Abstract

It is now established that modern neural language models can be successfully trained on multiple languages simultaneously without changes to the underlying architecture, providing an easy way to adapt a variety of NLP models to low-resource languages. But what kind of knowledge is really shared among languages within these models? Does multilingual training mostly lead to an alignment of the lexical representation spaces or does it also enable the sharing of purely grammatical knowledge? In this paper we dissect different forms of cross-lingual transfer and look for its most determining factors, using a variety of models and probing tasks. We find that exposing our LMs to a related language does not always increase grammatical knowledge in the target language, and that optimal conditions for lexical-semantic transfer may not be optimal for syntactic transfer.

1 Introduction

One of the most important NLP discoveries of the past few years has been that a single neural network can be successfully trained to perform a given NLP task in multiple languages without architectural changes compared to monolingual models (¨Ostling and Tiedemann, 2017; Johnson et al., 2017). Besides important practical advantages (fewer parameters and models to maintain), such multilingual Neural Networks (m-NNs) provide an easy but powerful way to transfer task-specific knowledge from high- to low-resource languages (Devlin et al., 2019; Conneau and Lample, 2019; Aharoni et al., 2019; Neubig and Hu, 2018; Arivazhagan et al., 2019; Artetxe and Schwenk, 2019).

These success stories have led to a need for understanding how exactly cross-lingual transfer works within these models. Figure 1 illustrates different possible characterizations of a trained m-NN: While the no-transfer scenario is rather easy to rule out, understanding which linguistic categories are shared, and to what extent, is more challenging.

Figure 1: Possible characterizations of a trained m-NN in terms of cross-lingual transfer levels.

In this work, we focus on the transfer of syntactic knowledge among languages and look for evidence that m-NNs induce a shared syntactic representation space while not receiving any direct cross-lingual supervision. To be clear, if we measure transfer among languages X and Y, every training sentence for language modeling will be either in language X or Y, while for machine translation every sentence pair will be either in language pair (X, Z) or (Y, Z). Thus, the only pressure to share linguistic representations is given by the sharing of the hidden layer parameters (possibly as well as some of the word embeddings).
Neural language models have been shown to implicitly capture non-trivial structure-sensitive phenomena like long-range number agreement (Linzen et al., 2016; Gulordava et al., 2018; Marvin and Linzen, 2018). However these studies have been confined to monolingual models. We then investigate the following questions:

- **RQ1:** Is m-NNs’ implicit syntactic knowledge of L2 increased by exposure to a related L1?
- **RQ2:** Do m-NNs induce a common representation space with shared syntactic categories?

Our research questions are reminiscent of well-known questions in the fields of psycholinguistic and second language acquisition, where a considerable body of work has shown that both lexical and syntactic representations are shared in the mind of bilingual individuals (Hartsuiker et al., 2004a; Vasilyeva et al., 2010). Taking inspiration from this body of work, we investigate what factors are needed for m-NNs to successfully transfer linguistic knowledge, including vocabulary overlap, language relatedness, number of training languages, training regime (joint vs sequential) and training objective (next word prediction vs translation to a third language).

In contrast to the current mainstream focus on BERT-like models, we evaluate more classical LSTM-based models trained for next word prediction or translation over a moderate number of languages (2 or 9). We choose this setup because (i) it allows for more controlled and easy-to-replicate experiments in terms of both training data and model configuration and (ii) LSTMs trained on a standard sequence prediction objective are more cognitively plausible and directly applicable to our main probing task, namely agreement prediction.

In this setup, we find limited and rather inconsistent evidence for the transfer of implicit grammatical knowledge when semantic cues are removed (Gulordava et al., 2018). While moderate PoS category transfer occurs, truly language-agnostic syntactic categories (such as noun or subject) do not seem to emerge in our m-NN representations. Finally, we find that optimal conditions for lexical-semantic transfer may not be optimal for syntactic transfer.

