese and Chinese. **Textual entailment:** The XNLI dataset is used (Conneau et al., 2018), but due to space constraints, its setup and results are relegated to Appendix B. As in most work on cross-lingual transfer, English is used as the source language for transfer in our evaluations.

Baselines. We perform extensive comparative experiments with two semi-supervised learning (SSL) techniques. Both require having a model fine-tuned on source data only. **Knowledge distillation (KD):** It distills and transfers knowledge of the source teacher model to the target domain by training a newly initialized student network to mimic teacher outputs on target data (Hinton et al., 2015). A variant of KD was proposed for NER by Wu et al. (2020), which also freezes the bottom three layers of mBERT during training (Wu & Dredze, 2019). **Self-training (ST):** It iteratively assigns pseudolabels to unlabeled target data and train on the most confident ones. Our implementation follows closely the work by Dong & de Melo (2019), which considered sequence classification.[5]

For IWDA experiments, the model is first fine-tuned on source only, then continue fine-tuned with the IWDA objective on both source and unlabeled target data. We also include results for when the true IWs are known and hard-coded as an upper bound on IWDA performance (**IWDA (oracle)**).

Experiments are performed on BERT-Base Multilingual Cased and XLM-R Large models. More details on IWDA and our baselines are included in Appendices C and D along with hyperparameter settings. Unless otherwise noted, results are from our implementation.

[5]These baselines are chosen because they require no more resources than the unlabeled target data provided, are not tailored to any particular model, and can be easily implemented on any existing models, which are qualities shared by IWDA. As many elaborate methods are also based on the same fundamental ideas as these baselines, we hope that they are representative of approaches based on SSL, if not exhaustive.

Table 3: MARC sentiment analysis (accuracy).

	en	de	es	fr	ja	zh
Supervised results (in-language)						
mBERT	58.50	61.19	57.76	57.05	57.97	53.74
Zero-shot baselines						
mBERT	58.50	44.80	46.49	46.02	37.37	38.48
XLM-R	62.05	62.52	59.04	56.43	54.32	51.42
Unsupervised learning						
Wu et al. (2020)	-	47.43	49.56	49.06	35.77	38.54
mBERT ST	58.25	50.74	48.80	47.96	42.10	41.40
mBERT IWDA	56.87	51.94	49.77	49.78	42.62	44.04
+ ST	56.41	**53.11**	**51.00**	49.91	43.59	45.27
mBERT IWDA (oracle)	55.96	51.95	50.83	**50.01**	**44.91**	**45.96**
XLM-R IWDA	60.20	61.34	56.64	55.58	55.00	50.36

4.1 Results on Standard Benchmarks

To begin, through evaluations on standard benchmarks, we demonstrate that IWDA brings performance gains via improving representations to be better-aligned across languages. Results on CoNLL and low-resource WikiANN NER are presented in Tables 1 and 2, and those on MARC in Table 3. Remaining results on WikiANN with mBERT are included in Table 6 in the appendix.

In all mBERT IWDA experiments, improvements upon zero-shot baseline are observed, and are accompanied by improved representation alignment. The average decrease in conditional feature shift is 21.60% and 22.33% on CoNLL with IWDA and IWDA (oracle) respectively (with 100% indicating perfect alignment), 51.53% and 64.77% on MARC, and 32.91% and 36.34% on WikiANN.

However, improvements sometimes fall short of SSL baselines, which we suspect is due to the noise introduced during the alignment process. Potential sources include fluctuations in IW estimates and insufficiently trained critics. By training IWDA with more passes on the data and improving the optimality of the critic, further improvements on CoNLL NER are observed (Table 5).

