Ranking Transfer Languages with Pragmatically-Motivated Features for Multilingual Sentiment Analysis

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Abstract

Cross-lingual transfer learning studies how datasets, annotations, and models can be transferred from resource-rich languages to improve language technologies in resource-poor settings. Recent works have shown that we can further benefit from the selection of the best transfer language. In this paper, we propose three pragmatically-motivated features that can help guide the optimal transfer language selection problem for cross-lingual transfer. Specifically, the proposed features operationalize cross-cultural similarities that manifest in various linguistic patterns: language context-level, sharing multi-word expressions, and the use of emotion concepts. Our experimental results show that these features significantly improve the prediction of optimal transfer languages over baselines in sentiment analysis, but are less useful for dependency parsing. Further analyses show that the proposed features indeed capture the intended cross-cultural similarities and align well with existing work in sociolinguistics and linguistic anthropology.

1 Introduction

Cross-lingual transfer of linguistic annotations, models, and raw corpora has been widely used in multilingual natural language processing tasks, including machine translation (Zoph et al., 2016; Johnson et al., 2017; Neubig and Hu, 2018), multilingual dependency parsing (Ammar et al., 2016; Ponti et al., 2018), and multilingual sentiment analysis (Prettenhofer and Stein, 2010; Zhou et al., 2016). In this paper, we focus on settings in which cross-lingual transfer learning is realized by incorporating annotated datasets from different transfer languages to improve task performance in the target language. This setup has been shown to be especially helpful in low-resource scenarios (Das and Hasegawa-Johnson, 2015; Agić et al., 2016).

However, not all transfer languages are equally helpful. Previous work has shown that selecting the right set of training languages can significantly boost the performance of cross-lingual models (Paul et al., 2009; Lin et al., 2019; Wang and Neubig, 2019; Wang et al., 2020). More specifically, Lin et al. (2019) explore the problem of language selection, where a model predicts the most effective set of training languages for a given target language. They proposed a framework that uses various syntactic and semantic features and showed that automatic language selection could significantly improve the effectiveness of cross-lingual learning.

Prior studies mainly introduced shallow lexical, syntactic, and semantic features of languages to understand the effectiveness of cross-lingual transfer. However, these features may be insufficient when the cross-lingual task is driven by pragmatic knowledge, as in the cross-lingual analysis of sentiment and emotion.\textsuperscript{1} Expression of subtle sentiment and emotion, such as subjective well-being (Smith et al., 2016), anger (Oster, 2019), or irony (Karoui et al., 2017), varies significantly by culture. Mohammad et al. (2016) have shown that, even with sound machine translation systems, achieving cross-lingual transfer by translating low-resource languages to high-resource languages and applying models trained on the high-resource languages is impeded by culture-specific

\textsuperscript{1}In linguistics, pragmatics has both a broad and a narrow sense. Narrowly, the term is used to refer to formal pragmatics. In the broad sense, which we employ in this paper, pragmatics refers to contextual factors in language use. We are particularly concerned with cross-cultural pragmatics and finding quantifiable linguistic measures that correspond to aspects of cultural context. These measures are not the cultural characteristics that would be identified by anthropological linguists themselves but are rather intended to be measurable correlates of these characteristics.
concepts. Some languages, for instance, Chinese and Korean, are used in East Asia in similar cultural contexts but possess significantly different syntactic structures (Jackson et al., 2019). In such cases, cross-cultural similarity can be one of the most important indicators for predicting cross-lingual transfer quality.

To operationalize cross-cultural similarity, we focus on three distinct aspects in the intersection of language and culture. First, every language and culture rely on different levels of context in communication. Western European languages, such as German and English, are generally considered low-context languages, whereas Korean and Japanese are considered high-context languages. Second, similar cultures construct and construe figurative language similarly (Casas and Campoy, 1995; Vulanović, 2014). Finally, emotion semantics is similar between languages that are culturally-related (Jackson et al., 2019). For example, in Persian (an Indo-Iranian language of Iran), both ‘grief’ and ‘regret’ are expressed with the same word anduh whereas ‘grief’ is colexified with ‘anxiety’ as dard in the Sirkhi dialect of Dargwa (a Dagestani language of Russia).

