Multilanguage Word Embeddings for Social Scientists: Estimation, Inference and Validation Resources for 157 Languages*

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Abstract

Word embeddings are now a vital resource for social science research. But it can be difficult to obtain high quality embeddings for non-English languages, and it may be computationally expensive to do so. In addition, social scientists typically want to make statistical comparisons and do hypothesis tests on embeddings, yet this is non-trivial with current approaches. We provide three new data resources designed to ameliorate the union of these issues: (1) a new version of `fastText` model embeddings; (2) a multi-language "a la carte" (ALC) embedding version of the `fastText` model; (3) a multi-language ALC embedding version of the well-known `GloVe` model. All three are fit to Wikipedia corpora. These materials are aimed at "low resource" settings where the analysts lack access to large corpora in their language of interest, or lack access to the computational resources required to produce high-quality vector representations. We make these resources available for 30 languages, along with a code pipeline for another 127 languages available from Wikipedia corpora. We provide extensive validation of the materials, via reconstruction tests and other proofs-of-concept. We also conduct human crowdworker tests, for our embeddings for Arabic, French, (traditional, Mandarin) Chinese, Japanese, Korean, Russian and Spanish. Finally, we offer some advice to practitioners using our resources.

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1 Motivation

Distributional word embeddings, i.e. vector representations of words and their meanings (e.g. Mikolov et al., 2013), have become an important component of the social science toolbox. Researchers have used them to study various social problems, including gender stereotypes (Caliskan, Bryson and Narayanan, 2017), emotion in political language (Gennaro and Ash, 2022), the cultural underpinnings of equality (Rodman, 2020) or the ideological placement of parliamentary parties (Rheault and Cochrane, 2020).

While powerful, traditional approaches to word embeddings have two features that mute their usefulness for social scientists. First, with some exceptions, most word embeddings that are easily accessible and well documented are for (modern) English. For users of other languages, it is often difficult to obtain high-quality embeddings that adjust to the specific local context in that language. For instance, for scholars working with Vietnamese political speeches, available embeddings trained on general, often noisy corpora may be inadequate. Second, it has proved non-trivial to place embeddings in a regression-like framework, such that one can answer questions of the form "does this group differ in a statistically significant way in terms of their embeddings of a given term"? In what follows, we provide resources for the union of these issues. In particular, we use the embedding models and multilingual data from the `fastText` project of Grave et al. (2018), and combine it with recent advances in so-called "a la carte" (ALC) embeddings from Khodak et al. (2018) and Rodriguez, Spirling and Stewart (2023). From there, we provide three new data resources purpose-designed for social science:

1. A new version of `fastText` embeddings, fit to Wikipedia corpora (as opposed to the "original" `fastText` that uses The Common Crawl data).[1] It is thus relatively free of typos and very rare 'junk' words.

2. A transformation matrix (one for each language) fit to these new `fastText` resources that allows for ALC embeddings and analysis.

3. A set of multi-language `GloVe` (Pennington, Socher and Manning, 2014) embeddings fit to

[1] See https://commoncrawl.org/

Wikipedia corpora, and ALC transformation matrices for these embeddings.

The `fastText` project underpins contribution (1) and provides two types of resources: first, a (open source) modeling architecture "that allows users to learn text representations"[2]. And second, the output of applying that embedding model to 157 languages for which training data comes from *Common Crawl* and Wikipedia. A strength of the `fastText` model is that it uses *subword* information in addition to the usual context word arrangement for prediction. See Supporting Information (SI) A for intuition on why this is helpful in practice. On inspection, we saw that *Common Crawl* includes a large number of typos and very rare terms (plus many English loan words). Beyond this potential for noise, note also that *Common Crawl* is not separated out by language—it is one combined corpus that requires non-trivial division for the end-user we have in mind here. Our first contribution then is to simply take the `fastText` *pipeline* and fit it to Wikipedia in various languages. Thus we have "our" version of `fastText` which is cleaner than the original (though the training domain is admittedly more restrictive).

Our second set of contributions—(2) and (3)—is to produce ALC embeddings. First, for this "new" version of `fastText`. Second, we provide ALC embeddings for `GloVe` which we also trained on Wikipedia corpora. Details on these embeddings can be found elsewhere (Khodak et al., 2018; Rodriguez, Spirling and Stewart, 2023)—see SI B and the worked example in SI I. The key is that they allow the analyst to produce high quality vector representations even when they have very little data. Indeed, they can produce reasonable embeddings for *single* instances of terms, assuming one has the context of that term and a sufficiently large corpus on which to pre-train embeddings. We provide those reasonable pre-trained embeddings using both `fastText` and `GloVe` models applied to Wikipedia, and we also provide the relevant (learned) *transformation matrix* required to use this technique. In keeping with the original presentations, we denote that matrix as $\mathbf{A}$.

At the time of writing, we have completed this process—and made the relevant files publicly available—for 30 languages (other than English). This may sound small, but as we explain below, it covers the majority of first and second language speakers on Earth, and the great majority of

[2] As described here: https://fasttext.cc/

all languages on the web. Regardless though, we have constructed pipeline production code for anyone who wishes to produce similar items for any one of the 157 languages originally provided via `fastText`.

Our materials are aimed at two—often overlapping sets—of *low resource* settings. First, analysts who work with languages that have relatively small corpora from which it is hard to learn high quality embeddings. For example, scholars who have political pamphlets from Korea may struggle to build embeddings from such a small corpus. The alternative, translating to a language for which embeddings do exist, may be unpalatable for many reasons. Second, analysts who do not have local access to the computational resources required to train embeddings models—we mean this both in terms of time/skill, and power *per se*.

We now validate these approaches and discuss their relative performance. We first show that the ALC representations work well relative to the "full" embeddings which they approximate. We then focus high cost efforts (i.e. crowdsourcing) on comparing (1) our version of `fastText` (fit to Wikipedia) against the original version of `fastText` and then (2) our version of `fastText` against an ALC version of our `fastText`. We do this because the `fastText` resources are the most innovative part of what we seek to provide.

2 Performance And Validation

The resources we provide are useful to the extent that they provide reasonable representations of concepts, especially political ones. We now show that this is the case.

2.1 Reconstruction: ALC embeddings provide reasonable approximations of the "truth"

Recall that ALC embeddings are an *approximation* to true ones, where "true" means the embeddings estimated from a very large corpus. We have the latter insofar as we can learn `fastText` or `GloVe` embeddings from, say, Wikipedia. We can then compare that truth to our estimate (our ALC embedding) of it. We would hope that our ALC embedding can reconstruct that truth and on average be "close" to it rather than "far" from it. These standards are vague in an absolute sense,

but they do allow us some comparison across languages and between embedding architectures. The unit of comparison in what follows is 100 random terms, constrained to have higher frequency than the median token in the corpus. In SI D we give a worked description of exactly how this test proceeds.

Ultimately, we have one summary mean for each architecture, and it is by construction between -1 and 1. If this number is 1, then the ALC embeddings (of our random terms) are perfectly approximating our "true" embeddings; if they are zero or even negative, they are doing a very poor job of approximation. In Figure 1 we report the results for all the languages we have worked with so far, including the mean (diamond) and the cosine for each of the 100 random terms (circles).

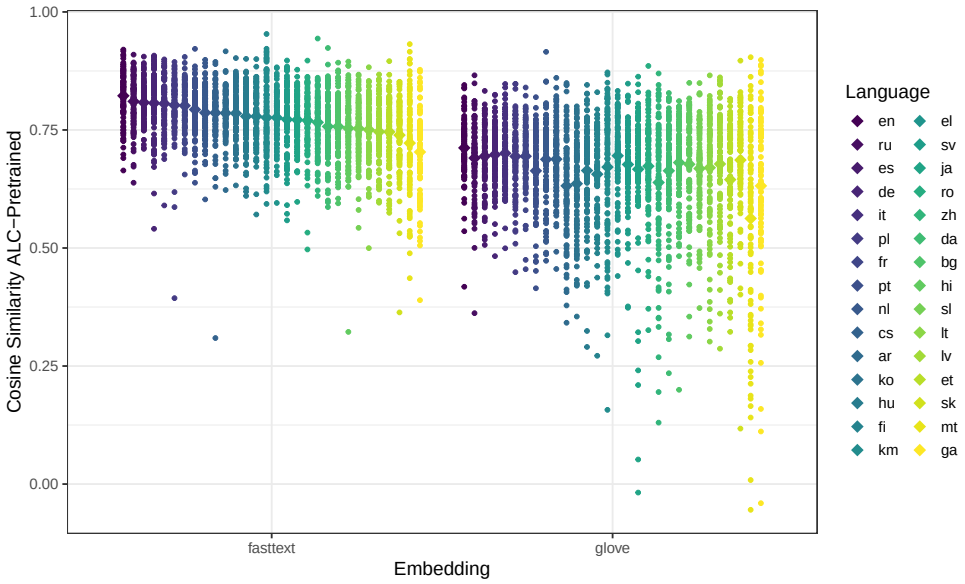


Figure 1: Reconstruction performance: cosine similarity between our ALC version of `fastText` and `GloVe` and those underlying architectures.

We have two immediate observations: first, ALC generally recovers both architectures' embeddings very well, for any language. It does better for `fastText` (means are higher) than for `GloVe`, but in general means are around 0.77 for `fastText` and 0.67 for `GloVe`. Second, there is non-trivial variation within and between languages. In particular, ALC does best when there is more training data—for example, English (`en`) has a higher mean than Irish (`ga`). And within languages with lower means, we see longer left tails—that is, there are more terms further from the mean where

ALC does a worse job of approximating the "truth". Again, this is mostly a consequence of training data availability.

A more qualitatively informative procedure is to check that words represented via our embeddings "mean" what we expect them to. We first verify this by studying a curated domain setting—specifically, translated English/Spanish speeches at the European Parliament (EP), 1999–2001 (Høyland, Sircar and Hix, 2009). We proceed as described in SI E.