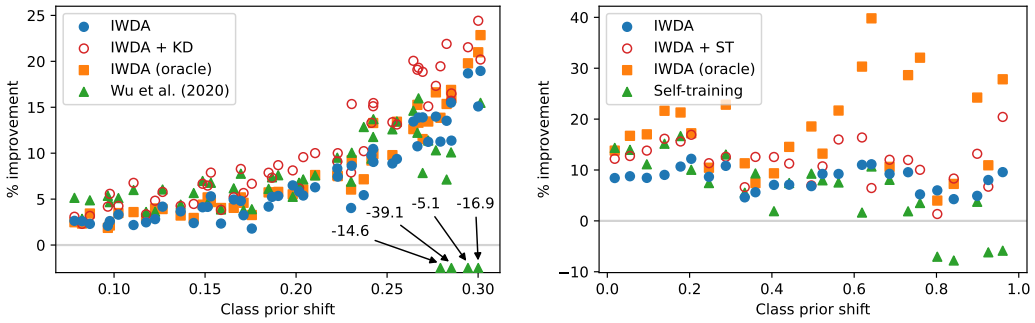
Another way to reduce noise is to perform a final-stage SSL training on the IWDA-aligned model. These experiments are labeled **IWDA + KD** and **IWDA + ST**, on which we observe some best results with mBERT on both tasks. This is an appealing strategy, because SSL algorithms theoretically depend on the assumption that the source and target domains are the same, IWDA training can be viewed as a preprocessing step on the feature representations to satisfy this assumption. We will revisit this point in the next section where we consider cross-lingual transfer under prior shifts.

On XLM-R models, IWDA also brings improvements on NER. However for MARC, drops in performance are observed. Here, we remark that the performance gain from IWDA (if any) will come from enhancements to the alignment of last-layer features in their current configurations, but not from learning entirely different representations with fundamentally better class-conditional alignment. This cannot be achieved absent target labels, additional supervision or resources. Hence, if the representations learned by the powerful XLM-R model during zero-shot training are already efficient, then the potentials of IWDA will be limited. Opportunities for further improvement in this case could come from additional supervision, e.g. Bari et al. (2021) achieve significant improvement via data augmentation and tri-training by leveraging the multilingual mask-filling ability of XLM-R.

4.2 Results Under Class Prior Shifts

In this section, we evaluate on datasets with large prior shifts, a likely property of real-world data that is insufficiently investigated for UCL, and contrast the brittleness of SSL baselines with the robustness of IWDA. Because of the lack of multilingual benchmarks exhibiting prior shifts, similar to Section 2.2 , we evaluate on smaller datasets subsampled from the German portion of CoNLL and the Japanese portion of MARC according to varying amounts of shifts.

Results plotting percent improvements over zero-shot baselines against the amount of prior shift are presented in Fig. 4. Although SSL baselines generally perform better than IWDA under mild to no shifts, their performances quickly deteriorate as prior shift increases, until eventually resulting in



(a) CoNLL English to German

(b) MARC English to Japanese

Figure 4: Percent improvement (in macro-averaged F_1) over zero-shot baselines of IWDA and SSL-based UCL baselines under varying class prior shifts, evaluated on datasets undersampled from benchmarks. Performance of SSL without prior shift correction deteriorates as shift increases.

negative transfer. IWDA on the other hand does not cause negative transfer from prior shifts owing to its estimation and correction capabilities. The relative success of IWDA demonstrates that it is possible to estimate prior shift from unlabeled target data. We also include results on MARC with XLM-R in Fig. 11.

In mBERT experiments, the average percent correction of prior shift, computed from the decrease in TV between true target domain priors and end-of-training estimates, normalized by the amounts of shift, is 87.33% on CoNLL (with 100% indicating perfect IW estimation), and 28.08% on MARC under shifts larger than 0.8 in TV. On MARC with smaller shifts, we observe estimates that are worse than assuming a uniform prior distribution (-335.80% in correction). This is because these are harder problems with noisy labels (as it is naturally difficult to distinguish a 2-star review from a 3-star one), the suboptimality of the source model from which IWDA is trained means that the initial representations may be conditionally misaligned, thereby affecting the accuracy of the initial as well as subsequent IW estimates.

Since IWDA brings improvements to class-conditional alignment, as already pointed out in the previous section, it is appealing to complement SSL and potentially more elaborated methods with IWDA to improve robustness to prior shift. As demonstrated in our IWDA + KD and ST experiments, SSL no longer suffer from negative transfer when preceded by IWDA, and altogether provide further performance gains.