## 2 Previous Work

### Multilingual Machine Translation

Early work on multilingual NMT focused on building dedicated architectures (Dong et al., 2015; Firat et al., 2016; Johnson et al., 2017). Starting from Johnson et al. (2017), m-NMT models are mostly built with the same architecture as their monolingual counterparts, by simply adding language identifying tags to the training sentences. Using a small set of English sentences and their Japanese and Korean translations, Johnson et al. (2017) showed that semantically equivalent sentences form well-defined clusters in the high-dimensional space induced by a NMT encoder trained on large-scale proprietary datasets. In the past few years, the focus has been on scaling to very large number of training languages and maximizing transfer accuracy for low-resource language pairs, while possibly preserving high-resource language accuracy (Neubig and Hu, 2018; Aharoni et al., 2019; Ariyazhagan et al., 2019), also known as the (positive)transfer-(negative)interference trade-off (Caruana, 1997). Kudugunta et al. (2019) analyze the similarity of encoder representations of different languages within a massively m-NMT model. They find that representation similarity correlates strongly with linguistic similarity and that encoder representations diverge based on the target language. However they do not disentangle the syntactic aspect from other types of transfer.

### Multilingual Sentence Encoders

A related line of work focuses on mapping sentences from different languages into a common representation space to be used as features in downstream tasks where training data is only available in a different language than the test language.

Artetxe and Schwenk (2019) use the encoder representations produced by a massively multilingual NMT system similar to Johnson et al. (2017) to perform cross-lingual textual entailment (XNLI) and document classification. m-BERT (Devlin et al., 2019; Devlin, 2018) and XLM (Conneau and Lample, 2019) are large-scale m-NNs trained on a masked LM (MLM) objective using mixed-language corpora. This results in general-purpose contextualized word representations that are multilingual in nature, without requiring any parallel data. m-BERT representations have been proved particularly successful for...
transferring dependency parsers to low- (or zero-)resource languages (Wu and Dredze, 2019; Kondratyuk and Straka, 2019; Tran and Bisazza, 2019). On the task of cross-lingual textual entailment (Conneau et al., 2018b), XLM-based classifiers come surprisingly close to systems that use fully-supervised MT as part of their pipeline (to translate the training or test data).

Conneau and Lample (2019) show that the unsupervised MLM objective can be successfully combined to a cross-lingual MLM objective (Translation Language Modeling) to also exploit the available parallel data within a single model. The resulting representations outperform all previous multilingual sentence encoders on XNLI, closing the gap with the MT-based pipelines.

Implicit Learning of Linguistic Structure A different line of work has analyzed what linguistic features are learnt by neural networks that are trained on downstream tasks such as language modeling, translation or textual entailment. Multiple studies have shown that neural networks implicitly encode a great deal of linguistic structure such as morphological classes (Belinkov et al., 2017; Bisazza and Tump, 2018), number agreement (Linzen et al., 2016; Gulordava et al., 2018) and other structure-sensitive phenomena (Marvin and Linzen, 2018). Recent work has extended these findings to BERT representations showing positive results on a variety of syntactic probing tasks (Tenney et al., 2019b; Tenney et al., 2019a; Jawahar et al., 2019). An extensive overview of this productive line of work is presented in (Belinkov and Glass, 2019). As pointed by the authors, the majority of such work has employed monolingual probing tasks and focused mainly on the English language.

Cross-lingual Transfer in m-BERT Two recent studies (Wu and Dredze, 2019; Pires et al., 2019) have found evidence of syntactic transfer in m-BERT using POS tagging and dependency parsing experiments. While this massive Transformer-based (Vaswani et al., 2017) architecture has received overwhelming attention in the past year, we believe that smaller, better understood, and easier to replicate model configurations can still play an important role in the pursuit of NLP model explainability. BERT analysis findings are sensational but often limited to a single model snapshot. Moreover, the large number of m-BERT training languages (approx. 100) added to the uneven language data distribution and the highly shared subword vocabulary, make it difficult to isolate transfer effects in any given language pair. Finally, recent research shows that modern LSTM-based architectures can be very competitive with Transformers while using much less parameters (Merity, 2019). The lack of recurrence in Transformers has also been linked to a limited ability to capture hierarchical structure (Tran et al., 2018; Hahn, 2019).