2.2 Crowdsourcing: similar aggregate performance, ALC delivers more technical terms

Another and somewhat easier way to assess the quality of our embedding resources in different languages is to look at the nearest neighbors of certain political terms. Consider Table 1. There we provide nearest neighbors (by cosine similarity) for the term `democracy` and `equality`. The nearest neighbors are drawn from two resources: our recompiled version of `fastText` and our ALC-based version of `fastText`. Consistent with our notes above, the training corpus is (English) Wikipedia.

democracy		**equality**	
our fT	our fT-ALC	our fT	our fT-ALC
democracy	democracy	equality	equality
democracy's	democratising	equalities	non-discrimination
democracies	democracy's	non-discrimination	inclusiveness
democratization	internationalism	anti-discrimination	antidiscrimination
social-democracy	parliamentarism	anti-discriminatory	anti-discrimination

Table 1: Nearest neighbors for English terms `democracy` and `equality`.

The good news is that these nearest neighbors make sense—that is, neither model produces "odd" results. Arguably, by moving beyond lexical similarities and similar wordstems, ALC produces slightly more "useful" results than the pure `fastText` model. The same is true when we analyze the French terms `nationalisme` (nationalism) and `racisme` (racism) for which the training corpus is French Wikipedia, per Table 2.

nationalisme		**racisme**	
our fT	our fT-ALC	our fT	our fT-ALC
nationalisme	nationalisme	racisme	racisme
nationalismes	l'internationalisme	racismes	l'antiracisme
néonationalisme	internationalisme	antiracisme	communautarisme
régionalisme	radicalisme	l'antiracisme	antiracisme
internationalisme	néonationalisme	l'homophobie	l'islamophobie

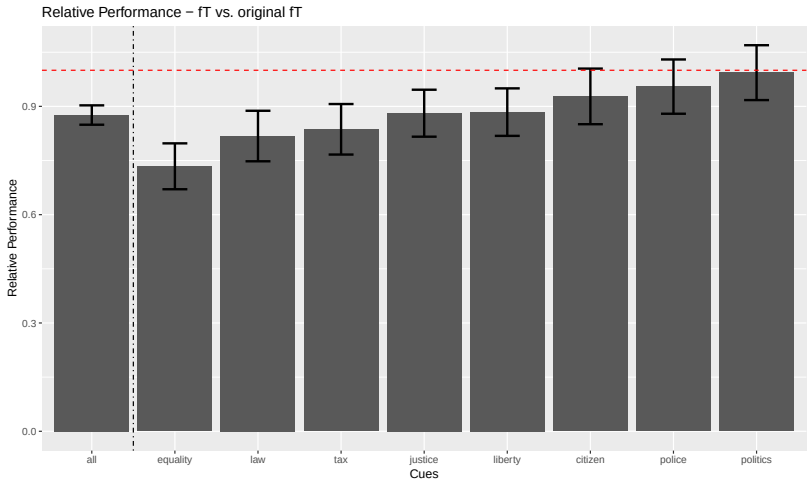
Table 2: Nearest neighbors for French terms `nation` and `racisme`.

To scale these sorts of comparisons between models, we turn to crowdsourcing (Benoit et al., 2016). Following Rodriguez and Spirling (2022), we designed a lightweight web application that shows crowdworkers a token with political connotations and then asks which of two words (drawn from two models) the worker thinks is a more plausible "context" term for that token. The 'political' tokens are: `law`, `liberty`, `equality`, `justice`, `politics`, `tax`, `citizen`, `police`. We translated the app into all of the (non-English) United Nations "Official Languages". These are: Arabic, (traditional Mandarin) Chinese, French, Russian and Spanish. In addition, we also created Japanese and Korean versions. If we take Rodriguez, Spirling and Stewart (2023) as sufficient evidence for the merits of ALC in English then, combined with our exercise, we "cover" around 45% of the world's first and second languages, and around 77% of the web's content languages.[3] Locating native speakers of these (non-English) languages was not trivial (and not cheap) in some cases. We worked with a specialist crowdsourcing firm for this purpose.[4] In SI F we give more details on this process.

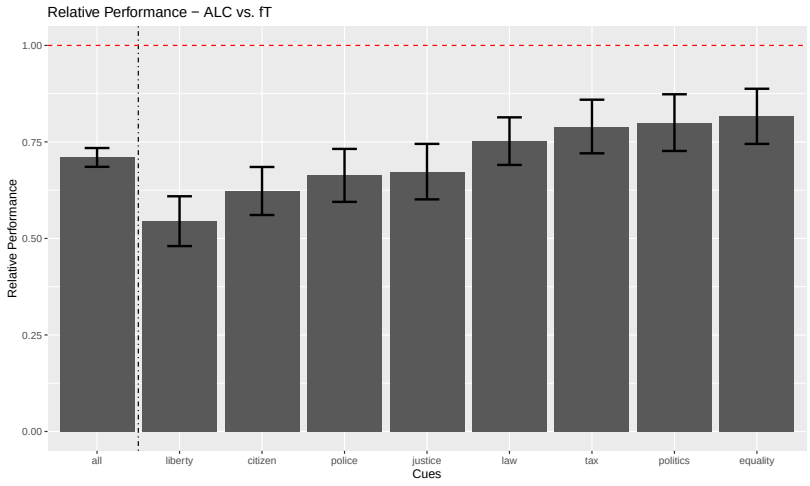
To reiterate, there are two sets of comparisons: original `fastText` vs our version and then our version of `fastText` vs an ALC version of that resource. In Figure 2 we give an overview of the results. In the top subfigure, we report the comparison of our version of `fastText` to the original `fastText`. Each bar represents a token in the task (far left bar is an overall result); we also include 95% confidence intervals. When that bar is higher than 1, respondents (on average) preferred our version, when below 1 they preferred the original. Ultimately, this comparison is equivocal, with the

[3] See, e.g. https://w3techs.com/technologies/overview/content_language.
[4] Specifically, *CloudResearch*.

original `fastText` being preferred in a couple of cases but mostly the difference is not statistically significant. The bottom subfigure compares our `fastText` to our ALC. Here we see that, for the crowdworkers, ALC is generally not the preferred option, though again this is equivocal in some cases.



(a) Comparing `fastText` versions



(b) Comparing `fastText` and ALC

Figure 2: Summary of crowdsourcing comparisons, all languages

Across languages, crowdworkers mostly do not see huge differences in quality, and have a mild preference for the (original) `fastText` resources (see SI G).[5] So does this mean that an analyst should always prefer the original `fastText` over our version, including the one using ALC? The answer is 'no', for two reasons. First, the ALC embeddings give one access to the inferential machinery we discussed above. That is, the ALC embeddings are by construction an approximation, but they also allow one to conduct regressions, do statistical tests etc. Second, and perhaps more fundamentally, these contest result disguise some important heterogeneity in use-cases. Put simply,

[5]There is a subtlety to interpreting the results here: note that the ALC embeddings are simply averaged over the entire corpus (on which the `fastText` embeddings are themselves trained). That is, the 'context' of the ALC embeddings is the whole corpus, whereas they are actually designed, and should be optimal, for much more local use.

crowdworkers prefer more obvious "everyday" or "vanilla" nearest neighbors, whereas our new resources are likely helpful to analysts interested in technical terms. To see this concretely, consider Arabic— specifically, the Arabic word for `law`, قانون. The ALC nearest neighbor is المشرع (`legislator`), whereas the `fastText` nearest neighbor is قانونًيا (`legally`). Going down the list, `fastText` returns many lexical neighbors like قانونى (`legal`) and قانونه (a combination of a function word and the original keyword). Meanwhile, ALC returns more context-specific terms like الإلزام (`binding`) and التشريع (legislation).

A final note on our crowdsourcing data is that the comparisons were based on minimal preprocessing and post-processing of the embeddings. For example, we imposed only very small minimum counts for a given term to be included in their set of embeddings, specifically a minimum frequency of 10 occurrences in the language-specific Wikipedia corpus. We did this so that the comparison was as 'raw' and clear as possible. But in our distributed resources, following some internal experiments, we adjusted the various cut-offs upwards. We did this especially for larger languages, to ensure more robust and sensible embeddings. Put otherwise, the relative ALC vs non-ALC crowd comparisons above are likely the worst-case scenario for ALC.[6]

3 Advice to Researchers using ALC

Our observations about ALC above are with reference to the relevant transformation matrix (**A**) having been estimated from the underlying corpus—specifically, Wikipedia. Unsurprisingly, whether this is appropriate for a given problem is a function of how 'close' the researcher's corpus is to Wikipedia. We now outline three gradated scenarios, with examples in the SI, to guide

[6]To reiterate, we provide full pipeline code such that users can recreate the resources under any pre or post-processing regime they wish.

researchers making such choices in practice:

1. Approximately in sample: if the researcher's local corpus is "close enough" to Wikipedia, then using our pre-fitted transformation matrix will work as well as anything else from the perspective of producing ALC embeddings. We demonstrate this with an example in SI H, where we use ALC embeddings for the German Wikipedia to identify homonyms.

2. Out of sample, small corpus. The researcher is out of sample if their corpus does not particularly resemble Wikipedia. If their corpus is too small to fit local models, we recommend using our estimated **A** matrix, and carefully checking its validity. We give an example for this case using French and Italian parliamentary corpora in SI I.

3. Out of sample, large corpus. If their corpus is large, then we advise researchers to simply fit a local transformation matrix using our pipeline code—and indeed, potentially fit their own embeddings. Of course this involves a judgement call: the user must decide whether their inferences are better with our **A** for the language and corpus at stake, or with their own (and/or with their own local embeddings). To provide some calibration here, we did local fitting of **A** to our various parliamentary corpora, using our Wikipedia based embeddings in all cases. The results are satisfactory for the *Congressional Record* (median speech length 215 words), but unsatisfactory for the French and Italian corpora (median speech lengths 40 and 140 words respectively).

