

Latent Aspect Detection via Backtranslation Augmentation

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ABSTRACT

Within the context of review analytics, aspects are the features of products and services at which customers target their opinions and sentiments. Aspect detection helps product owners and service providers identify shortcomings and prioritize customers' needs. Existing methods focus on detecting the surface form of an aspect falling short when aspects are latent in reviews, especially in an informal context like in social posts. In this paper, we propose data augmentation via natural language backtranslation to extract latent occurrences of aspects. Specifically, we presume that backtranslation *i)* can reveal latent aspects because they may not be commonly known in the target language and can be generated through backtranslation; *ii)* augments context-aware synonymous aspects from a target language to the original language, hence addressing the out-of-vocabulary issue; and *iii)* helps with the semantic disambiguation of polysemous words and collocations. Through our experiments on well-known aspect detection methods across semeval datasets of restaurant and laptop reviews, we demonstrate that review augmentation via backtranslation yields a steady performance boost in baselines in all datasets. We further contribute LADy¹ (🐙), a benchmark library to support the reproducibility of our research.

1 INTRODUCTION

The key characteristic of customers' opinions is to target aspects of a product or service to convey an opinion. For example, the review *"forced us to buy pricey dresses by cheap behavior"* entails the aspects *'dress'* and *'seller'* toward which opinions of *'pricey'* and *'cheap behavior'* is expressed with *'negative'* sentiments, respectively. Aspect detection is crucial in customers' review analysis in e-commerce and social platforms [19]; it helps product owners and service providers to identify shortcomings and prioritize improvements according to customers' needs, hence maintaining revenues and preventing customer churn [1, 14, 33].

Existing methods to detect aspects in reviews and their respective opinions and sentiments have primarily expanded into two subtasks: *i)* *aspect term* sentiment analysis which extracts explicit term(s) that point to an aspect either by tagging the terms [16, 17] or delineating the span of the terms [31, 36] in the review's text (fine-grained terms), and *ii)* *aspect category* sentiment analysis which maps a review into a set of predefined coarse-grained (higher-order) categories of aspects [13, 25, 28]. In our example, an aspect term extraction method would tag *'dresses'* as an aspect. However, it falls short of detecting a latent or implicit occurrence of an aspect

Table 1: Sample reviews: [latent] vs. explicit aspects.

original	"[seller] forced us to buy pricey dresses through cheap behavior"
farsi	"فروشنده با رفتار زنده، ما را مجبور به خرید لباس های گران می کرد"
backtranslated	"with cheap behavior, seller forced us to buy expensive clothes"
original	"served me the wrong dish!"
spanish	"me sirvió la comida equivocada!"
backtranslated	"served me the wrong food!"

like *'seller'*. An aspect category detection method would detect the categories *'clothing'* for *'dress'* along with *'staff'* for *'seller'*, irrespective of explicit or latent occurrences of aspects.

On the one hand, aspect term sentiment analysis approaches forego the latent occurrences of aspects in reviews, as seen earlier in the example for *'seller'*. Indeed, when writing a review, the customer may write about her opinion and overall rating while overlooking the aspects' terms for a product or service due to being part of common knowledge. As shown in the literature, 35% of reviews on restaurants and electronics include latent aspects [5, 30]. The need for latent aspects detection is even more pressing in online social review platforms where reviews are unsolicited, short, noisy, informal, and mostly rely on social background knowledge and context. Furthermore, aspect term extraction methods fall short in the presence of out-of-vocabulary (oov) aspects, i.e., aspects that have been *unseen* in the training dataset. On the other hand, although aspect category sentiment analysis approaches are agnostic to the occurrence of aspect terms, they heavily rely on occurrences of other parts of a review, such as opinion terms whose latency renders aspect category detection challenging.