5 Conclusion and Future Work

From the observations on multilingual neural LMs that cross-lingual transfer performance is strongly correlated with representation invariance and negatively affected by class prior shift, we proposed importance-weighted domain alignment (IWDA) for unsupervised cross-lingual learning. Experiment results support our findings, and show that IWDA is effective at the estimation and correction of class prior shift from unlabeled data, and robust to large shifts, under which in contrast existing UCL approaches based on SSL could result in negative transfer. As prior shift is a prevalent issue under unsupervised settings, more care to it is necessary in the design of future UCL algorithms for them to achieve good performance not only on curated benchmarks, but also on real-world data.

While our present implementation of IW estimation with the moment-matching approach is largely effective, future work on the search and study of potentially more stable estimation methods would enable IWDA to achieve better and more consistent transfer performance. Since the strength of IWDA lies in its ability to detect prior shifts and improve on class-conditional representation alignment, with our experiments on combining IWDA and SSL baselines as a preliminary demonstration of its potential usefulness as a feature preprocessing step and in improving robustness to prior shifts, it would be of interest to investigate its benefits on stronger models and methods towards better cross-lingual transfer.

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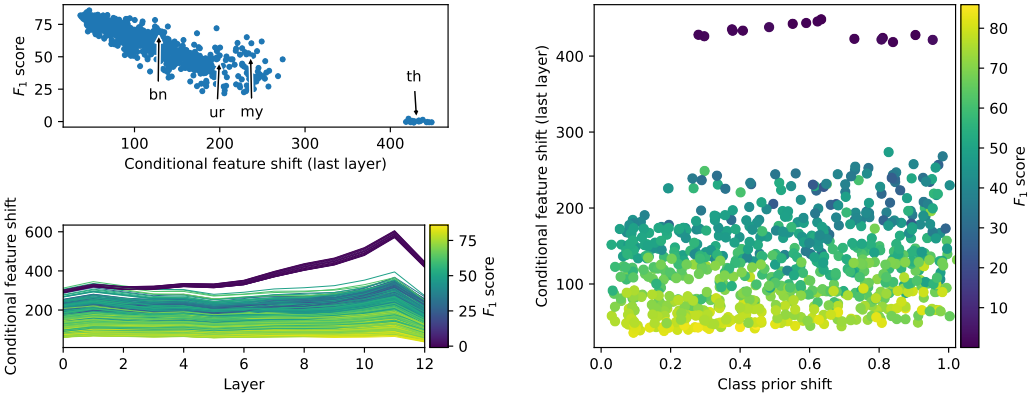


(a) Last and intermediate feature alignment

(b) Feature alignment and class prior shift

Figure 5: Feature invariance, class prior shift, and mBERT zero-shot transfer performance trained in English and evaluated on undersapmled WikiANN NER datasets, covering 39 target languages (cf. the same plots on MARC, figs. 1a and 3). Note that Thai is much less aligned with English.

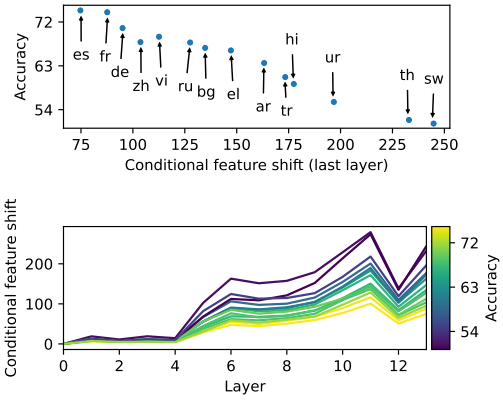
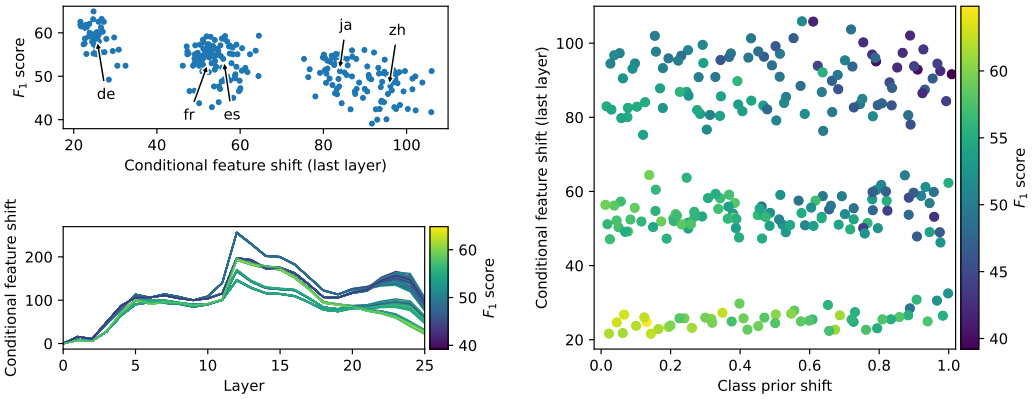