To the extent researchers are seeking more concrete advice, our evidence suggests using our estimated quantities as a first cut on the problem. If they seem suitable and can be validated then one can build out from there. If they do not seem suitable, consider estimating your own with the code we provide. In any case, our resources are a reasonable comparison point for any such work.

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Online Supporting Information:

Multilanguage Word Embeddings for Social Scientists: Estimation, Inference and Validation Resources for 157 Languages

Contents (Appendix)

A Why fastText?

A strength of the fastText model is that it uses *subword* information in addition to the usual context word arrangement for prediction. To see why this is helpful, consider the following (invented) sentence from a news story about the UK:

> The Chancellor announced new policies on tax deductions that affect parents.

Suppose we want to use this sentence to learn a representation—and embedding—of tax. A "traditional" architecture like Word2Vec (Mikolov et al., 2013) might build embeddings by taking into account the whole context words around tax, like policies and deductions. By contrast, fastText would use subwords like pol, oli, lic, ici, cie, ies etc *in addition* to policies itself (and deductions and its subwords). This can result in better predictions (and thus higher quality embeddings) because words that are not identical but that contain similar parts (like policy and policies) are not treated as completely separate entities. This is helpful when, say, a specific form

of a word was rare in the training documents but for which we still have some information from other tokens that were more common.

B ALC embeddings

In the ALC setting, the embeddings are derived from the additive information of pre-trained word embeddings in the context windows around the target word. However, simply averaging embeddings of context words over-emphasizes common words (e.g. "stop" words) (Khodak et al., 2018; Rodriguez, Spirling and Stewart, 2023). To produce "good" word representations, i.e. to recover existing word vectors $\mathbf{v_w}$, one would therefore want to rotate away from such common components by multiplying the simple additive composition of embeddings $\mathbf{u}_w$ with a "transformation matrix" $\mathbf{A}$.

$$\mathbf{v_w} \approx \mathbf{A}\mathbf{u_w} = \mathbf{A}\left(\frac{1}{|\mathbf{C_w}|}\sum_{c\in\mathbf{C_w}}\sum_{\mathbf{w}'\in c}\mathbf{v_{w'}}\right) \tag{1}$$

with the set of contexts $\mathbf{C_w}$ for word w, contexts c and context word embeddings $\mathbf{v_{w'}}$. This yields an *approximation* to the "true" embeddings of the terms of interest, but allows for high-quality "local" representations of terms in the relevant embedding space. In principal, this weighting matrix can be learned from the data by minimizing the error between existing word vectors (locally trained or relying on large pre-trained corpora) and their respective additive context embeddings:

$$\hat{\mathbf{A}} = \arg\min_{\mathbf{A}} \sum_{w=1}^{W} \alpha(n_w)\|\mathbf{v}_w - \mathbf{A}\mathbf{u}_w\|_2^2 \tag{2}$$

Here $\alpha(n_w)$ weights up words (embeddings) that are more common in the corpus and about which we have more information. This is a simple linear regression problem, and learning the transformation matrix is not particularly hard. What makes it difficult in practice is obtaining data on which to estimate $\mathbf{A}$. We use Wikipedia for this purpose, and thus provide the transformation matrix for every language so far processed.

C Details on Training Process

C.1 Wikipedia Corpora

As the largest free online encyclopedia, available in more than 200 languages, Wikipedia provides an important resource for multilanguage natural language processing. Importantly, because the articles are curated, the underlying text corpora are of high quality and the corpora ensure broad coverage in terms of topics and content. We downloaded the XML Wikipedia dumps for each language[7], using the latest month available at the time of the respective download.[8]

[7] https://dumps.wikimedia.org/

[8] See the code pipeline for the specific corpora used.

C.2 Preprocessing Choices

The first preprocessing step is to extract the text content from the XML dumps. For this purpose, we follow the `fastText` pipeline and use the `WikiExtractor` from apertium[9]. In a second step, we implement some light preprocessing of the resulting corpora. In particular, we remove punctuation (except for punctuation within tokens), remove extra white space and set all characters to lower case. Finally, we tokenize the raw text. As before, we largely follow choices made by the original `fastText` (Grave et al., 2018) to ensure better comparability of our models with existing options. We use the Stanford word segmenter for Chinese (Chang, Galley and Manning, 2008) and Mecab for Japanese (Kudo, 2005). For languages written using the Latin, Cyrillic, Hebrew or Greek scripts, we use no separate tokenizer, but split based on white space. For all remaining languages, we use the ICU tokenizer (Rui, 2020).

Additionally, when training the models (`fastText`, `GloVe` and their respective ALC embeddings), we apply a hard minimal frequency threshold for the respective vocabulary. This helps to clean out noisy parts of the corpus and thus significantly improves the fit of all models. We base our choice on the language-specific threshold on the size of the Wikipedia corpora and vocabulary by language[10]. Specifically, we impose a minimal frequency cutoff of 50 for English, 25 for medium-sized languages (i.e. German, Spanish, Italian, French, Russian, Swedish and Dutch), 15 for small-to-medium-sized languages (i.e. Czech, Finish, Hungarian, Portuguese) and 10 for all smaller languages. As this step turned out to be crucial for out-of-sample performance of our quantities, scholars who use our code pipeline to train resources from Wikipedia for their language might want to experiment with the size of the threshold in their particular case.

Note that the crowdsourcing validation in the main text was done with a previous version of our resources. Following some internal experiments and out-of-sample performance tests, we adjusted some preprocessing and training choices after our crowdsourcing survey. Table 3 details the exact differences across the two iterations of our resources.

[9] https://github.com/apertium/WikiExtractor
[10] https://meta.wikimedia.org/wiki/List_of_Wikipedias

Category	Current Resources (as of June 2023)	Previous Resources (Crowdsourcing)
Preprocessing	• Remove punctuation btw tokens (i.e. emulate `quanteda`) • Remove extra white space • Set characters to lower case	• Remove *all* punctuation • Remove extra white space • Set characters to lower case • Remove numbers
`GloVe` training	• Vector size: 300 • Window size: 5 • Vocab min count: language-specific • x_{max} in weighting: 100 • Maximum iterations: 50	• Vector size: 300 • Window size: 5 • Vocab min count: 5 • x_{max} in weighting: 10 • Maximum iterations: 10
`fastText` training	• Skip-gram model • Vector size: 300 • Window size: 5 • Vocab min count: language-specific • Negative sampling: 10	• CBOW model • Vector size: 300 • Window size: 5 • Vocab min count: 5 • Negative sampling: 10
ALC	• Vocab min count: language-specific	• Vocab min count: 10

Table 3: Changes in training procedure across iterations of ALC resources.

C.3 Training of fastText Embeddings

Next, we train `fastText` models (Grave et al., 2018) for this preprocessed and tokenized text using a context window of 5 and setting the dimensions of the word vectors to 300. For the dictionary, we impose the minimal frequency of occurences in the entire corpus described in Section C.2, and use negative sampling of size 10.

C.4 Training of GloVe Embeddings

Similarly, we train `GloVe` (Pennington, Socher and Manning, 2014) to our cleaned corpora. Again, we set a language-specific minimal word frequency described in Section C.2, a vector size of 300 and a context size of 5. We further impose similar parameters as in Pennington, Socher and Manning (2014), i.e. we set $x_max = 100, \alpha = 3/4$ and a maximum iteration of 50.

C.5 Training of ALC Embeddings

Finally, for both `fastText` and `GloVe` embeddings, we then train ALC embeddings (Khodak et al., 2018; Rodriguez, Spirling and Stewart, 2023) to obtain the relevant transformation matrices. To handle the large size of the respective corpora, we use a chunk-based learning approach. That is, we read in the relevant preprocessed corpus by chunk and perform the following operations by chunk:

1. Retain vocabulary with a minimum term frequency of the language-specific threshold
2. Create a feature-cooccurrence-matrix (FCM) using `conText`[11], with a window size of 5 and equal weighting

[11] https://github.com/prodriguezsosa/conText

3. Obtain a corresponding feature-embedding-matrix that provides additive context-specific feature embeddings (i.e., the $\mathbf{u_w}$ in Equation (1)), averaged over all embedding instances in a given chunk

To obtain the un-transformed additive embeddings for all features across the *entire* corpus, we then simply average the chunk-specific additive embeddings for each feature across the chunks. This is possible, because the additive context embeddings from step 3 are themselves simple averages of the respective instance-specific additive context embeddings in a given chunk. We do this for all features appearing with a frequency of at least the language-specific threshold across the entire corpus. Finally, we train the corresponding transformation matrix following Equation (2), where we use $\log(n_w)$ for $\alpha(n_w)$.

D Reconstruction Tests: Full Description

To fix ideas, suppose we are working with Spanish, and have Spanish Wikipedia as our large, pre-training corpus ($\sim$ 639 million tokens, $\sim$ 850 thousand types). We proceed as follows:

1. Draw 100 random terms from the corpus. The only requirement on these terms is that they have higher frequency counts than the median token in the corpus.
2. Putting those 100 terms aside, produce embeddings for the large corpus via our cleaned version of `fastText` and `GloVe`. Thus we have two sets of "true" embeddings.
3. Obtain an A matrix in the usual ALC way, for both architectures' embeddings.
4. For the 100 held out terms, for both architectures, produce an ALC embedding for each term.
   (a) For any given random term, say `pulpo` (Spanish for `octopus`), we now have an ALC embedding from `fastText` and from `GloVe`.
   (b) Calculate the cosine similarity between our ALC embedding of `pulpo` from `fastText` and the "true" fastText embedding; calculate the cosine similarity between our ALC embedding of `pulpo` from `GloVe` and the "true" `GloVe` embedding.
5. Repeat steps 4a and 4b for all of the 100 random held out words. Calculate the mean cosine distance from the "true" embeddings.