The key contribution of our work is pragmatically-driven features that capture cross-cultural similarity: language context-level ratio, literal translation quality, and the emotion semantic distance (§3). Extensive analysis of each feature verifies that they indeed capture the intended linguistic patterns, and thereby align with prior work from sociolinguistics and linguistic anthropology (§4). We further evaluate each feature’s effectiveness by incorporating them in a transfer-language ranking model, focusing on two NLP tasks: sentiment analysis and dependency parsing (§6). Our results corroborate our hypothesis that the pragmatically-motivated features boost the baseline for sentiment analysis but not for dependency parsing, suggesting a connection between sentiment and pragmatics (§7).²

2 Problem Formulation

We define our task as the language selection problem: given the target language ltgt, our model ranks transfer languages ltf by their usefulness when transferred to ltg. Formally, we define transferability of a language pair (ltf, ltg) as how useful ltf is to a model for ltg. Effectiveness of cross-lingual transfer is often measured by joint training or zero-shot transfer performance (Wu and Dredze, 2019; Schuster et al., 2019). In this work, we quantify transferability as zero-shot performance, following Lin et al. (2019). For a given target language ltg and n candidates of additional (source) transfer languages Ltf = {l(1)tf, . . . , l(n)tf}, our goal is to train a model that ranks languages in Ltf by their transferability.

Figure 1 illustrates the training procedure of the transfer language ranking model that follows the set up in Lin et al. (2019). Before training, we first need to extract optimal transferability rankings, which can be used as the training data of the language ranking model (Step 1). For a given target language ltg, we evaluate the zero-shot performance of a model trained solely with transfer language ltf and tested on ltg, denoted as ztf,lg. After evaluating ztf,lg for each candidate transfer language in Ltf, we obtain the optimal ranking of languages rlg by sorting languages according to their transferability to ltg. Note that the optimal rankings depend on the task and its characteristics.

Next, we train the language ranking model (Step 2). The ranking model predicts the transferability ranking of candidate transfer languages. Each source, target pair (ltf, ltg) is represented as a vector of language features ftf,lg, which may include phonological similarity, typological similarity, word-overlap to name a few. The ranking model takes ftf,lg of every ltf ∈ Ltf as input, and predicts the transferability ranking rlg. Us-

²Both code and data used in this paper are available at https://github.com/hwijeen/langrank.
ing $r_{tg}$ from the previous step as training data, the ranking model learns to find optimal transfer languages using language features. Once the model is trained, it can be used to predict transferability for an unseen language pair, without the expensive computation process in step 1.

3 Pragmatically-motivated Features

Our main contribution is in proposing novel features to include in $f$ that correlate with cultural similarities across languages. We hypothesize that these cultural similarities are essential to effectively rank transfer languages in pragmatics-driven tasks.

Language Context-level Ratio The language context-level ratio (LCR) feature approximates the extent to which a pair of languages differ in leaving the identity of entities and predicates to context. For example, an English sentence Did you eat lunch? explicitly indicates the pronoun you, whereas the equivalent Korean sentence 점심 먹었어요? (= Did you eat lunch?) omits the pronoun. This is related to the concept of context-level, which is considered one of the distinctive attributes of a language’s pragmatics in linguistics and communication studies (Nada et al., 2001). If two languages have similar levels of context, their speakers are more likely to be from similar cultures (Nada et al., 2001). To capture this linguistic quality, we compute the pronoun- and verb-token ratio, $ptr(l_k)$ and $vtr(l_k)$ for each language $l_k$, using part-of-speech tagging results. We first run language-specific POS-taggers over each language’s large monolingual corpus.\(^3\) Next, we compute $ptr$ as the number of pronoun tokens over the number of all tokens. $vtr$ is obtained likewise with verb tokens. Low $ptr$, $vtr$ values may indicate that a language leaves the identity of entities and predicates, respectively, to context.