Figure 6: Feature invariance and mBERT zero-shot transfer performance trained in English and evaluated on XNLI dataset.

A Additional Analyses and Findings from Section 2

In this section, we provide descriptions to additional results for the analysis in Section 2, and additional findings for interested readers.

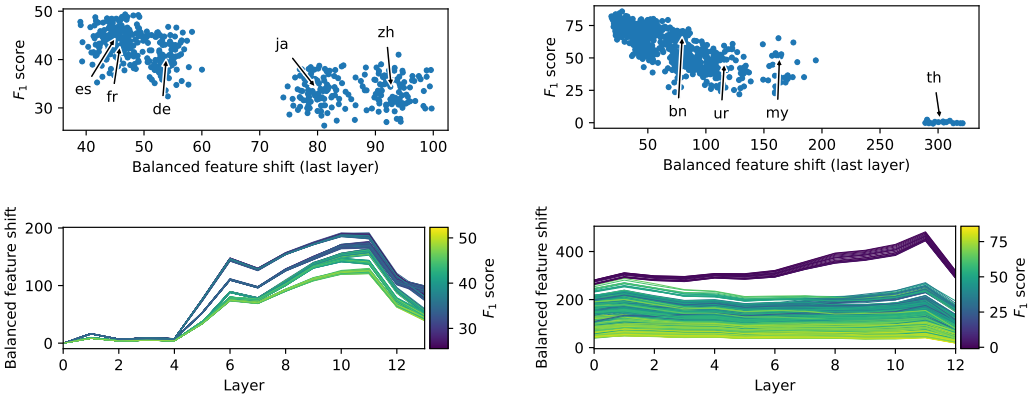
Similar to the plots included in Section 2, by plotting zero-shot transfer performance against representation alignment and prior shift on 39 target languages from the WikiANN dataset in Fig. 5, we aim to demonstrate that the findings on the relation are consistent regardless of linguistic properties or pre-training resourcefulness.



(a) Last and intermediate feature alignment

(b) Feature alignment and class prior shift

Figure 7: Feature invariance, class prior shift, and XLM-R zero-shot transfer performance trained in English and evaluated on MARC.



(a) MARC

(b) WikiANN

Figure 8: Class-balanced alignment of target language features with English features on two datasets vs. mBERT transfer performance (cf. class-conditional alignment in Fig. 1). These are intended to illustrate that the correlation between performance and feature alignment is not an artifact of having a linear predictor on last-layer features.

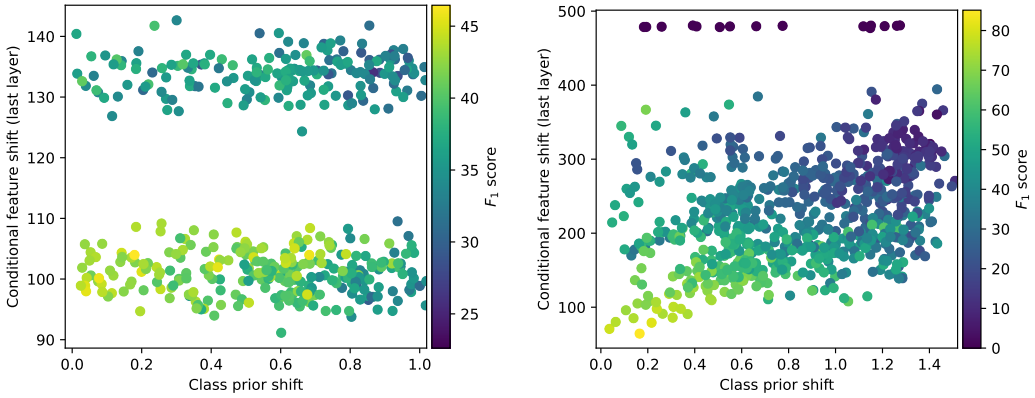
In Fig. 6, performance is compared against representation alignment on the XNLI textual entailment dataset, which is a high-level task. As the same conclusions are supported by these results, this shows that the findings are also consistent across tasks.