E English-Spanish "translation" at the European Parliament

We want to check that check that words represented via our embeddings "mean" what we expect them to. We verify this by studying a curated domain setting—specifically, translated English/Spanish speeches at the European Parliament (EP), 1999–2001 (Høyland, Sircar and Hix, 2009). To summarize: first, we produce an 'English' corpus of speeches either originally in English or translated from Spanish to English. Then, we produce a 'Spanish' corpus of speeches either originally in Spanish or translated from English to Spanish.

More specifically, for the English and Spanish speech data in Høyland, Sircar and Hix (2009), we proceed as follows:

1. Gather all speeches originally in English in the EP (denote as `en_orig`), and obtain their (expert) translation to Spanish (`en_to_es`).

2. Gather all speeches originally in Spanish in the EP (`es_orig`), and obtain their (expert) translation to English (`es_to_en`).

3. Combine `en_orig` and `es_to_en` into one English corpus. Use ALC to obtain the nearest neighbors of the word `but`. Compare the cosine similarity ratio ($\frac{\texttt{en\_orig}}{\texttt{es\_to\_en}}$) for each nearest neighbor to `but`.

4. Combine `es_orig` and `en_to_es` into one Spanish corpus. Use ALC to obtain the nearest neighbors of the word `pero`. Compare the cosine similarity ratio ($\frac{\texttt{en\_to\_es}}{\texttt{es\_orig}}$) for each nearest neighbor to `pero` (the Spanish translation of `but`).

The results of this exercise for the two corpora are displayed in Figure 3. We use different plotting figures to denote whether the nearest neighbor in question is from the Spanish corpus only, shared between the corpora, or from the English corpus only. To understand the figure, start with the left panel—the combined English corpora. If we assume that (a) politicians whose native languages differ (English or Spanish) do not use `but` in systematically different ways and (b) that translation is noiseless (perfect), then we would anticipate that the cosine ratio for the nearest neighbors will be 1. That is, we anticipate that, say, a term like `because` (its embedding) will be as close to `but` in the originally English corpus as in the *translated to* English corpus. This is, in fact, what we see. And we see it for all top 10 nearest neighbors. Turning to the right part of the plot, and with evidence in hand that assumptions (a) and (b) hold from the left panel, we would hope that the nearest neighbors for `pero` will also line up at 1. If they do, we have evidence that ALC "works" for Spanish—that is, it produces reasonable nearest neighbors for terms we might care about, with which professional translators would concur. This is exactly what we see.

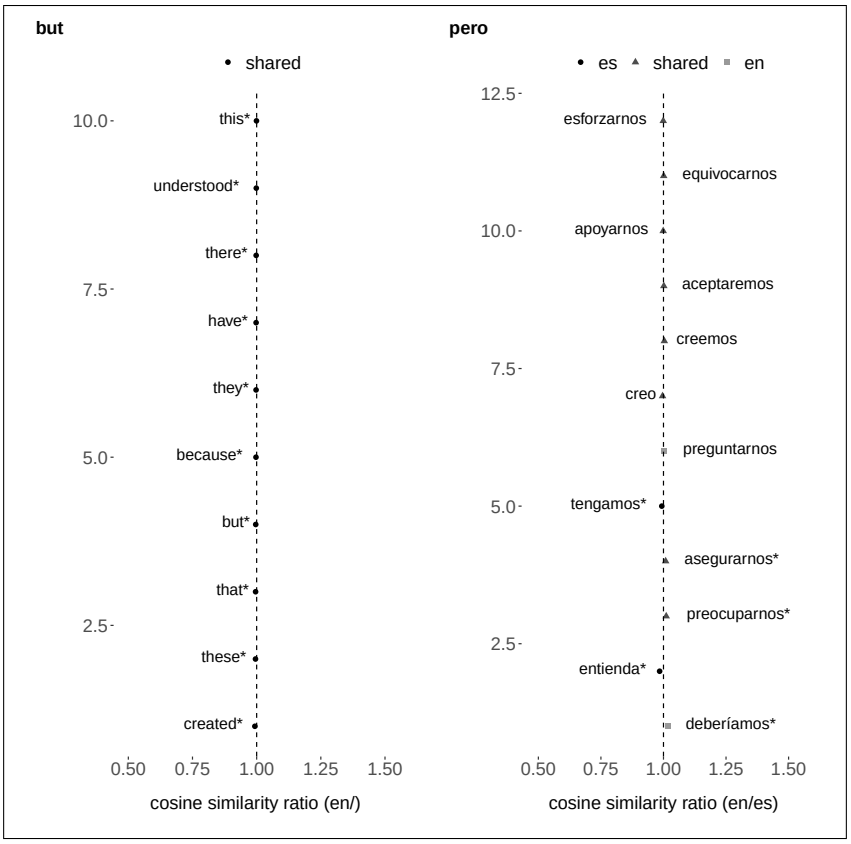


Figure 3: Translation Exercise: Cosine Similarity Ratio for ALC Nearest Neighbors is almost always 1 for translated and original texts in English and Spanish.

Notice that the embeddings themselves are *not* being translated between English and Spanish. Indeed, a feature of our multilanguage representations is that they inhabit different spaces (one per language). Our point here is that a technique (ALC) we believe works for English also works for other languages (in this case, Spanish).

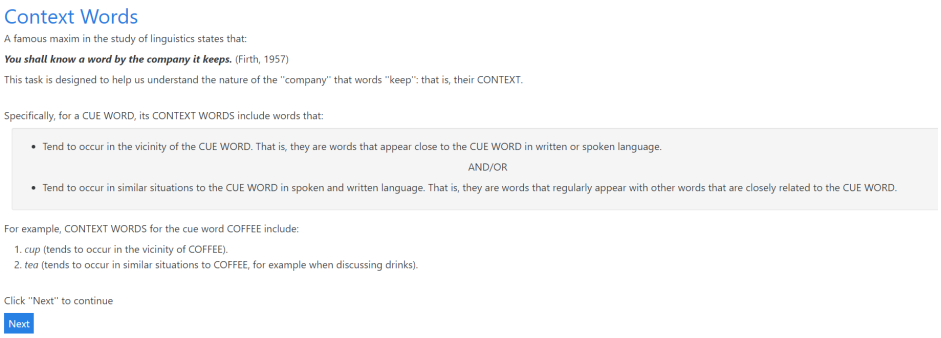
F Multilanguage Crowdsourcing Details

For the crowdsourcing validation of our resources, we first employ the three embedding models we aim to compare (the original `fastText` embedding model from (Grave et al., 2018), our `fastText` model trained on Wikipedia and our ALC model using our `fastText` model for the underlying pretrained embeddings) to obtain the top 20 nearest neighbors in the 7 relevant languages for the 8 political keywords (`law`, `liberty`, `equality`, `justice`, `politics`, `tax`, `citizen`, `police`) using our Wikipedia corpora. Following Rodriguez and Spirling (2022), we then build a simple app that prompts crowdworkers to compare the resulting nearest neighbors for these models. After a short introduction of the task and the general idea of keywords and context words, we ask crowdworkers to indicate which model produces nearest neighbors that best meet the definition of a context word (Figure 4 shows the task description in English). For this, we use pairwise comparsions, i.e., a given crowdworker either compares (1) the original `fastText` model to our `fastText` model or (2) our

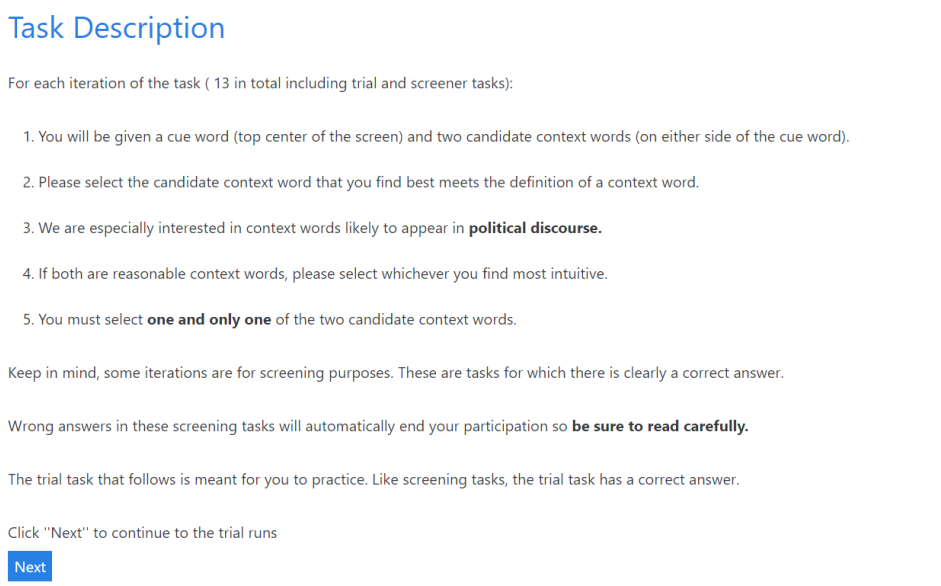
ALC model to our `fastText` model. Instead of showing the crowdworkers *all* nearest neighbors for a given keyword across the two models in the comparison, we randomly select a nearest neighbor from each set of the 20 nearest neighbors. To rule out ties, we also remove draws where nearest neighbors are identical across the two models in the comparison. We then translate the app in all relevant 7 languages with the help of native speakers. Figure 5 shows an example of a pairwise comparison for `policeman` in Japanese and `tax` in Russian. In collaboration with *CloudResearch*[12] we then field these apps in the following regions, recruiting 50 crowdworkers for each language:

- Arabic: Saudi Arabia, Egypt, Algeria
- Chinese (traditional): Taiwan
- French: France, Canada (Quebec)
- Japanese: Japan
- Korean: South Korea
- Spanish: Mexico, Costa Rica, Colombia
- Russian: Russia, Belarus