In this paper, we propose review augmentation through natural language backtranslation to address the latent occurrence and out-of-vocabulary aspects in aspect term extraction methods while overcoming the performance drain caused by the latency of fine-grained terms in aspect category detection methods. Specifically, we translate a review from its original language (e.g., english) to a target language (e.g., french), and then translate it back to the original language using a machine translator (e.g., Meta's n11b [6]). We presume this round-trip translation generates diverse paraphrases of a review while withholding semantic context [34], as a result of which:

- (1) Backtranslation can reveal latent aspects as they may not be commonly known in the target language. For instance, when *"forced us to buy pricey dresses by cheap behavior"* is translated to farsi as: *"فروشنده با رفتار زنده، ما را مجبور به خرید لباس های گران می کرد"*, followed by a backtranslation to english, *"with cheap behavior, seller forced us to buy expensive clothes"*, it brings up *'seller'*;
- (2) Backtranslation can address out-of-vocabulary aspects by augmenting *context-aware* synonymous aspects from the target language to the original language, as opposed to simple synonym

¹github.com/fani-lab/LADy

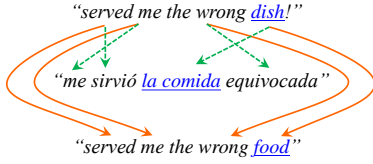



Figure 1: Term alignment.

replacement [7, 35]. For example, when “... served me the wrong *dish!*” is translated to spanish as “... me sirvió *la comida equivocada!* ...”, followed by a backtranslation to english “... *served me the wrong food!*”, ‘food’ appears for ‘dish’, compared to ‘bowl’ or ‘plate’; (3) Backtranslation can disambiguate polysemous terms and collocations, leading to the detection of latent aspects. For instance, translating “... through cheap behavior” to spanish “... a través de su comportamiento insignificante”, and backtranslating to english “... through her petty behavior” maps the term ‘cheap’ to ‘petty’, which is more semantically related to behavior of a person, leading to the detection of the latent aspect ‘staff’, as opposed to other semantics like ‘inexpensive’ for ‘dresses’.

For similar reasons, backtranslation has been employed in opinion mining [10, 29] and other various natural language processing tasks [9, 18, 24]. However, there has been no study on its synergistic impacts on aspect detection, to the best of our knowledge. In this paper, we systematically benchmark aspect detection models when their training sets of reviews in english are augmented with backtranslated versions through various languages from different language families and study the effects on the performance in terms of information retrieval metrics at top- k predicted aspects. We further contribute LADy¹ () , an open-source, extensible, and standard benchmark library, to support the reproducibility of our research. Through our experiments on well-known supervised and unsupervised aspect detection baselines across semeval datasets of 2014, 2015, and 2016, on restaurant and laptop domains, we demonstrate that review augmentation via backtranslation has led to a steady performance boost in baselines in different domains.

2 PROBLEM DEFINITION

Our goal is to explore the synergistic impact of natural language backtranslation as an augmentation technique on the aspect detection task, especially when aspects are *latent*.

DEFINITION 1 (Aspect Detection). Given a review after normalization of its raw text in a natural language l as a bag (set) of terms $r_p = \{i\}$ about a product or a service p concerning an aspect $a \in A_p$ which may not be in r_p , i.e., $a \notin r_p$ or $a \in r_p$, the aspect detection aims at identifying aspect a in r_p . A_p is the set of all aspects of the product or service p and \mathcal{R}_p is the set of all p ’s reviews.

3 AUGMENTATION VIA BACKTRANSLATION

While languages share underlying commonalities referred to as linguistic *universals* or cross-linguistic generalizations due to the common neurobiological basis of the human brain [11], they carry differences on the surface, including phonetics, morphological units (terms), syntax, and semantics, especially in an informal context like in social posts. Particular examples are ellipsis in writing when we omit terms that are superfluous or can be understood from

the context in one language but need to be explicitly mentioned in another language like in “[seller] forced us to buy pricey dresses through cheap behavior” in which ellipsis occurred in the aspect ‘seller’ in english as opposed to its translation in farsi, as shown in Table 1. In this paper, we aim to employ the textual ellipsis differences in various natural languages to uncover latent aspects in reviews through language backtranslation as well as addressing out-of-vocabulary aspects. Our research includes two main pipeline components: (1) review backtranslation, which is further divided into two subcomponents of backtranslation and semantic alignment, and (2) review aspect detection.