We then compare these values between the target language $l_{tg}$ and transfer language $l_{tf}$, which leads to the following definition of LCR:

$$\text{LCR-pron}(l_{tf}, l_{tg}) = \frac{ptr(l_{tg})}{ptr(l_{tf})}$$

$$\text{LCR-verb}(l_{tf}, l_{tg}) = \frac{vtr(l_{tg})}{vtr(l_{tf})}$$

Literal Translation Quality Literal translation quality (LTQ) quantifies how well literal translation, i.e., word-by-word translation using a bilingual dictionary\(^4\), works for a given language pair’s multiword expressions (MWEs). The motivation is that culturally similar languages share figurative language, including idiomatic MWEs and metaphors. For example, like father like son in English can be translated word-by-word into a similar idiom tel père tel fils in French. However, in Japanese, a similar idiom 鳥の子は鶏 (Kaeru no ko wa kaeru) “A frog’s child is a frog.” cannot be literally translated.

Since we do not have a well-curated list of MWEs in every language, here we follow the MWE extraction approach from Tsvetkov and Wintner (2010); for each language, we use PMI\(^5\) (Daille, 1994) to extract top-$k$ MWE from a large news-crawl corpus (Goldhahn et al., 2012). However, the news-crawl corpus is often noisy, and thus extracted MWEs contain many data-specific artifact n-grams. To filter those out, we exploit another smaller but reasonably large monolingual corpus, the TED talk dataset (Qi et al., 2018). We choose top-$k$ MWEs in terms of PMI\(^5\) that appeared in both monolingual corpora. In this paper, we used $k = 500$.

After retrieving MWEs, we use a bilingual dictionary of $l_{tf}$ and $l_{tg}$ and a parallel corpus between the pair to measure $LTQ(l_{tf}, l_{tg})$.\(^5\) For each n-gram in $l_{tg}$’s MWEs, we first look for target sentences in the parallel corpus that contain the n-gram. Then, per the found sentence, we look at each word of the n-gram and its potential translations in transfer language using the bilingual dictionary. For any word in the n-gram, if there is any word translation in the source sentence, we consider this as hit, otherwise as miss. And we calculate $hit \text{ ratio as } \frac{hit}{(hit+miss)}$ for each n-gram found in the parallel corpus. Finally, we average the hit ratios of all n-grams and set it as $LTQ(l_{tf}, l_{tg})$.\(^6\)

Emotion Semantics Distance Emotion semantic distance (ESD) measures how similarly emotions are worded between languages. This is inspired by Jackson et al. (2019), where they use colexification patterns to capture the semantic similarity of languages. However, colexifica-

\(^3\)List of POS taggers, tokenizer and monolingual corpus used in the paper is in the Appendix A.2.

\(^4\)https://github.com/kakaobrain/word2word

\(^5\)We used TED talk dataset for the parallel corpus.

\(^6\)We further standardize the score (z-score) over the transfer language.
tion patterns require human annotation, and existing annotations may not be comprehensive. Here, we extend the method by using cross-lingual word embeddings.

We define $ESD$ as the average distance of emotion word vectors in transfer and target languages, after aligning word embeddings into the same space. More specifically, we use 24 emotion concepts defined in Jackson et al. (2019) and use bilingual dictionaries to expand each concept into every other language. We then remove the emotion words from the bilingual dictionaries, and use the remaining word pairs to align word embeddings of source into the space of target languages. Theoretically, if words of the same emotion concept in different languages have exactly the same meaning, they should be aligned to the same point despite the lack of supervision. However, because each language possesses different emotion semantics, emotions in each language are scattered into different positions. Finally, we define $ESD$ as the average cosine distance between languages:

$$ESD(l_{tf}, l_{tg}) = \frac{\sum_{e \in E} \cos(v_{tf,e}, v_{tg,e})}{|E|}$$

where $E$ is the set of emotion concepts and $v_{tf,e}$ is the aligned word vector of language $l_{tf}$ for emotion concept $e$.

### 4 Feature Analysis

In this section, we verify whether each pragmatically-motivated feature correlates with the intended pragmatic information.

#### 4.1 LCR and Language Context-level

$ptr$ approximates how often discourse entities are indexed with pronouns rather than left conjecturable from context. Similarly, $vtr$ estimates the rate at which predicates appear explicitly as verbs. In order to examine to what extent these features reflect context-levels, we plot languages on a two-dimensional plane where the x-axis indicates $ptr$ and the y-axis indicates $vtr$ in Figure 2. The plot reveals a clear pattern of context-levels in different languages. German, which is one of the low-context languages (Hall, 1989), possesses the second largest value of $ptr$. On the other extreme are located Korean and Japanese with low $ptr$, which are representative of high-context languages. One thing to notice is the isolated location of Turkish with a high $vtr$. This is morphosyntactically plausible as a lot of information is expressed by affixation to verbs in Turkish.