[12] https://www.cloudresearch.com/



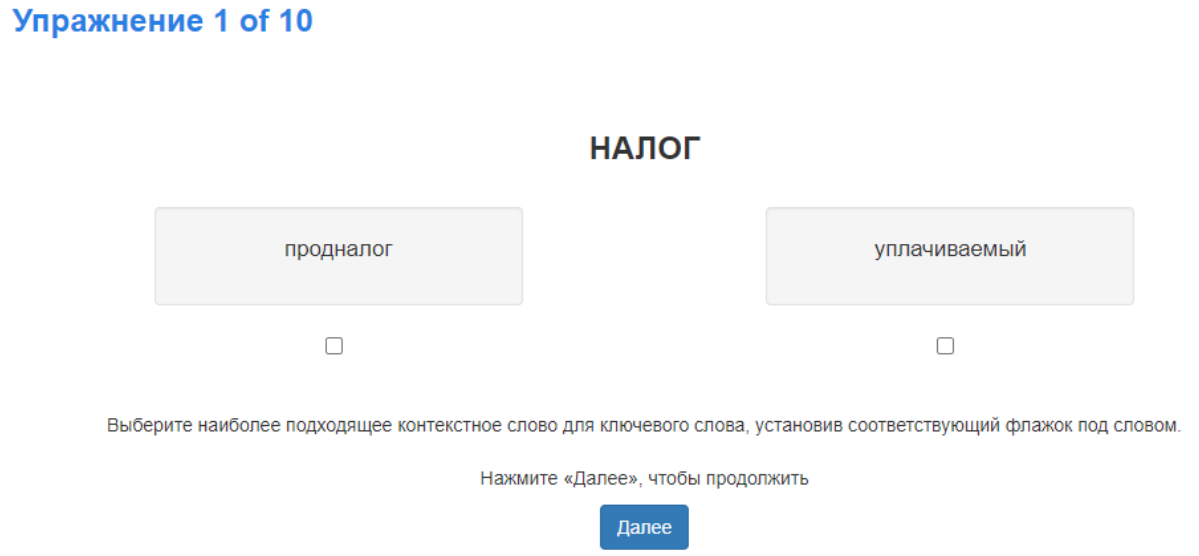
(a) General Introduction



(b) Task Description

Figure 4: Crowdsourcing Instructions

(a) Example of Pairwise Comparison in Japanese

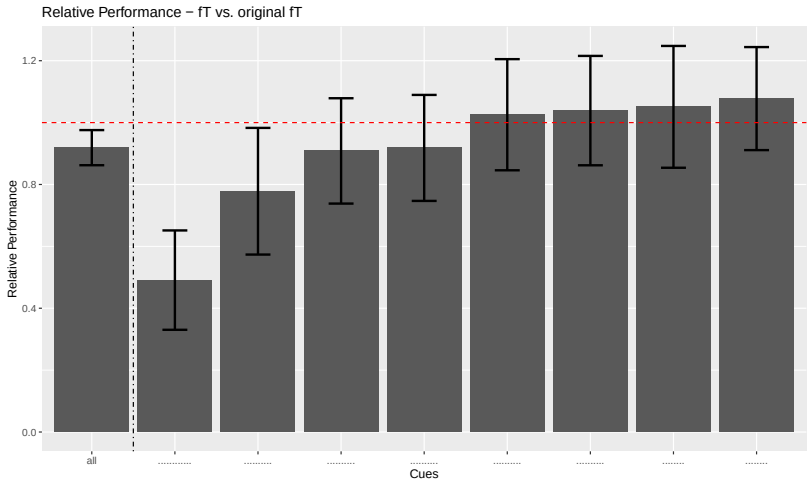


(b) Example of Pairwise Comparison in Russian

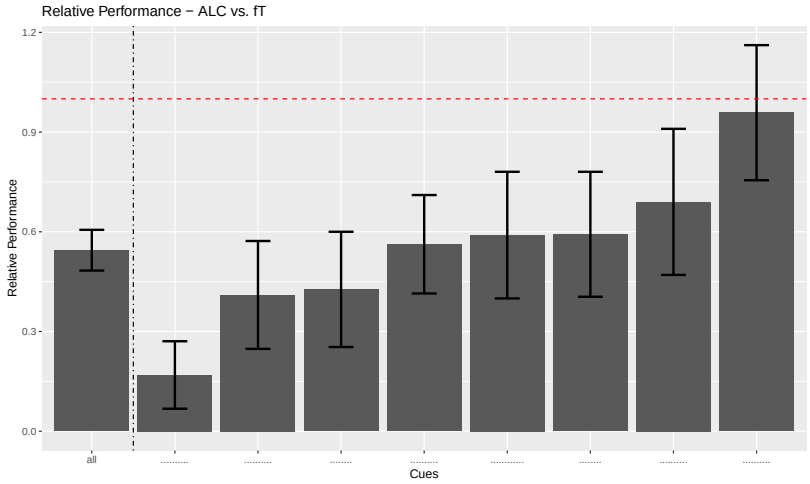
Figure 5: Crowdsourcing Examples

G Full Crowdsourcing Results: Model v Model

G.1 Arabic



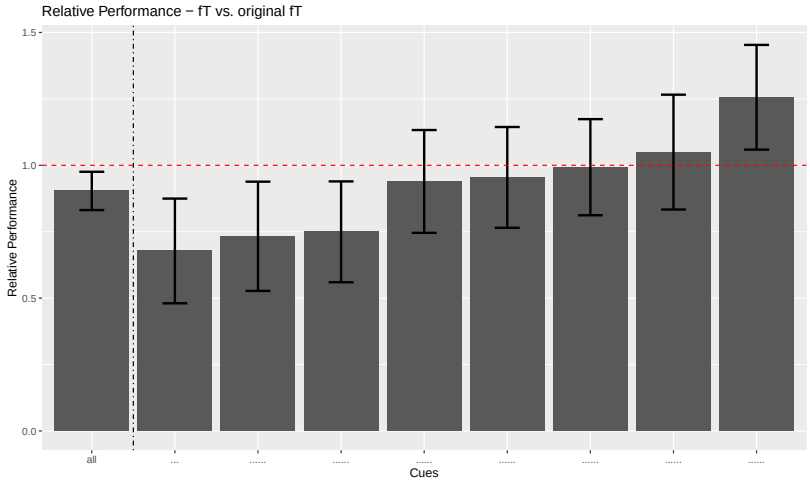
(a) Comparing `fastText` versions for Arabic



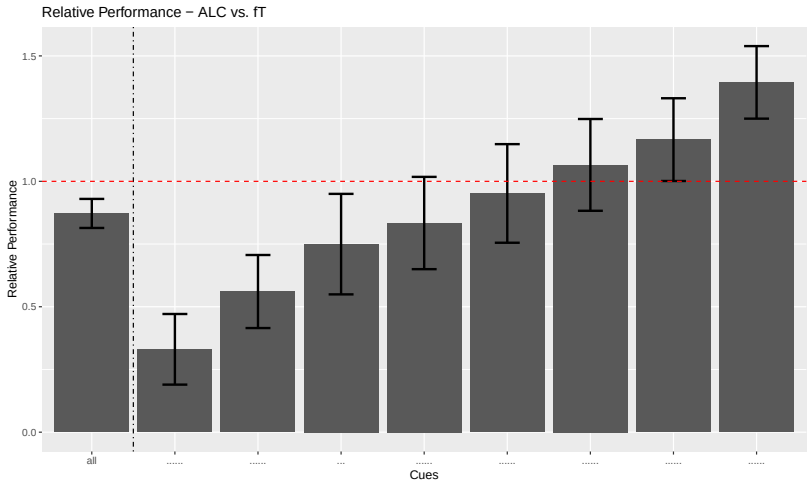
(b) Comparing `fastText` and ALC for

Figure 6: Summary of crowdsourcing comparisons for Arabic.

G.2 Chinese (Mandarin)



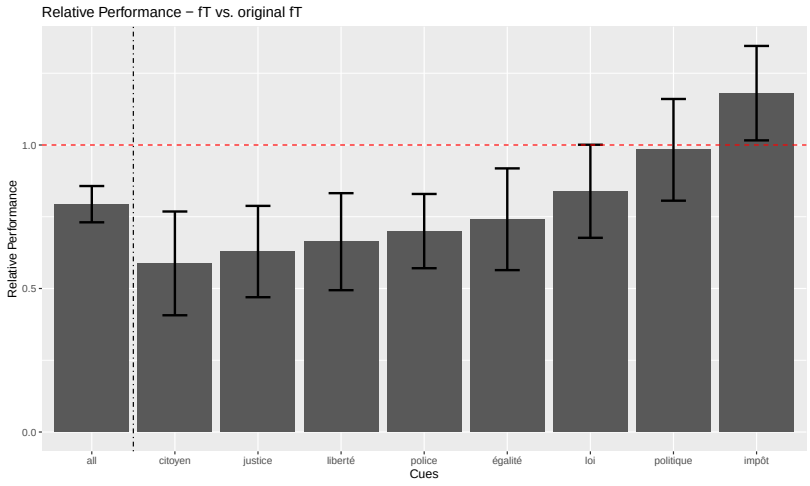
(a) Comparing `fastText` versions for Chinese



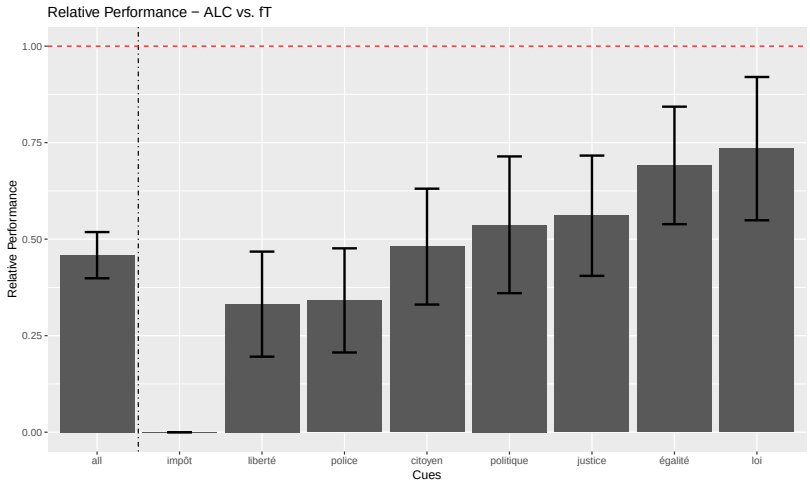
(b) Comparing `fastText` and ALC for Chinese