Finally, in Fig. 7, performance on MARC is compared against representation alignment and prior shift using XLM-R as the transfer model. The result shows that the findings are furthermore consistent across models.

A.1 Evaluating Models Trained on Skewed Source Data

In Section 2, the relation between feature invariance, class prior shift and zero-shot transfer performance is studied when transferring from a relatively balanced source dataset. Here, we show that when the model is fine-tuned on source datasets with skewed prior distributions, the effects of class prior shift are more pronounced.

For this study, on MARC, we undersample from the English portion a source dataset according to the prior distribution of 0.1486, 0.0643, 0.0803, 0.1928 and 0.5141, reflective of the distribution



(a) MARC

(b) WikiANN

Figure 9: Conditional feature shift and class prior shift vs. zero-shot performance on MARC and WikiANN. **Model was trained on skewed source training data.** Cf. figs. 3 and 5b (axis limits have changed), the impact on performance from class prior shift is more pronounced.

of product ratings on Amazon.com. We produce the same plot of Fig. 3 for a mBERT model fine-tuned on this skewed dataset in Fig. 9a. Compared to when the source is class-balanced, here, the correlation between performance and conditional feature alignment has weakened, and that with class prior shift has strengthened.

On WikiANN, potentially due to NER being a structured prediction problem where there exist dependencies between tokens in the same sentence, although the original English portion of the dataset is considerably skewed (with 50.75% of the tokens belonging to class O, i.e. not part of an entity mention), there appears to be little to no correlation between class prior shift and model performance (Fig. 5b); not until we evaluated an mBERT that was zero-shot fine-tuned on undersampled English WikiANN where only sequences containing tokens with label O are kept, so that 80.92% of the tokens belong to class O (Fig. 9b).

B Additional Experiment Results from Section 4

In this section, we provide a description of the setup and discuss the results of XNLI experiments. Because XNLI does not provide human-generated but only machine-translated training data for languages other than English (Conneau et al., 2020a), similar to the experiment considered in Bari et al. (2021), we partition the XNLI training split into portions of size 20,000 (equal to 5% of the original size), and randomly select disjoint partitions to use as source and target data. To avoid domain shift between train and test due to translation artifacts (Artetxe et al., 2020a), our test set is also selected from the machine-translated portion of the dataset.

Note that due to our setting, our results are not comparable to those evaluated on the standard XNLI benchmark. Instead, the goal here is to evaluate the benefits of improving feature alignment for higher-level tasks.

The results are included in Table 4, and it is observed that IWDA only brings slight improvements. This may also be due to the small transfer gap between zero-shot and supervised results under our setting, which means that representations are already largely aligned.

C Implementation Details of IWDA

Feature Alignment. In our implementations, we used Wasserstein-1 loss for the adversarial loss ℓ_{ad} (Arjovsky et al., 2017), which we observed to be more responsive to importance-weighted class prior correction than cross-entropy loss, which corresponds to Jensen-Shannon divergence under optimality (Goodfellow et al., 2014; Ganin et al., 2016). The Lipschitz requirement on the adver-

Table 4: XNLI textual entailment UCL transfer results (from English; accuracy).