#### 4.2 LTQ and MWEs

Since human-curated lists of figurative language MWE (gold MWEs) are not always available for all languages, LTQ uses n-grams with high PMI scores (PMI MWEs) as proxies. Nonetheless, for languages that have manual annotations, we can still use it to evaluate the quality of selected MWEs and the resultant LTQ. We collected ground-truth MWEs in multiple languages from Wiktionary. For example, the trigrams in the PMI MWEs, keep an eye and take into account, were considered to be in the gold MWEs as keep an eye peeled and take into account were in the list.

Secondly, to validate using PMI MWEs as proxies, we compare the LTQ of PMI MWEs with the LTQ using Gold MWEs. More specifically, us-
ing the same procedure and dataset explained in §3, we obtained the LTQ scores of each language pair with target languages limited to the four European languages mentioned above. For each target language, we then measured the Pearson correlation coefficient of LTQ scores between two lists. The average coefficient was 0.92, which indicates a strong correlation between the LTQ of two lists, and thus justifies using PMI MWEs for all other languages.

4.3 ESD and Cultural Grouping

We investigate what is carried by ESD by visualizing and looking at the nearest neighbors of emotion vectors. Jackson et al. (2019) revealed that the emotion of hope clusters with different kinds of emotion depending on the language family it belongs to using word collocations. For instance, in Tai-Kadai languages hope appears in the same cluster as want and pity, while hope clusters with good and love in Nakh-Daghestanian language family. Our results derived from ESD also support evidence to this finding, even without using word collocations. For instance, the nearest neighbors to the French word for hope was worry and regret, while they were found as joy and good for Hindi hope.

We further investigate the suggested ESD feature and show that it is an indicator of cultural similarity. We present a network of languages in Figure 3a based on ESD. Languages are represented as different nodes and color-coded according to the predefined cultural areas in Table 1. To draw edges, we set each language as the target language, and sort other languages according to ESD. When a language is in the list of top-\(k\) closest languages, an edge exists between the two languages.

In Figure 3, we compare two graphs based on different linguistic features. Figure 3a uses ESD to draw edges between languages while Figure 3b uses syntactic distance provided by the URIEL package (Littell et al., 2017). We see that the languages sharing same cultural areas form cohesive clusters in Figure 3a compared to Figure 3b. The portion of edges within the cultural areas were 76% of all edges in Figure 3a while it was 59% in Figure 3b. These results indicate that ESD effectively extracts linguistic information that aligns well with the commonly shared perception of cultural groups.

5 Dataset

We apply the proposed features to train a ranking model for two distinctive tasks: multilingual sentiment analysis (SA) and multilingual dependency parsing (DEP). We hypothesize that high-order information such as pragmatics would assist sentiment analysis while it may be insignificant for dependency parsing, where lower-order information such as syntax are relatively stressed. This section reports the dataset used for each task.

Sentiment Analysis As there is no single sentiment analysis dataset covering a wide variety of languages, we collected various review datasets from different sources. All samples are labeled as either positive or negative. In case of datasets rated with scores ranging from 1 to 5, we mapped 1–2 to negative and 4–5 to positive. We settled on a dataset consisting 16 languages categorized into five distinct cultural groups: Western Europe, Eastern Europe, East Asia, South Asia, Middle
Table 1: Data statistics for the sentiment analysis task. Datasets are reviews of different domains and of different sizes. We divided 16 languages into five cultural groups based on cultural similarities.

| Cultural Area | Languages       | Domain | Size     |
|---------------|-----------------|--------|---------|
| West Europe   | German          | product| 56333   |
|               | French          | product| 20771   |
|               | English         | restaurant| 1472  |
|               | Spanish         | restaurant| 1396  |
|               | Dutch           | restaurant| 1089  |
| East Europe   | Russian         | restaurant| 2289  |
|               | Czech           | movie| 54540   |
|               | Polish          | product| 26284   |
| East Asia     | Chinese         | electronics| 2333  |
|               | Korean          | movie| 18000   |
|               | Japanese        | product| 21095   |
| South Asia    | Hindi           | product| 2707    |
|               | Tamil           | movie| 417     |
| Middle East   | Arabic          | hotel| 4111    |
|               | Persian         | product| 3904   |
|               | Turkish         | restaurant| 907    |

East. Table 1 summarizes data in different groups with their size and domain.