Cross-lingual Transfer in the Bilingual Mind Measuring the extent to which dual-language representations are shared in the mind of bilingual subjects is a long-standing problem in the field of second language acquisition (Kellerman and Sharwood Smith, 1986; Odlin, 1989; Jarvis and Pavlenko, 2008; Kootstra et al., 2012). Among others, Hartsuiker et al. (2004b) present evidence of cross-lingual syntactic priming in bilingual English-Spanish speakers, which are more inclined to produce English passive sentences after having heard a Spanish passive sentence. Using neuroimaging techniques in a reading comprehension experiment with in German-English bilinguals, Tooley and Traxler (2010) report that the processing of L1 and L2 sentences activates the same brain areas, pointing to the shared nature of syntactic processing in the bilingual mind. Taking inspiration from this body of work, we investigate what factors trigger cross-lingual transfer of syntactic knowledge within m-NNs.

3 Probing Tasks

To answer our RQ1, we choose the task of Number Agreement. For our RQ2 we look at less complex syntactic tasks such as PoS tag classification and Dependency relation classification, and contrast them with a lexical-semantic task (word translation retrieval). We choose these tasks because they can be framed as simple classification (or ranking) problems and have a direct linguistic interpretation. We do not consider parsing because it is a complex task with a highly structured prediction space requiring dedicated model components.

1We use the term POS category prediction instead of POS tagging to denote the fact that labels are predicted from the neural activations of each word independently from neighboring labels.
3.1 Number Agreement

Number agreement describes the instance where a phrase and its arguments or modifiers must agree in their number feature. Number agreement can occur between a subject-predicate pair (the son_{sg} of my neighbors goes_{sg}), noun-quantifier pair (many_{pl} huge trees_{pl}), etc. Linzen et al. (2016) first proposed the subject-verb agreement task to assess the ability of a LSTM-based LM to capture non-trivial language structure, by checking if the correct verb form was assigned a higher probability than the wrong one, e.g.\( \text{prob}(\text{were}|\text{context}) > \text{prob}(\text{was}|\text{context}) \) in the sentence The boys, who were lost in the forest were/was found. LM performance was shown to be mostly affected by the number of agreement attractors.

**Task** We adopt the dataset by Gulordava et al. (2018), henceforth called G18, which extends the evaluation of Linzen et al. (2016) to more languages and more agreement constructions, automatically harvested from corpora using POS patterns. G18 also introduced two conditions to test whether a model relies on semantic cues or purely grammatical knowledge to predict agreement:

1. Original : Sentences automatically extracted from corpora;
2. Nonce : Nonsensical but grammatical sentences created by randomly replacing all content words in the original sentence with random words with same morphological class.

Thus, this is one of few existing tasks that allow us to measure the transfer of grammatical knowledge in isolation. Using the G18 benchmark, we compare m-NNs with monolingually trained models, in order to compare if the addition of a related language improves the long-range agreement accuracy of the monolingual model. We expect this to happen for languages that have the same number agreement patterns, like French and Italian.

**Data and Training details** Similar to G18, we build our corpora from Wikipedia articles and train 2-layer LSTMs with embedding and hidden layer size of 650, for 40 epochs. All models are trained on next word prediction and do not receive any specific supervision for the syntactic task.