	en	ar	bg	de	el	es	fr	hi
Supervised results (English + machine translation)								
mBERT	73.60	65.32	68.58	68.94	66.32	71.18	69.28	63.02
XLM-R	84.36	77.48	79.08	80.42	80.26	81.18	80.16	70.82
Zero-shot baselines								
mBERT	73.60	60.64	60.60	67.12	63.14	67.58	67.06	57.30
XLM-R	84.36	74.72	77.42	78.58	77.68	80.26	79.14	68.12
Unsupervised learning								
mBERT ST	73.04	60.20	63.40	66.30	62.00	67.92	67.16	56.62
mBERT IWDA	73.03	**61.16**	64.16	**67.30**	62.68	68.28	**67.34**	57.92
+ ST	73.10	60.28	64.18	66.66	62.44	68.02	66.96	57.70
mBERT IWDA (oracle)	72.94	60.74	**64.62**	67.02	**63.22**	**68.88**	67.06	**58.88**
XLM-R ST	84.35	74.78	**78.14**	78.10	77.60	79.48	79.26	67.20
XLM-R IWDA	84.61	74.31	77.32	78.36	77.22	80.14	79.54	67.92
+ ST	84.51	**75.62**	77.36	**78.82**	77.46	79.94	79.20	67.94
XLM-R IWDA (oracle)	84.69	74.68	77.98	78.58	**78.22**	79.78	**79.74**	**68.24**
	ru	sw	th	tr	ur	vi	zh	
Supervised results (English + machine translation)								
mBERT	67.66	57.32	63.36	63.02	48.60	68.24	69.62	
XLM-R	78.24	68.14	77.24	74.02	49.68	77.20	77.08	
Zero-shot baselines								
mBERT	64.30	47.28	51.40	57.36	43.16	62.98	63.70	
XLM-R	76.84	64.30	73.82	72.30	45.82	74.92	75.20	
Unsupervised learning								
mBERT ST	64.32	47.76	53.40	57.80	46.04	62.88	63.90	
mBERT IWDA	**65.06**	47.78	**54.80**	58.00	44.24	63.60	65.08	
+ ST	64.56	**48.26**	53.78	57.92	**46.94**	63.40	65.12	
mBERT IWDA (oracle)	64.84	45.96	54.50	**59.36**	46.76	**64.28**	**65.82**	
XLM-R ST	76.90	64.60	73.94	72.00	47.26	73.82	74.54	
XLM-R IWDA	**76.94**	64.20	74.12	71.64	45.70	74.44	74.94	
+ ST	76.84	**65.70**	**74.14**	72.30	**47.12**	74.14	75.86	
XLM-R IWDA (oracle)	76.90	64.56	**74.14**	**72.84**	46.98	**75.20**	**76.10**	

Table 5: CoNLL NER UCL transfer results (from English; macro-averaged F_1), with 40 epochs of IWDA fine-tuning, $\lambda_{\text{iw}} = 2\eta_{\text{iw}}$, and alternating updates to the adversary with 4 updates to f per update to g (see Appendix C for definitions; cf. Table 1).

	en	de	es	nl
IWDA	91.19	72.91	76.93	78.62
+ Our KD	90.68	73.83	77.87	79.96
IWDA (oracle)	91.32	72.47	77.24	79.31

sarial function class $\mathcal{F} \ni f$ is satisfied with the soft constraints provided by zero-centered gradient penalty, which penalizes the gradient of f evaluated on random points on the feature space between source and target inputs (Thanh-Tung et al., 2019).

(Pseudo-)Class conditioned feature alignment, proposed by Long et al. (2018), is performed for added stability, under which the outer product between features $z = g(x)$ and the output probability produced by the current classifier $h(z)$, $z \otimes h(z)$, is taken and fed to the adversary f.

Combining everything, the joint loss computed on a minibatch of source examples $(x_i, y_i)_{i=1}^n$ and target examples $(x'_j)_{j=1}^m$ is given by the following (cf. the minimax objective in Section 3)

$$\frac{1}{n}\sum_{i=1}^{n} \ell(h(g(x_i)), y_i) + \lambda_{\text{da}} \left(\frac{1}{n}\sum_{i=1}^{n} f(g(x_i) \otimes h(g(x_i))) - \frac{1}{m}\sum_{j=1}^{m} f(g(x'_j) \otimes h(g(x'_i))) \right) - \frac{\lambda_{\text{gp}}}{\tilde{n}} \sum_{i=1}^{\tilde{n}} \|(\nabla f)(\tilde{z}_i)\|^2,$$

where $\tilde{n} = \min(n, m)$ and $\tilde{z}_i$ is a random point on the line connecting $g(x_i)$ and $g(x'_i)$ ($\lambda_{\text{da}} = 0.005, \lambda_{\text{gp}} = 10$ in our experiments). The adversary f is optimized to maximize this loss, Trans-