3.1 Review Backtranslation

Let \mathcal{L} be the set of languages. Given a review $r_p = \{i\} \in l \in \mathcal{L}$, we translate it to language $l' \in \mathcal{L}$ resulting in review $r'_p \in l'$ and backtranslate it to l which results in $r_p^+ = \{i^+\}$. We create an augmented review set \mathcal{R}_p^+ by adding augmented reviews to the original set \mathcal{R}_p , which is used for the training phase. The original set \mathcal{R}_p can also be augmented with multiple or *all* languages in \mathcal{L} .

3.1.1 Backtranslation. In our study, without loss of generality to any machine translation models, we apply Meta’s ‘no language left behind’ (nllb) [6], an open-source neural machine translator capable of providing high-quality translations between 200 languages. We deliberately chose nllb for its particular focus on realizing a universal translation system while prioritizing the needs of underserved communities for low-resource natural languages, as opposed to a small dominant subset of natural languages; it enables review backtranslation augmentation via a vast variety of natural languages with distinct properties. Further, nllb is open-sourced to foster transparency and can be smoothly integrated into any pipeline with few lines of code. For this paper, we translated english reviews into french, german, spanish, and farsi from indo-european language family, chinese from sino-tibetan language family, and arabic from afro-asiatic language family.

We employ the same nllb translator to bring the translated reviews back to english. As shown in Table 1, a backtranslated version of a review may carry term replacement (e.g., ‘food’ for ‘dish’) and/or new terms (e.g., ‘seller’), among other changes. Although Yu et al. [34] have shown that natural language backtranslation preserves the semantic context, i.e., an original piece of text and its backtranslated versions are about the same topic, we have observed otherwise in review analysis, especially when using languages whose family is different from english’s like chinese or arabic. For example, the review “the duck confit is always amazing” became “the duck crib is always fantastic” after backtranslation via chinese where the aspect ‘duck confit’ (‘food’) has semantically drifted to ‘duck crib’ (‘furniture’). To preserve semantic context consistency during backtranslation, we filter out backtranslated versions of original reviews that are semantically drifted, as explained in the next section.

3.1.2 Semantic Alignment. To alleviate semantic drift in backtranslation augmentation, we perform pairwise term alignment [27] between the original review and backtranslated versions to ensure accurate and meaningful machine translation. Term alignment matches the aspect terms of an original review

Table 2: Statistics on original and backtranslated reviews.

dataset	#reviews	avg #aspects	exact match					
			chinese	farsi	arabic	french	german	spanish
semeval-14-laptop	1,488	1.5846	0.1763	0.2178	0.2727	0.3309	0.3214	0.3702
semeval-14-restau	2,023	1.8284	0.1831	0.2236	0.2929	0.3645	0.3724	0.4088
semeval-15-restau	0,833	1.5354	0.2034	0.2312	0.3021	0.3587	0.3907	0.4128
semeval-16-restau	1,234	1.5235	0.2023	0.2331	0.2991	0.3556	0.3834	0.4034

with a corresponding term in the backtranslated review. Moreover, it matches the aspect terms of the original review with its corresponding *aligned* backtranslated aspect terms. Figure 1 displays an example where ‘dish’ in the original review has matched with ‘food’ in the spanish-backtranslated version. For term alignment, we use simalign-itermax by Sabet et al. [27], an unsupervised approach to align terms (also phrases) in a pair of parallel texts by calculating the pairwise cosine similarities between the embeddings of words in the source and target texts.

We further apply semantic similarity on pairs of review and backtranslated versions using declutr by Giorgi et al. [12] and filtered out backtranslated reviews with less than a threshold (e.g., 0.5) semantic similarity.

3.2 Review Aspect Detection

To assess the contribution of review augmentation using backtranslation, we train two instances of an aspect detection model: one is trained on an original dataset in language l , i.e., \mathcal{R}_p , and another one is trained on augmented datasets via language l' , i.e., \mathcal{R}_p^+ . We cross-compare the performance of two instances of the model on the same test set with no augmentation.

4 EXPERIMENTS

We seek to answer the following research questions:

RQ1: Does augmentation via natural language backtranslation improve the performance of aspect detection models?