Figure 7: Summary of crowdsourcing comparisons for Chinese (Mandarin)

G.3 French



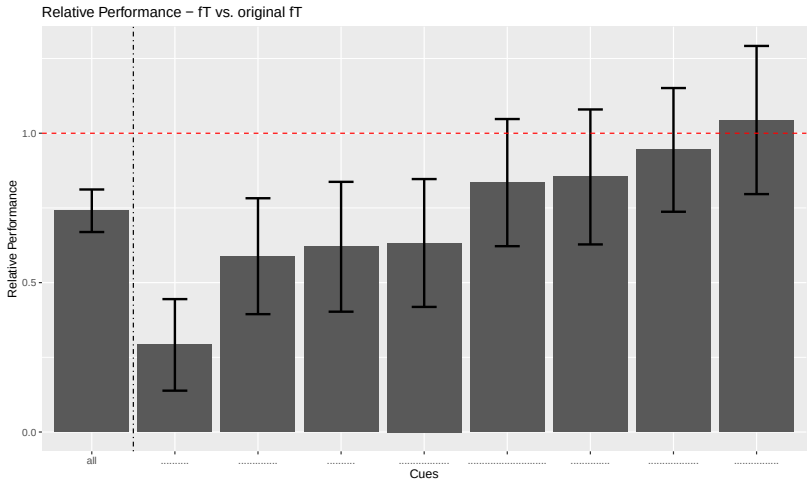
(a) Comparing `fastText` versions for French



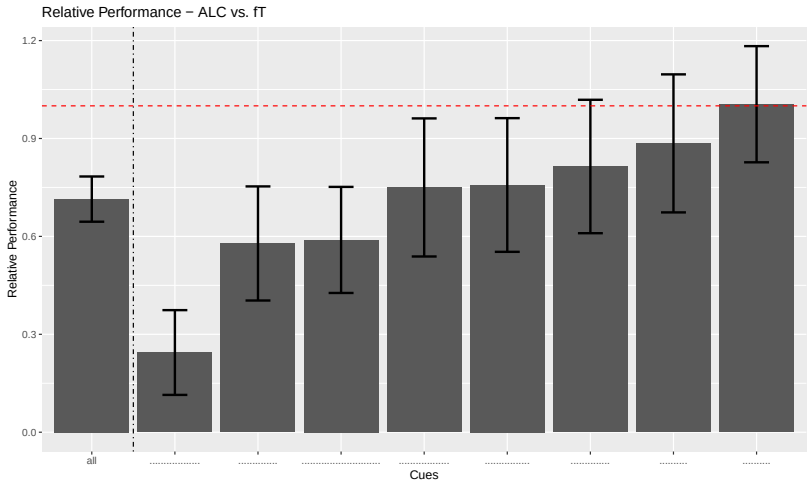
(b) Comparing `fastText` and ALC for French

Figure 8: Summary of crowdsourcing comparisons for French.

G.4 Russian



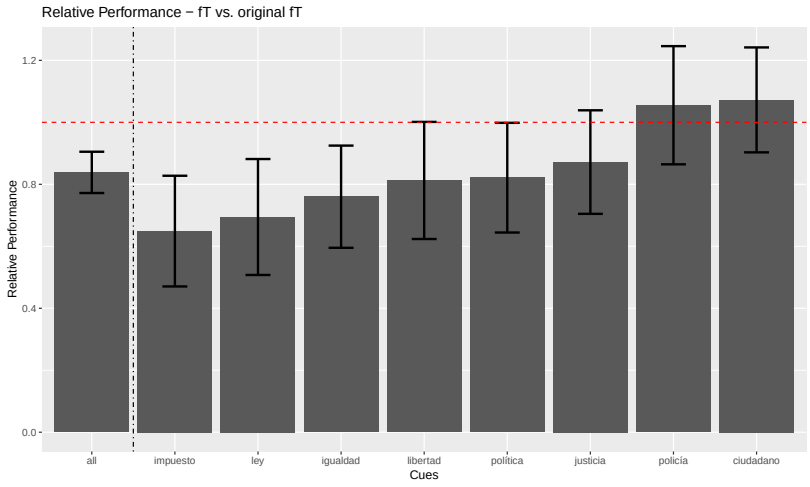
(a) Comparing `fastText` versions for Russian



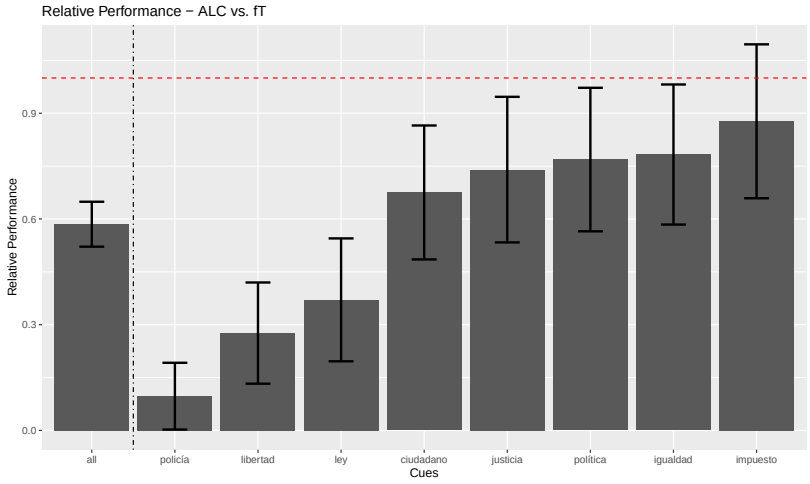
(b) Comparing `fastText` and ALC for

Figure 9: Summary of crowdsourcing comparisons for Russian.

G.5 Spanish



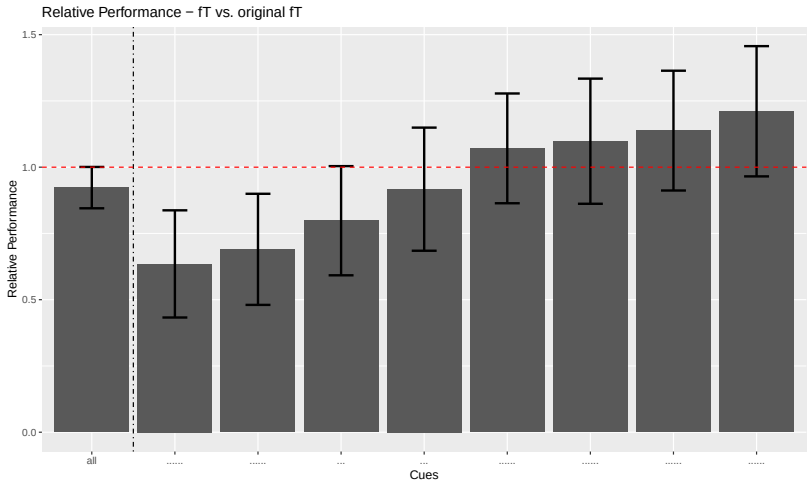
(a) Comparing `fastText` versions for Spanish



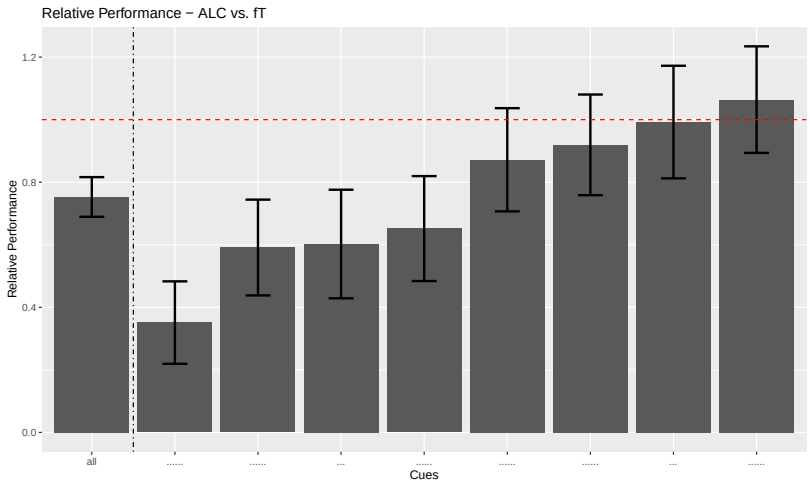
(b) Comparing `fastText` and ALC for Spanish

Figure 10: Summary of crowdsourcing comparisons for Spanish.