\( L_1 \) is our helper language and \( L_2 \) is the target language on which we measure agreement accuracy. Fig. 2 shows the various training setups used by our models. To simulate a low-resource setup and possibly increase the chances of transfer, we train our bilingual LMs on a shuffled mix of a larger \( L_1 \) corpus (\( L_{1\text{large}} \), 80M tokens) and a smaller \( L_2 \) corpus (\( L_{2\text{small}} \), 10M tokens). \( L_2 \) is oversampled to approximately match the amount of \( L_1 \) sentences. This bilingual model (\( \text{LM}_{L_1+L_2\text{small}} \)) is compared to a baseline monolingual LM trained on a small \( L_2 \) corpus (\( \text{LM}_{L_2\text{small}} \)). As upper bound, we also show the results of a model trained on more \( L_2 \) data (80M). This model performs closely to the results reported by G18 with a similar setup.

Most experiments in this paper are performed by joint training, i.e. the model is trained on the mixed language data since initialization. However in Sect. 4.2\footnote{Another difference regards the dependency classification: Blevins et al. (2018) uses constituency parsing and Tenney et al. (2019b) predicts dependency arcs given word pairs, both of which are easier setups than ours.} we also evaluate pre-training: i.e. the LM is first trained on \( L_1 \) data, then after convergence, it continues training on \( L_2 \) data (see Fig. 2). A language tag is introduced at the beginning of each sentence. The vocabulary for each language consists of the 50k most frequent tokens, with the remaining tokens replaced by the unknown tag. The bilingual vocabulary is the union of the language-specific vocabularies, resulting in a total of 88k words in our main language pair (French-Italian). In Sect. 4.2\footnote{Another difference regards the dependency classification: Blevins et al. (2018) uses constituency parsing and Tenney et al. (2019b) predicts dependency arcs given word pairs, both of which are easier setups than ours.} we compare this setup (called natural overlap) to a no-overlap setup where all words are prepended with a language tag, resulting in a bilingual vocabulary of 100k words.

3.2 Cross-lingual Syntactic Category Classification

To verify whether basic syntactic categories are shared among different language representations in m-NNs, we inspect the neural activations of our trained LMs when processing a held-out corpus. Specifically we build linear classifiers to predict either the PoS tag or the Dependency label (type of relation to the head) of a word from its corresponding hidden layer representation. The setup is similar to studies such as Blevins et al., 2018\footnote{Another difference regards the dependency classification: Blevins et al. (2018) uses constituency parsing and Tenney et al. (2019b) predicts dependency arcs given word pairs, both of which are easier setups than ours.} and Tenney et al., 2019b\footnote{Another difference regards the dependency classification: Blevins et al. (2018) uses constituency parsing and Tenney et al. (2019b) predicts dependency arcs given word pairs, both of which are easier setups than ours.}, however our diagnostic classifiers are trained on \( L_1 \) and tested on \( L_2 \)\footnote{Another difference regards the dependency classification: Blevins et al. (2018) uses constituency parsing and Tenney et al. (2019b) predicts dependency arcs given word pairs, both of which are easier setups than ours.}. If syntactic categories are shared, we expect to see minor drops in classification
accuracy compared to a classifier trained and tested on L2. In other words, we ask whether, e.g., French and Italian adjectives or subjects are recognizable by the same neural activations.

**Probing Labels** Coarse-grained PoS and Dependency labels are taken from the Universal Dependency Treebank \( ([\text{Nivre et al., } 2019]) \).

**Data and Training details** We first apply the PoS and Dependency probing tasks to the Wikipedia-based LMs described in Sect. 3.1.

To study the effect of training objective (next word prediction vs translation to a third language), in Sect. 5.2 we perform another series of controlled experiments using the Europarl\(^3\) parallel corpus. Our dataset consists of \( L1 \rightarrow \text{English} \) parallel sentences, where \( L1 \) is one of 9 languages chosen from three different language families: French, Italian, Portuguese, Spanish (Romance); German, Dutch, Swedish and Danish (Germanic) and Finnish (Uralic), with about 45.9M tokens for each language pair.

The NMT models implement a standard attentional sequence-to-sequence architecture based on 4-layer bidirectional LSTMs (Bahdanau et al., 2015) with embedding and hidden layer size of 1024. To maximize comparability between translation and language modeling objectives, the LMs in these experiments are also 4-layer bidirectional (BiLMs, à la Peters et al. (2018)) with the same hidden layer size, trained on the source-side portion of our Europarl dataset.