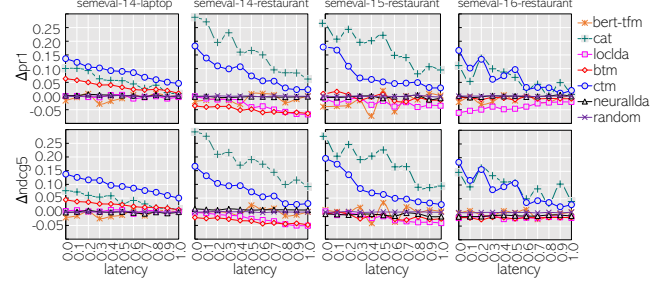
RQ2: Does backtranslation augmentation improve the performance of aspect detection models when aspects are *latent*?

RQ3: Is the impact of augmentation consistent across datasets from different review domains?

4.1 Setup

4.1.1 Datasets. Our benchmark includes well-known publicly available semeval datasets of reviews in english for aspect detection. We used training sets of semeval-14’s reviews on restaurants and laptops [22], and semeval-15 and semeval-16’s reviews on restaurants [20, 21]. Following the literature [17, 28], we segmented reviews into sentences and performed our experiments on each sentence as an individual review assuming each sentence entails one aspect. Table 2 shows the datasets’ statistics.

4.1.2 Backtranslation and Semantic Alignment. We randomly divided a dataset into 85% training and 15% test sets of reviews. We augmented the training set of reviews through backtranslation using Meta’s nllb [6]. Table 2 shows the average scores of exact match metric between original reviews and their respective backtranslated versions per dataset after filtering out backtranslated reviews with less than 0.5 semantic similarity for semantic drift. As seen, backtranslated versions of reviews from languages that belong to the same family as english, including spanish, french and german, are more similar compared to chinese and arabic.


Figure 2: Performance gain in latent aspect detection.

We further merge all backtranslated reviews from all different languages into one set, referred to as *all*, to explore the impact of backtranslation from all languages at once.

4.1.3 Baselines. We benchmarked the following supervised and unsupervised aspect detection models.

bert-tfm [17] is a *supervised* tagging-based method that employs contextual embeddings of reviews from bert [8] followed by a self-attention layer.

cat [28] is a simple yet effective *unsupervised* aspect detection method. It forms a candidate set of aspect terms whose part of speech is of type noun. An input review is then transformed into an attention matrix using pretrained vector representations of constituent terms. Finally, it selects an aspect term that has the highest similarity with the weighted vector of the input review.

loclda [4] is an *unsupervised* method following the same assumption as in topic modeling methods; the review’s terms are generated based on an aspect (topic). The model uses latent Dirichlet allocation [3].

btm [15, 32] is an *unsupervised* method with a special focus on short texts like reviews. It learns the aspects by directly modeling the generation of term cooccurrence pairs (biterns) in the entire review dataset to address the problem of sparse term occurrences in loclda.

neurallda [26] is an *unsupervised* topic modeling method based on variational autoencoder, which encodes the term occurrence vector representation of reviews onto a continuous latent representation as aspects.

ctm [2] extends neurallda with the concatenation of the term occurrence vector and pretrained dense contextual vector representation from a bert-based transformer, e.g. sentencebert [23], in the input.

random is a naive method that chooses an arbitrary term as the review’s aspect to provide a minimum base for comparison.

For the complete list of baselines’ hyperparameters, see LADy (🔗) codebase.