G.6 Japanese



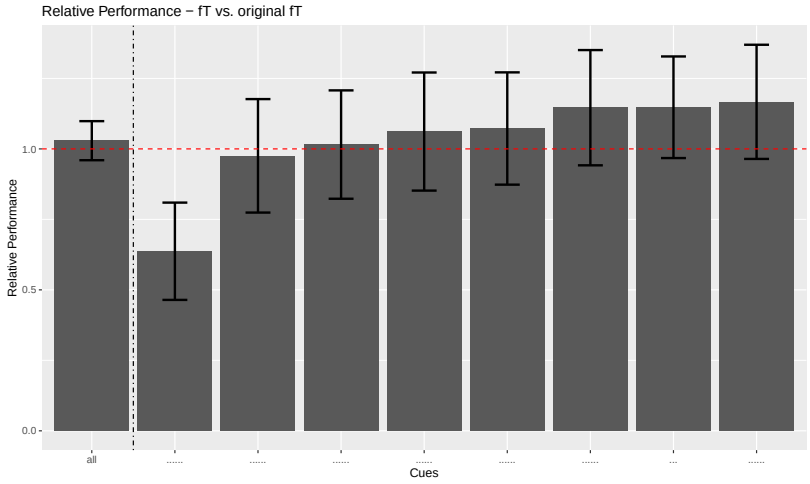
(a) Comparing `fastText` versions for Japanese



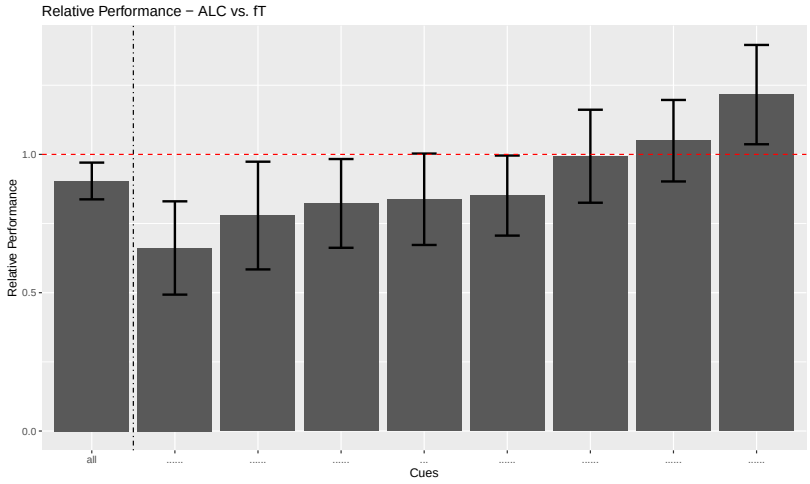
(b) Comparing `fastText` and ALC for Japanese

Figure 11: Summary of crowdsourcing comparisons for Japanese.

G.7 Korean



(a) Comparing `fastText` versions for Korean



(b) Comparing `fastText` and ALC for Korean

Figure 12: Summary of crowdsourcing comparisons for Korean.

H Approximately In Sample

If the researcher's local corpus is "close enough" to Wikipedia, then using our pre-fitted transformation matrix will work as well as anything else from the perspective of producing ALC embeddings. Inevitably, there is ambiguity in "close enough", but one way to diagnose whether this is true is to e.g. inspect nearest neighbors and compare them to the researcher's substantive priors.

To give an example of a limiting case (i.e. of being as close as possible to the training data), we illustrate the capacity of ALC to identify homonyms, i.e. terms that have identical spelling across contexts but different meanings. For instance, the German term `kiefer` means both `pine` and `jaw` and the term `erde` can imply both `Planet Earth` and `soil`. If ALC works well with corpora that are close to or identical to Wikipedia, we would expect the context-specific embeddings to uncover

these differences in meaning across contexts. As Table (4) and Figure (13) indicate, this is in fact the case. We embed each instance of the terms `kiefer` and `erde` *a la carte* by applying our `fastText` quantities (pre-trained embeddings and transformation matrix) to the German Wikipedia. We then cluster these ALC embeddings using k-means (for $k = 2$). Table (4) shows the nearest neighbors to the center of each cluster. Evidently, the first cluster of `kiefer` contains terms related to teeth and jaw bone, while the second cluster only includes other tree species, such as larch (`lärche`) or spruce (`fichte`). Similarly, the first cluster of `erde` captures terms such as vegetation cover (`planzendecke`) and rocks (`gesteinsbrocken`), whereas the second cluster is most closely related to words relevant to planet, sun or moon. Given these patterns, it is not surprising that these ALC clusters are also well-separated in two principal components dimensions (Figure (13))—note the homogeneity of the word-senses, with relatively little overlap on the first dimension.

kiefer		**erde**	
Cluster 1	Cluster 2	Cluster 1	Cluster 2
scherengebiss	fichten	erde	himmelskörpers
praemaxillare	nadelbaumarten	erdklumpen	magnetosphäre
protraktil	waldkiefer	erdnester	planetenoberfläche
oberkieferknochen	schwarzkiefer	gesteinsbrocken	sonnenoberfläche
kieferknochen	lärche	waldboden	sonnennähe
pharyngealia	weißtanne	pflanzendecke	meteoroiden
schläfenbein	weymouth-kiefer	lufthülle	sonnensystems
zwischenkieferbein	douglasie	vegetationsdecke	erde-mond
oberkiefers	weiß-tanne	menschenhand	äquatorebene
gaumenbein	balsam-tanne	menschenwelt	himmelskörpern

Table 4: Nearest neighbors to ALC clusters of German homonyms `kiefer` and `erde`.

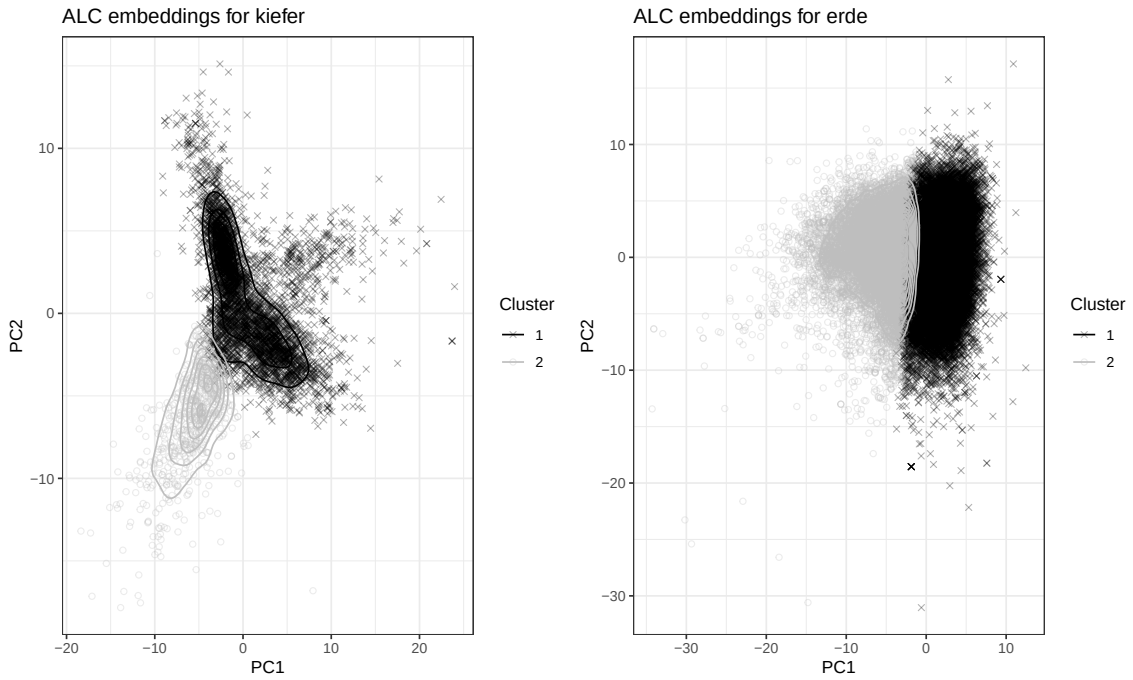


Figure 13: Identification of clusters in German homonyms `kiefer` (pine, jaw) and `erde` (Earth, soil).

I Out of Sample, "Small" Corpus

We use parliamentary corpora from the French and Italian parliamentary debates, as compiled by the *ParlaMint* project (Erjavec et al., 2023). In both examples, we use our pre-trained `fastText` embeddings together with the corresponding transformation matrices trained on Wikipedia. The first example uses the parliamentary minutes from the French National Assembly (*Assemblée Nationale*) for the period 2019-2020, which yields a corpus of about 216,000 documents. We show how ALC can capture changes in the meaning of certain keywords over time; specifically, how the connotation of `liberty` changes in French parliamentary debates before and after the Covid-19 outbreak. Figure (14) shows the average cosine similarity between ALC embeddings for `liberté` and our `fastText` pre-trained embeddings for relevant terms, including `pluralisme` (`pluralism`), `urgence` (`emergency`) and `visite` (`visit`). As one would expect, the figure shows how the usual nearest neighbors of `liberté`, i.e. `pluralisme`, `équité` and `discrimination`, experience a sharp drop in their cosine similarity with the ALC embedding of `liberté`. In contrast, *a priori* less closely related terms, such as `covid`, `urgence` and `visite`, show a substantially larger cosine similarity with `liberté` once the virus became a major health crisis in France. These dynamics are particularly stark in April 2020, when the Covid cases reached their first peak and the French government enacted a strict lockdown.

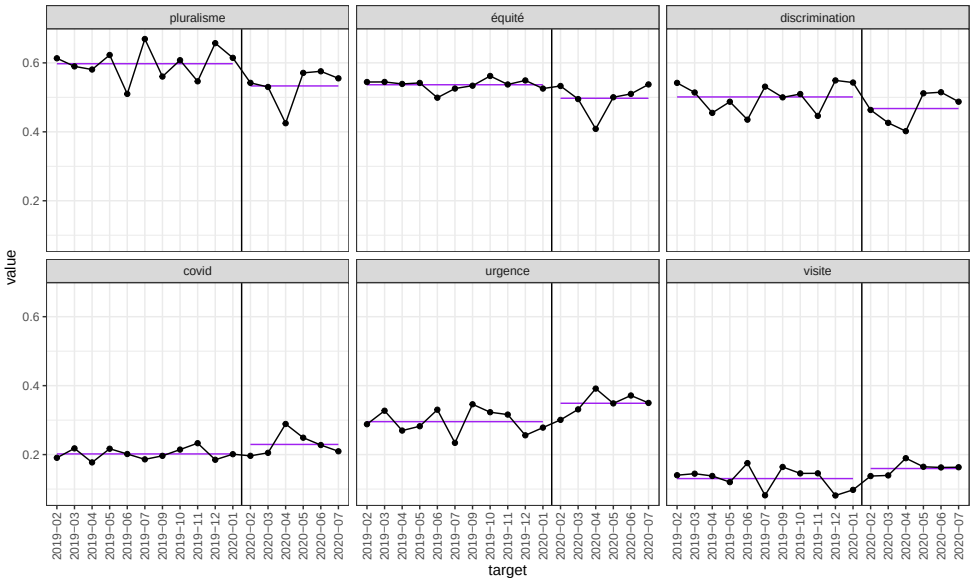


Figure 14: Average cosine similarity between ALC embeddings of `liberté` and pre-trained embeddings of relevant terms by month.