### 3.3 Word Translation Retrieval

To put syntactic transfer in contrast with other types of transfer effects, we also experiment with word translation retrieval (henceforth abbreviated as WTR). This was used as a probing task for cross-lingual word embeddings in (Lample et al., 2018; Conneau et al., 2018a) and involves calculating the distance (measured by cosine similarity) between the embedding of a source language word (e.g., *bonjour*) and that of its translation (e.g., *buongiorno*). Since the task is context independent, only the word-type embeddings are probed. We interpret precision in this task as a measure of the alignment of two word embedding spaces, that is lexical-semantic transfer.

**Lexicon** The bilingual lexicon from MUSE (Lample et al., 2018) is used as gold standard for this task. This lexicon is available for several language pairs and also includes polysemous words (many-to-many pairs). For each language pair, the bilingual lexicon consists of 1,500 source and 200k target words.

### 4 Does Exposure to L1 Improve Implicit Syntactic Knowledge on a Related L2?

To answer RQ1 we use the number agreement task, which is explained in detail in Sect. 3.1 We choose Italian (IT) and Russian (RU) from the G18 dataset as our target languages \( L2 \). As helper languages, \( L1 \),

\[^3\text{http://www.statmt.org/europarl/v7/}\]
we choose French (FR) and Spanish (ES) for $L_2$ Italian, and French and Ukrainian (UK) for $L_2$ Russian, which allows us to study the impact of language relatedness. Accuracy is calculated as follows: for each sentence in the $L_2$ benchmark, if the probability of the correct verb form is higher than the incorrect form, the agreement is said to be correct, and wrong otherwise.

Figure 3: Agreement results in Wikipedia-based LMs. Freq: Frequency baseline. $L_2$s and $L_2_l$: respectively small and large monolingual models for either Italian or Russian. $L_1 + L_2$s: bilingual LMs. Main comparison in each setup is made between the blue and orange bars.

4.1 Main Results

In this first set of experiments, the bilingual models are trained by joint training and their vocabulary is the union of the vocabularies in the two languages (natural overlap). See also Sect. 3.1. Figure 3 shows the results of our models. As in (Gulordava et al., 2018), the frequency baseline selects the most frequent word form (singular or plural) for each sentence.

When we look at the Original sentences, we see that the bilingual models outperform the respective small monolingual models in the closely related pairs ES→IT (86.8 vs 79.8) and UK→RU (90.4 vs 88.2). However the addition of FR data results in lower accuracies on both $L_2$s. While this was expected in the unrelated pair FR→RU, the large drop in FR→IT is harder to explain.

When semantic cues are removed (Nonce sentences), ES→IT is the only bilingual model to outperform its monolingual counterpart (80.7 vs 79.4), while the accuracy drop in FR→IT gets even larger (72.4 vs 79.4). This shows that exposing the model to a related language $L_1$ is not guaranteed to improve implicit syntactic knowledge of $L_2$, even though the rules of number agreement are largely shared between $L_1$ and $L_2$. On the contrary, our experiments suggest that in some cases $L_1$ negatively interferes with the task in $L_2$.

4.2 Effect of Training Regime and Vocabulary Overlap on Agreement

Could transfer in FR→IT be hampered by some of our experimental choices? To consolidate our findings, we experiment with a different training regime (pre-training) and a different vocabulary construction method (no-overlap).

As shown in Table 1 both training regime and vocabulary overlap have a visible effect on the transfer of syntactic knowledge between FR and IT. Pre-training considerably reduces the negative interference effect observed in joint training, and even leads to a higher accuracy on Original sentences in the no-overlap setup (83.2 vs 79.8). Eliminating vocabulary overlap (None) also leads to better agreement scores in most cases. The best gain overall is obtained by the jointly trained model with no overlap (85.7
vs 79.8) in the Original sentences, whereas no gain is observed in the Nonce sentences.