Since the data came from heterogeneous sources, each language’s dataset varied in size and domain: sizes ranging from 417 (Tamil) to 625918 (German), and domains including hotel, restaurant, product, and movie reviews. To alleviate the size disparity between languages, we randomly took the subset of datasets with size larger than 100K (Japanese, German, French, Korean) while preserving their label distribution.

Dependency Parsing In order to compare the effectiveness of the proposed features on syntax-focused tasks, we selected datasets of the same set of 16 languages from Universal Dependencies v2.2 (Nivre et al., 2018).

6 Evaluation Setup

In this section, we describe the cross-lingual models used in each of the two tasks and the transfer language ranking model with its evaluation metric.

SA Cross-lingual model We performed supervised fine-tuning of multilingual BERT (mBERT) (Devlin et al., 2019) for the sentiment analysis task, as it showed strong results in various text classification tasks in cross-lingual settings (Sun et al., 2019; Xu et al., 2019; Li et al., 2019). mBERT is a multilingual extension of BERT pre-trained with 104 different languages, including the 16 languages we used throughout our experiment. The model is shown to be highly effective in cross-lingual transfer even between languages using different scripts (K et al., 2019; Pires et al., 2019). We used a concatenation of mean and max pooling of the representations from mBERT’s penultimate layer, as it outperformed the standard practice of using the [CLS] token. The concatenated representation was passed to a fully connected layer for prediction. The performance measure is the macro F1 score on the held-out test set. To extract optimal transfer rankings, we conducted zero-shot transfer with mBERT: fine-tuned mBERT on transfer language data and tested it on target language data.

DEP Cross-lingual model For dependency parsing, we adopted the setting from Ahmad et al. (2018), performing cross-lingual zero-shot transfer on the same set of languages as the sentiment analysis task. We trained deep biaffine attentional graph-based models (Dozat and Manning, 2016), which achieved state-of-the-art performance in dependency parsing for many languages. To cope with multilingual vocabulary, we adopted an offline embedding method (Smith et al., 2017) that maps pretrained word embeddings of different languages into the same space. The performance was evaluated using labeled attachment scores (LAS).

Ranking model For the transfer language ranking model, we used Gradient boosted decision trees (Ke et al., 2017) trained with LambdaRank (Burges et al., 2007), which is one of the state-of-the-art models for ranking tasks. As in prior work, we optimized normalized discounted cumulative gain (NDCG) to train the model (Järvelin and Kekäläinen, 2002).

Evaluation metric We evaluate the ranking models’ performance with two standard metrics designed for ranking problems: Mean Average Precision (MAP) and NDCG. MAP is computed by averaging the precision at each relevant item (AP), and averaging all AP scores for multiple ranking tasks. We set relevant items as the top-3 languages in terms of zero-shot performance following Lin et al. (2019). NDCG enables more
fine-grained grading considering ranking positions rather than assuming a binary concept of relevance/irrelevance. Here, we use NDCG@3 as the evaluation metric. We report the model’s average test performance using leave-one-out cross-validation.

7 Experiments

We investigate the performance of the ranking model with the proposed features over two distinct downstream tasks: Sentiment Analysis (SA) and Dependency Parsing (DEP).

7.1 Baseline

Lin et al. (2019) We briefly describe the 13 features used in Lin et al. (2019) to train the ranking model. The dataset size in transfer language (tf_size), target language (tg_size), and the ratio between the two (ratio_size) are included. Type-token-ratio (TTR) is a measure of lexical diversity, defined by the ratio between number of unique words and number of tokens. word_overlap measures lexical similarity between a pair of languages. Other features are various types of distance between a pair of languages queried from the URIEL package (Littell et al., 2017): geographic (geo), genetic (gen), inventory (inv), syntactic (syn), phonological (phon) and featural (feat), adopted from linguistic databases such as WALS (Dryer and Haspelmath, 2013), Glottolog (Hammarström et al., 2020), and PHOIBLE (Moran and McCloy, 2019).