The second example uses embedding regressions to illustrate how the 2015 refugee crisis in Europe altered partisan differences in debates around issues of immigration in Italy's federal parliament. Using text from all parliamentary speeches for 2014-2017 ($N = 20,747$), we regress the ALC embeddings for immigration-related terms (i.e. `immigrati, immigrazione, immigrato, immigrate, immigrazioni`) across 6-month periods on a binary indicator for whether the speaker's party is part of the government or opposition. The multivariate regression analogy is

$$\mathbf{Y} = \beta_0 + \beta_1 Government + \mathbf{E} \tag{3}$$

Figure (15) depicts the norm of β_1 for each period. When the estimate increases, this indicates that the use of `immigr*` becomes less similar across government and opposition parties. The estimates show that speakers from different parliamentary camps differ throughout the entire period, and most strongly in the months between September and December 2015—a period with large and unexpected waves of refugees arriving in Southern Europe. Figure (16) further highlights that this discontinuity in semantic differences is indeed meaningful. The figure shows terms that are most closely related with opposition and government parties in relation to issues of immigration before and after the large influx of refugees. Specifically, we show the cosine similarity ratio of the ALC embeddings for immigration-related terms across opposition and government parties, shortly before (subfigure (a)) and after (subfigure (b)) the refugee crisis began. In early 2015, both types of parliamentary camps discussed issues of immigration in similar ways, often sharing nearest neighbors such as emergency (`emergenziale`) or applicants (`richiedenti`). In the later months of 2015, in contrast, the vocabularies are radically different between government and opposition parties. While opposition parties still seem to talk about immigration in more general terms (e.g. invoking terms lexically related to `immigrazione`), government parties now mention normative challenges of immigration as well as legal constraints, e.g. the Schengen area or the "Bossi-Fini law". It is

worth noting that we excluded stop words from the Italian parliamentary corpus to improve on the performance of ALC in this case. It is possible that excluding stop words can "help" the transformation matrix in screening out common directions in the embeddings space, and users may want to test the importance of removing vs. keeping stop words in their relevant language and use case. Taken together, these two examples across different parliamentary settings highlight the power of ALC to capture and illustrate semantic differences across time and groups.

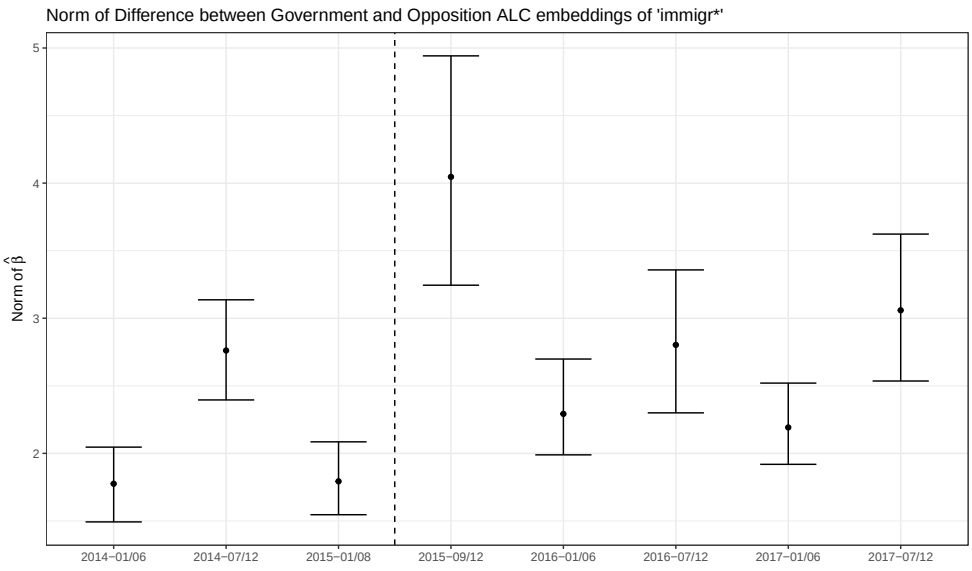
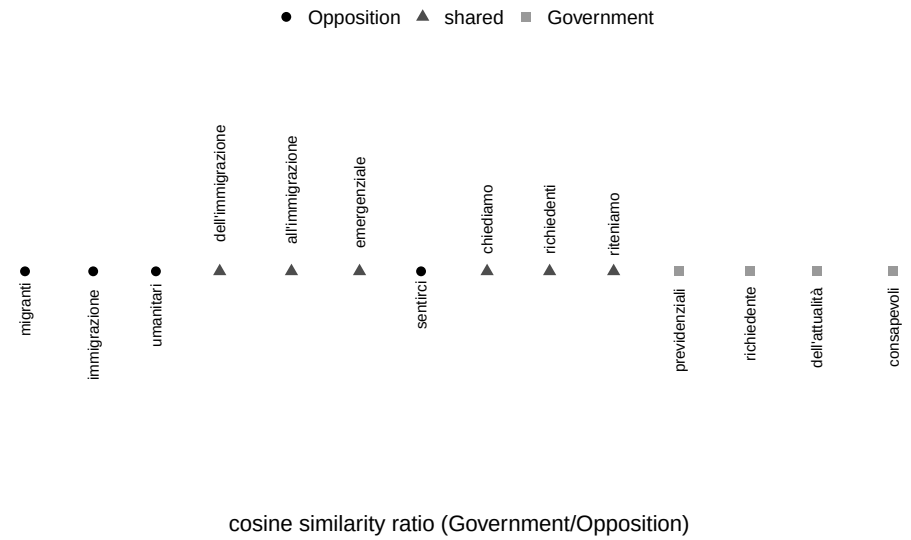
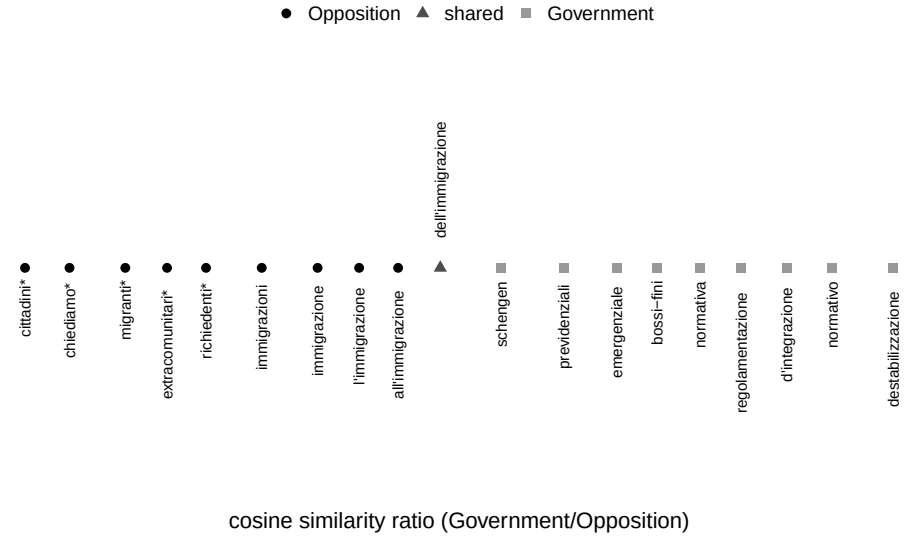


Figure 15: Relative semantic shift of `immigr*` between government and opposition parties.



(a) 2015-01/08



(b) 2015-09/12

Figure 16: Discussion of immigration diverged between government and opposition parties after the 2015 European refugee crisis

Readers may reasonably ask whether fitting the **A** matrix locally in this case would have resulted in "better" (more locally precise) embeddings. Our answer here is "no", as Table (5) shows. The table compares our pre-trained quantities and their application with locally trained embeddings to the French parliamentary debates. Columns 1 and 3 list the nearest neighbors for `liberté` for the pre-trained embeddings (our `fastText` and locally trained `GloVe`), and columns 2 and 4 show the nearest neighbors for the corresponding ALC embeddings of `liberté`. Evidently, our

`fastText` resources capture meaningful connotations of the key word, both for pre-trained and ALC embeddings. In contrast, locally trained quantities work well for `GloVe`, but not for its ALC version. That is, inspecting column 4, we see that the nearest neighbors for the ALC embedding of `liberté` depict only function words, such as `encore` or `aussi`. Note that we excluded stop words in the underlying parliamentary corpus (except for the training of the GloVe model) to facilitate a better local fit. So while our general suggestion would be to fit the relevant quantities locally if the corpus is large enough, in this particular case that size requirement was not fulfilled.

our fT	our fT-ALC	local GloVe	local GloVe-ALC
liberté	l'irresponsabilité	liberté	c'est
libertés	non-discrimination	d'expression	aussi
d'expression	l'impartialité	droit	tout
démocratie	d'impartialité	respect	car
conditionelle	pluralisme	principe	bien
légalité	légalité	contraire	surtout
pluralisme	d'exigence	toute	aujourd'hui
laïcité	contrevient	garantir	fait
dignité	l'inconstitutionnalité	choisir	faire
l'égalité	d'autrui	démocratie	encore

Table 5: Nearest neighbors for `liberté` for different pretrained embeddings and transformation matrices. The ALC embeddings use the French parliamentary corpus from Erjavec et al. (2023), 2017-2020.