In summary, we find limited and inconsistent evidence of transfer of purely grammatical knowledge in our bilingual models. Also contrary to our expectations, sharing more parameters (natural overlap) and mixing languages since the beginning of training leads to more negative interference than positive transfer in the FR-IT pair.

| Bilingual (FR+IT_{small}) | Joint Training | Pre-Training | IT_{large} |
|---------------------------|---------------|-------------|------------|
| Original                  | Natural       | None        | Natural    |
| 79.8                      | 74.8          | 85.7        | 79.8       |
| Nonce                     | 79.4          | 72.4        | 77.6       |
|                           |               |             | 77.7       |
|                           |               |             | 76.8       |
|                           |               |             | 79.4       |

Table 1: Impact of training regime and vocabulary overlap on agreement accuracy (FR→IT).

5 Do m-NNs Induce Shared Syntactic Categories?

Predicting long-range agreement is not a trivial task: besides learning agreement rules, the model has to discern several syntactic categories such as number, PoS and dependencies (e.g. the distinction between subject and other noun phrases for subject-verb agreement). This brings us to RQ2 where we ask if our m-NNs induce a representation space with shared syntactic categories. We assume this is a necessary condition to enable transfer of purely grammatical knowledge, like agreement in nonce sentences.

Figure 4: Semantic vs syntactic transfer in Wikipedia-based FR-IT bilingual LMs: (a) Word translation retrieval precision (P@5) measures lexical-semantic transfer; (b) PoS classification accuracy and (c) Dependency classification accuracy measure syntactic transfer. The classifiers are always tested on L2 (Italian), and trained on either L2 or L1 (French). If syntactic categories were perfectly shared across languages, we should observe no drop between the blue and the orange bars. Dashed red lines show the majority baselines for both (b) and (c).

5.1 Effect of Training Regime and Vocabulary Overlap on Syntactic Category Transfer

In this section we examine the same FR-IT Wikipedia-based LMs described in section 4.2. Figure 4(a) shows that joint training yields better alignment of the word embedding spaces compared to the pre-training setup, which confirms recent findings by Ormazabal et al. (2019). Secondly, eliminating vocabulary overlap does not necessarily imply less alignment. Interestingly, recent work on m-BERT/XLM models has also shown that vocabulary overlap has a much smaller effect on transfer than previously believed (Wu et al., 2019). An exception to this is the combination of pre-training and disjoint vocabulary (dubbed P/D), which gives near zero alignment of both lexical and syntactic spaces. We conclude from
this that sharing hidden layers is not a sufficient ingredient to adapt a pre-trained model on a new (even if related) language, and that specific techniques should be used when joint training is not a viable option (Wang et al., 2019; Artetxe et al., 2019).

Moving to the transfer of syntactic categories (Fig. 4(b) we find that all cross-lingually trained PoS classifiers (except P/D) perform much better than the majority baseline but notably worse than the corresponding monolingually trained classifiers. As for dependency classification (Fig. 4(c)), accuracies are low overall and no cross-lingual classifier outperforms the majority baseline. In summary, some form of syntactic transfer indeed occurs, but truly language-agnostic syntactic categories (such as noun or subject) have not emerged in our m-NN representations.

5.2 Training Objective, Number of Input Languages, and Language Relatedness

We now study whether a different training objective, namely translation to a third language (English), leads to more syntactic transfer amongst the input languages. We also check whether number of input languages and language relatedness play a significant role in the emergence of shared syntactic categories. All models in this section are jointly trained with natural vocabulary overlap on the Europarl corpus, and compared to their randomly initialized equivalents following Zhang and Bowman (2018). Dependency classification results are omitted as they are always below majority baseline.