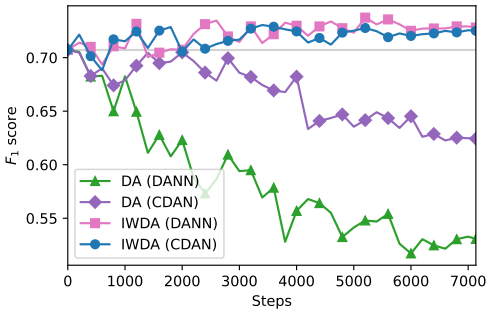


Figure 10: mBERT UCL transfer performance from English CoNLL NER to German, using IWDA feature alignment applied on last-layer token embeddings, and domain adaptation (DA) without class prior correction (using Wasserstein-1 adversarial loss). F_1 is plotted against the number of optimizer steps. Because of increasingly erroneous alignment as result of prior shift, DA performance deteriorates as training progresses. Performing (pseudo)class-conditional feature alignment (CDAN) protects DA from the effects of prior shift to some degree (Long et al., 2018), compared to DANN (Ganin et al., 2016).

Figure 11: Percent improvement over zero-shot performance of IWDA and SSL-based UCL baselines under varying class prior shifts, evaluated on MARC Japanese with XLM-R.

formers feature mapping g is optimized to minimize the first two terms, and the linear classifier h is optimized to minimize the first term only.

Prior Shift Estimation. On the estimation of importance weights (IWs), for added stability, we use the regularized estimator inspired by (Azizzadenesheli et al., 2018) that penalizes the amount of estimated shift. Here, for simplicity, we use ℓ_2-squared penalty implemented as weight decay, $\sum_{i=1}^{k}(w_i - w_0)^2$. By default, $w_0 = \mathbf{1}$, which corresponds to no prior shift.

Given first moment statistics of source confusion, $C_{ij} := p_S(\hat{y} = i, y = j)$, and target output distribution, $\nu_i := p_T(\hat{y} = i)$, the IWs are estimated by minimizing the following objective w.r.t. w,

$$\sum_{i=1}^{k}\left(\nu_i - \sum_{j=1}^{k} C_{ij} w_j\right) + \lambda_{\text{iw}} \sum_{i=1}^{k}(w_i - w_0)^2,$$

($\lambda_{\text{iw}} = \eta_{\text{iw}}$ in our experiments, where η_{iw} is the learning rate for w). Because obtaining the first moment statistics from the entire training set is expensive, they are updated with exponential decay on (unbiased) estimates $\hat{C}, \hat{\nu}$ obtained from minibatches in each forward-pass, $C_t = (1 - \eta_{\text{iw-stats}})C_{t-1} + \eta_{\text{iw-stats}}\hat{C}$, and similarly for $\hat{\nu}$ ($\eta_{\text{iw-stats}} = 0.005$ in our experiments).

To minimize potential effects from the miscalibration of neural models (Guo et al., 2017; Alexandari et al., 2020), hard confusion matrix and target output distribution are used in the estimation of IWs (Lipton et al., 2018; Garg et al., 2020).

For initialization, before the start of IWDA fine-tuning, C_0, ν_0 are warmed up with data from the training sets, and w is computed using C_0, ν_0 with the quadratic program described in Tachet des Combes et al. (2020). Since w will be likely be incorrect as features are not yet aligned, we set $w_0 = (1 - \lambda_{\text{iw-init}})w + \lambda_{\text{iw-init}}\mathbf{1}$ ($\lambda_{\text{iw-init}} = 0.25$ in our experiments, and linearly decays to 0 over the first 10% of optimization steps).

Optimization. AdamW optimizer is applied to all parameters, with learning rate of 5×10^{-4} for the adversary and IW, and 1×10^{-5} for mBERT. Linear learning rate schedule is applied to mBERT

and IW, and 10% warm up is applied to mBERT and λ_{da}. The batch size is set to 8. No truncation on the input texts is performed (although sequence length is limited to 512 due to modeling constraints of mBERT).

For each minibatch of examples from the source and target domains, one gradient step is applied on updating h, w (followed by a projection to satisfy $w \geq 0$ and $w^\top p_S^Y = 1$), and the first moment statistics C, ν are updated. When simultaneous adversary updates are used, one gradient step is also applied on g and f. Otherwise, with alternating updates, it is applied on either g or f.