Lin et al. (2019) – TTR Prior work suggests that type-to-token ratio (TTR) encodes a significant amount of cultural information (Richards, 1987). Therefore, to examine the cultural information contained by each pragmatically-inspired feature and their contribution to performance more precisely, we exclude TTR from the 13 features introduced in Lin et al. (2019) and set it as another baseline.

7.2 Individual Feature Contribution

We added three pragmatically-inspired features one-by-one on top of Lin et al. (2019) – TTR baseline, as shown in Table 2. We also compare these results with the baseline and baseline plus all three pragmatically-inspired features (ALL).

The results show that adding individual pragmatically-inspired feature always improved the baseline either in MAP or NDCG for sentiment analysis. In contrast, for dependency parsing, pragmatically-inspired features degraded performance in most cases. In particular, when TTR was excluded from the baseline, a slight improvement in performance was observed. The contrasting results indicate that the pragmatic features capture additional information that help sentiment analysis but disturb tasks distant from pragmatics, exemplified as DEP in our case.

7.3 Group-wise Contribution

As shown in the previous experiment, the same pragmatic information can be helpful to different extents depending on the downstream task. We further investigate what kind of information aids each task by conducting group-wise comparisons. To this end, we group the features into five categories: Data-specific, Typology, Geography, Orthography, and Pragmatic. Data-specific features include tf_size, tg_size, and ratio_size. Typological features include geo, syn, feat, phon, inv distances. Geographic features include geo distance in isolation. Orthographic feature is the word_overlap between languages. Finally, the Pragmatic group consists of TTR and the three proposed features, LCR, LTQ, and ESD.

Table 3 reports the performance of models trained with respective feature category. Interestingly, two tasks showed significantly different distributions; SA had the best performance with the Pragmatic group, and DEP had it with the Typology group. This again confirms that features indicating the cross-lingual transferability can be different depending on the target task. More surprisingly in SA, using Pragmatic features performed comparably to using all features reported in Ta-
Pragmatic group played the most important role for sentiment analysis. In case of dependency parsing, typological features were the most important.

Table 3: Evaluation results of feature groups.

|                | SA            | DEP            |
|----------------|---------------|----------------|
|                | MAP | NDCG | MAP | NDCG |
| Data-specific  | 50.7 | 85.4 | 15.6 | 55.0 |
| Typology       | 17.4 | 60.7 | 39.2 | 79.8 |
| Geography      | 5.7  | 55.0 | 9.7  | 65.1 |
| Orthography    | 19.3 | 56.6 | 21.4 | 60.5 |
| Pragmatic      | 58.7 | 88.0 | 23.6 | 71.8 |

Table 4: Relative ranking of the transfer languages Arabic, Japanese and Korean when target language is Turkish.

| Lin et al. (2019) | Pragmatic | Optimal |
|-------------------|-----------|---------|
| 1                 | jpn       | ara     |
| 2                 | ara       | jpn     | kor    |
| 3                 | kor       | kor     | jpn     |

8 Analysis

Improvement in performance of the ranking model on sentiment analysis showed that the proposed features provide meaningful information. In this section, we provide a qualitative analysis with an example ranking prediction and show how the feature is related to the geographical distance.

8.1 Controlled experiment

The performance of cross-lingual transfer depends not only on the cultural similarity between transfer and target languages but also on other factors, including dataset size and label distribution. To better understand the importance of cultural similarity in sentiment analysis, we conduct a controlled experiment; we fixed the dataset size and label distribution for all languages, and extracted the optimal transferability rankings. Note that all data were down-sampled to match the size and label distribution of the second smallest Turkish dataset. The rankings of the controlled experiment were then used to train two ranking models with different features: 13 features from Lin et al. (2019) and the proposed 3 pragmatic features.