![Figure 5: Semantic (word translation retrieval) vs syntactic (PoS classification) transfer in Europarl-based bidirectional m-NNs. (a,b) Effect of training objective: next word prediction vs translation to English. (c,d) Effect of number of input languages (2 vs 9) and language relatedness (FR-IT vs FR-DE) for the bidi-LM objective. Horizontal black lines (b,d) refer to the corresponding randomly initialized m-NNs.](image)

**Learning Objective** As shown in Fig. 5(a,b), the translation objective has a slightly negative impact on the alignment of word embedding spaces when all other factors are fixed. The translation objective also leads to lower PoS accuracy (monolingually probed), confirming previous results by Zhang and Bowman (2018). However, translating to English does result in visibly better cross-lingual transfer of PoS categories (mono/cross-lingual drop of $-27.7$ for translation vs $-37.2$ for language modelling), showing that what are optimal conditions for lexical-semantic may no be optimal for syntactic transfer.

**Number of Source-side Languages** For the remaining experiments we look at the (bidirectional) LM objective as this is the main focus in this paper. As shown in Fig. 5(c,d), moving from 2 input languages to 9 results in lower WTR precision but higher cross-lingual PoS accuracy. This suggests that adding more languages does not cause m-NN representations to lose syntactic information and actually leads to more sharing of syntactic categories across languages. The generality of this remark is however restrained by our findings on language relatedness.
**Language Relatedness** Fig. 5(c,d) also shows that moving from a very related pair of input languages (FR-IT) to a less related one (FR-DE) results in dramatically lower transfer of both lexical-semantics and syntactic categories. To substantiate this finding, we extend the analysis of our 9-language LM to more training-test pairs (we select a subset of languages for which a sizeable UD treebank exists). The results in Fig. 5 confirm that, for both lexical-semantics and syntax, the related languages French, Italian and Spanish report considerably higher values than those involving German, while the smallest drop (−6.45) is seen between FR→FR and FR→IT. While we expected transfer to depend on relatedness, we did not expect the effect to be so large given that German is not completely unrelated from the Romance languages. In the future we would like to extend our analysis to even less related languages.

![Figure 6](image)

Figure 6: Pairwise semantic and syntactic transfer in our 9-language bidirectional LM. Only a subset of languages is shown. Non-applicable (monolingual) settings in (a) are greyed out. Diagonal values in (b) are scores of monolingual L2→L2 classifiers, while remaining values are for cross-lingual L1→L2 ones.

### 6 Conclusions

We have presented an in-depth analysis of various factors affecting cross-lingual syntactic transfer within m-NNs. Our main result is a negative one: transfer of purely grammatical knowledge (specifically long-range agreement in nonce sentences) is very limited in general and strongly depends on the specific choice of source-target languages. Namely, small gains were only reported on ES→IT, while a considerable drop was reported on FR→IT and almost no change was reported on UK→RU. When semantic cues were not removed (original sentences), transfer levels were overall higher with a peak of +7% absolute in ES→IT, but FR→IT still suffered a considerable loss (-5%). While ES is arguably closer to IT than FR, we cannot yet find a convincing linguistic explanation for the large differences observed. Our second set of experiments shows that POS categories are shared to a moderate extent, but dependency categories are not at all shared in our multilingual models. This suggests that syntactic knowledge transfer within m-NN’s is rather shallow, and may explain the negative agreement transfer result.

Next, our experiments with different training objectives and number of input languages, show that what are optimal conditions for the alignment of word embedding spaces (lexical-semantic transfer) may not be optimal for syntactic transfer, and vice versa. Language relatedness is by far the most determining factor for both word embedding alignment and POS transfer. And finally, scaling from two languages to a mix of nine languages from three different families results in better POS transfer between related languages but considerably worse between unrelated ones. Taken together with recent findings by [Wu et al. (2019)](Wu2019), our results suggest that scaling to highly multilingual models may improve syntactic transfer among the most related languages by decreasing the per-language capacity, but may also exacerbate the divergence among less related ones. Thus modern m-NNs are still far from acquiring a true interlingua.
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