This set of hyperparameters was found to work well for IWDA on most datasets and languages evaluated in the present work. For discussions on hyperparameter tuning for unsupervised cross-lingual learning, we refer interested readers to Artetxe et al. (2020c).

D Description of SSL Baseline Approaches

Knowledge Distillation (Our KD). In our implementation, we follow the original paper by Hinton et al. (2015) more closely. Where the KD method by Wu et al. (2020) sets Softmax temperature to 1 and does not use examples from the source domain for distillation, we set the temperature to 3 and use the source labeled data for distillation for both soft targets and hard targets with a relative weight of 0.1. Same as Wu et al. (2020), the losses on the soft targets are computed with MSE for numerical stability. The learning rate is 1×10^{-4}, and the batch size is 32.

In addition, Wu et al. (2020) observed that when distilling from a zero-shot fine-tuned teacher mBERT, better performance is achieved when the teacher is also trained with bottom three layers frozen. Therefore, for fair comparison, the zero-shot models on which our KD implementation is applied are also fine-tuned with frozen bottom layers (Table 1). We did not freeze any layers during the training of the models involved in IWDA experiments.

Self-Training (ST). Our implementation follows Dong & de Melo (2019) closely, in which we first obtain a zero-shot fine-tuned model, and then continue to fine-tune it on source and target data with high-confidence pseudolabels. Self-training is performed for 4 epochs. In each epoch, on MARC, we fine-tune on 50000 examples randomly selected on the source domain, and 4000 examples from each class on the target domain by confidence with their predicted labels. For experiments in Section 4.2, the sample sizes are scaled down to 5000 and 400, as the size of undersampled MARC datasets is 20000. The learning rate is 1×10^{-5}, and the batch size is 128.

Table 6: WikiANN NER UCL transfer results (from English; macro-averaged F_1). Partial zero-shot results from explicitly word-aligned mBERT (Wu & Dredze, 2020) are included for comparison.

	en	af	ar	bg	bn	de	el	es	et	eu
Supervised	83.73	91.36	87.62	92.64	92.69	89.47	90.55	91.42	91.58	91.72
Zero-shot	83.73	77.63	40.68	77.89	68.55	79.01	71.19	76.73	76.74	59.76
IWDA	83.93	77.50	37.59	78.57	71.05	78.86	72.19	83.37	79.16	67.11
IWDA (oracle)	83.93	77.18	37.29	79.65	72.19	79.07	72.13	83.72	80.23	72.69
	fa	fi	fr	he	hi	hu	id	it	ja	jv
Supervised	92.11	91.20	90.15	85.19	86.10	92.67	91.88	91.44	73.18	73.71
Zero-shot	40.27	77.87	80.47	56.55	66.08	76.55	60.67	80.67	27.49	61.51
IWDA	28.32	78.43	79.99	56.57	64.37	76.00	51.35	80.46	38.05	61.48
IWDA (oracle)	46.33	79.56	83.78	57.62	67.01	76.69	72.00	80.99	34.98	60.57
	ka	kk	ko	ml	mr	ms	my	nl	pt	ru
Supervised	86.55	85.06	87.71	82.68	85.42	93.27	69.08	91.37	91.45	88.28
Zero-shot	66.41	46.87	60.52	53.33	57.97	67.63	50.16	82.16	80.07	65.61
IWDA	67.14	48.15	61.18	53.75	61.80	69.78	55.86	81.03	82.40	66.00
IWDA (oracle)	67.39	49.11	63.29	59.47	61.55	69.01	60.22	81.05	83.66	72.00
	sw	ta	te	th	tl	tr	ur	vi	yo	zh
Supervised	88.98	83.53	78.53	76.84	93.64	92.35	93.29	90.83	82.93	81.14
Zero-shot	69.35	50.22	50.63	1.31	69.57	73.78	35.78	71.19	49.29	43.29
IWDA	67.56	53.93	52.09	1.60	75.16	74.36	75.79	80.20	52.07	49.90
IWDA (oracle)	67.40	55.46	53.84	8.39	76.50	78.64	74.98	78.85	54.60	56.26