Table 4 shows the relative ranking of predicted and optimal rankings when the target language is Turkish. When Turkish is the target, Arabic, Japanese, and Korean are a particularly interesting subset of transfer languages. Korean and Japanese are similar both typologically and culturally. Turkish and Korean are typologically very similar, yet in cultural terms, Turkish is more similar to Arabic. Therefore, we specifically focus on how the predicted ranking of these three languages differ according to the features used to represent the language pair.

In the controlled setting, the relative optimal ranking of the three languages is Arabic, followed by Korean and Japanese. The optimal ranking indicates the important role of cultural resemblance, considering the rich historical relationship shared between Arabic- and Turkish-speaking communities. The model with pragmatic features was able to choose Arabic as the best transfer language, suggesting that imposed cultural similarity information from the features helped the ranking model learn the cultural tie between the two languages. On the other hand, the baseline model of Lin et al. (2019) ranked Japanese the highest (over Arabic), possibly because these features focus on typological similarity over cultural similarity.

8.2 Correlation with Geographical Distance

Regarding the cluster of languages in Figure 3a, some might suspect that geographic distance \( (\text{geo}) \) might be able to substitute the suggested pragmatic features. For instance, Korean and Japanese were the most relevant languages for Chinese in Figure 3a, which can also be explained by geographical proximity. Do our features add additional pragmatic information, or can they be subsumed by geographical distance?

To verify this speculation, we evaluate Pearson’s correlation coefficient between the pragmatic features and geographical distance. The most correlated feature, \( ESD \), had a positive correlation \( (r = 0.4) \) with geographic distance. The least correlated feature was \( \text{LCR-verb} \ (r = 0.027) \). \( \text{LTQ} \) and \( \text{LCR-pron} \ correlated by -0.31 and 0.17, respectively. These results suggest that the pragmatic features contain extra information that cannot be entirely subsumed by geographic distance.
9 Related Work

Auxiliary Language Selection in Multilingual tasks There has been active work on leveraging multiple languages to improve cross-lingual systems (Neubig and Hu, 2018; Ammar et al., 2016). Adapting auxiliary language datasets to the target language task can be practiced through either language-selection or data-selection. Previous work on language-selection mostly relied on leveraging syntactic or semantic resemblance between languages (e.g., ngram overlap) to choose the best transfer languages (Zoph et al., 2016; Wang and Neubig, 2019). Meanwhile, work on data-selection finds applicable samples in transfer languages that enhance performance in the target language task (Wang and Neubig, 2019; Do and Gaspers, 2019), motivated by previous studies in domain adaptation (Ruder and Plank, 2017; Plank and van Noord, 2011). Our approach is an extension to the former, language-level selection, but focused on pragmatic similarity, which has been left unexplored by previous studies.

Cross-lingual Sentiment Classification Cross-lingual sentiment classification (CLSC) has been studied primarily in the low-resource settings. Traditional methods in CLSC often rely on machine translation systems (Wan, 2009) or bilingual resources (Barnes et al., 2018) to transfer resources from high to low resource languages. Approaches such as Chen et al. (2018) attempt to eliminate this need by introducing an adversarial network that promotes language-invariant features. Recent works on multilingual pretrained language models have facilitated seamless transfer by providing a universal vocabulary that supports more than a hundred languages (Devlin et al., 2019; Lample and Conneau, 2019). Many subsequent studies have examined the cross-lingual ability of these models (Wu and Dredze, 2019; Pires et al., 2019; K et al., 2019). Still, our work is the first to focus on aiding knowledge transfer in CLSC by operationalizing pragmatic knowledge.

10 Conclusion

In this work, we propose three pragmatically-inspired features that can help determine the optimal transfer languages: language context-level ratio, literal translation quality, and emotion semantic distance. Our features aim to capture linguistic patterns that indicate cultural similarities between languages, and analyses confirm that they correlate well with the existing literature. Experimental results show that appending these features to a transfer language ranking model can significantly improve performance in sentiment analysis, while not as much in dependency parsing. These results suggest the importance of pragmatic information for sentiment-involved tasks, and we expect to see even greater performance gain with more pragmatically-driven tasks such as hate speech detection and sarcasm identification. We leave this exploration for future work.

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### A Supplemental Material

#### A.1 Dataset for Sentiment Analysis

| Dataset                                    | Languages | Domain    | Size  | POS/NEG |
|--------------------------------------------|-----------|-----------|-------|---------|
| SemEval-2016 Aspect Based Sentiment Analysis | Chinese   | electronics | 2333  | 1.53    |
|                                            | Arabic    | hotel     | 4111  | 1.54    |
|                                            | English   | restaurant | 1472  | 2.14    |
|                                            | Dutch     | restaurant | 1089  | 1.43    |
|                                            | Spanish   | restaurant | 1396  | 2.82    |
|                                            | Russian   | restaurant | 2289  | 3.81    |
|                                            | Turkish   | restaurant | 907   | 1.32    |
| SentiPers                                 | Persian   | product   | 3904  | 1.8     |
| Amazon Customer Reviews                    | French    | product   | 20771 | 8.0     |
|                                            | German    | product   | 56333 | 6.56    |
|                                            | Japanese  | product   | 21095 | 8.05    |
| CSFD CZ                                   | Czech     | movie     | 54540 | 1.04    |
| Naver Sentiment Movie Corpus              | Korean    | movie     | 18000 | 1.0     |
| Tamil Movie Review Dataset                 | Tamil     | movie     | 417   | 0.48    |
| PolEval 2017                              | Polish    | product   | 26284 | 1.38    |
| Aspect based Sentiment Analysis            | Hindi     | product   | 2707  | 3.22    |

Table 5: Datasets for sentiment analysis.

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12 [http://alt.qcri.org/semeval2016/task5/](http://alt.qcri.org/semeval2016/task5/)
13 [https://arxiv.org/ftp/arxiv/papers/1801/1801.07737.pdf](https://arxiv.org/ftp/arxiv/papers/1801/1801.07737.pdf)
14 [http://nlp.kiv.zcu.cz/research/sentiment](http://nlp.kiv.zcu.cz/research/sentiment)
15 [https://github.com/e9t/nsmc](https://github.com/e9t/nsmc)
16 [https://www.kaggle.com/sudalairajkumar/tamil-nlp](https://www.kaggle.com/sudalairajkumar/tamil-nlp)
17 [http://clip.ipipan.waw.pl/PolEval?action=AttachFile&do=view&target=poleval-2017-task-1ab-gold-2.0-tei.tar.gz](http://clip.ipipan.waw.pl/PolEval?action=AttachFile&do=view&target=poleval-2017-task-1ab-gold-2.0-tei.tar.gz)
18 [http://www.lrec-conf.org/proceedings/lrec2016/pdf/698_Paper.pdf](http://www.lrec-conf.org/proceedings/lrec2016/pdf/698_Paper.pdf)
## A.2 List of POS Taggers and Monolingual corpus

| Language  | POS Tagger          | Tokenizer   |
|-----------|---------------------|-------------|
| Arabic    | RDR POS Tagger\(^{19}\) | PyArabic\(^{20}\) |
| Chinese   | Jieba\(^{21}\)     | Jieba       |
| Danish    | RDR POS Tagger      | NLTK        |
| Dutch     | RDR POS Tagger      | NLTK        |
| Greek     | RDR POS Tagger      | NLTK        |
| English   | RDR POS Tagger      | NLTK        |
| French    | RDR POS Tagger      | NLTK        |
| German    | RDR POS Tagger      | NLTK        |
| Hindi     | RDR POS Tagger      | NLTK        |
| Japanese  | Kytea\(^{22}\)     | Kytea       |
| Korean    | Mecab\(^{23}\)     | Mecab       |
| Persian   | RDR POS Tagger      | NLTK        |
| Russian   | RDR POS Tagger      | NLTK        |
| Spanish   | RDR POS Tagger      | NLTK        |
| Tamil     | RDR POS Tagger      | NLTK        |
| Turkish   | RDR POS Tagger      | NLTK        |

Table 6: List of POS taggers.

\(^{19}\)https://github.com/datquocnguyen/RDRPOSTagger
\(^{20}\)https://github.com/linuxscout/pyarabic
\(^{21}\)https://github.com/fxsjy/jieba
\(^{22}\)https://github.com/neubig/kytea
\(^{23}\)https://github.com/konlp/konlp/