4.1.4 Evaluation Methodology. We performed 5-fold cross-validation on a training set for model training and validation, which results in one trained model per fold. Given a review of the test set, we compared the ranked list of predicted aspect terms by the model of each fold with the observed aspect terms and reported the average performance of models in all folds by information retrieval metrics, including normalized discounted cumulative gain (ndcg) as well as classification metrics including precision (pr) and recall (rec). To evaluate how backtranslation augmentation helps with our trained model in detecting latent aspects, given a

Table 3: The average performance of 5-fold models with backtranslation augmentation and lack thereof on the test set.

	bert-tfm [17]			cat [28]			loclda [4]			btm [15, 32]			ctm [2]			neurallda [26]			random		
	pr1	rec5	ndcg5	pr1	rec5	ndcg5	pr1	rec5	ndcg5	pr1	rec5	ndcg5	pr1	rec5	ndcg5	pr1	rec5	ndcg5	pr1	rec5	ndcg5
semeval-14-laptop																					
none	0.6194	0.6487	0.6235	0.4591	0.6362	0.5598	0.1188	0.1536	0.1308	0.0705	0.1079	0.0908	0.0286	0.0459	0.0379	0.0116	0.0179	0.0155	0.0000	0.0000	0.0000
+chinese	0.6018	0.6347	0.6102	0.5409	0.6564	0.6082	0.1179	0.1680	0.1407	0.1080	0.1309	0.1173	0.0732	0.1003	0.0844	0.0054	0.0063	0.0059	0.0000	0.0000	0.0000
+farsi	0.6074	0.6314	0.6092	<u>0.5369</u>	<u>0.6685</u>	<u>0.6112</u>	0.0875	0.1390	0.1148	<u>0.1438</u>	0.1321	<u>0.1276</u>	0.0384	0.0593	0.0501	0.0054	0.0086	0.0066	0.0000	0.0000	0.0000
+arabic	0.6018	0.6237	0.6039	0.5154	0.6537	0.5959	0.1000	0.1420	0.1194	0.1107	0.1342	0.1177	0.0464	0.0770	0.0608	0.0063	0.0085	0.0070	0.0018	0.0010	0.0012
+french	<u>0.6184</u>	0.6290	<u>0.6112</u>	0.5168	<u>0.6685</u>	0.6040	0.1223	0.1705	0.1462	0.1170	0.1430	0.1263	0.0518	0.0910	0.0733	0.0045	0.0076	0.0061	0.0018	0.0019	0.0018
+german	0.6055	0.6336	0.6096	0.5315	<u>0.6685</u>	0.6103	0.1411	0.1890	0.1621	0.1000	0.1206	0.1068	<u>0.0991</u>	<u>0.1199</u>	<u>0.1066</u>	0.0036	0.0060	0.0049	0.0000	0.0009	0.0004
+spanish	0.6018	0.6291	0.6092	0.5356	0.6711	0.6127	0.1188	0.1669	0.1414	0.1045	<u>0.1431</u>	0.1225	<u>0.0500</u>	<u>0.0768</u>	<u>0.0638</u>	0.0045	0.0048	0.0047	<u>0.0009</u>	<u>0.0017</u>	<u>0.0015</u>
+all	0.6028	0.6194	0.6025	0.5195	0.6510	0.5966	0.1188	0.1549	0.1336	0.1339	0.1476	0.1347	0.1652	0.2007	0.1757	0.0134	0.0149	0.0130	0.0000	0.0001	0.0001
semeval-14-restaurant																					
none	0.6061	0.6564	0.6293	0.3442	0.5478	0.4519	0.2428	0.2845	0.2557	0.1717	0.2361	0.1995	0.0368	0.0941	0.0682	0.0099	0.0307	0.0221	0.0000	0.0002	0.0001
+chinese	0.6121	<u>0.6627</u>	0.6338	0.6221	0.8248	0.7395	0.1980	0.2656	0.2270	0.1743	0.2236	0.1945	0.2020	0.1994	0.1863	0.0046	0.0309	0.0203	0.0000	0.0001	0.0001
+farsi	0.5946	0.6390	0.6166	0.6133	0.8159	0.7321	0.1770	0.2803	0.2322	0.1664	0.2238	0.1920	0.1289	0.1912	0.1604	0.0105	0.0493	0.0312	<u>0.0007</u>	<u>0.0013</u>	<u>0.0008</u>
+arabic	0.6054	0.6558	0.6286	0.6221	0.8265	0.7417	<u>0.2408</u>	<u>0.2866</u>	<u>0.2548</u>	0.1678	0.2336	0.1980	0.1724	<u>0.2218</u>	<u>0.1909</u>	0.0026	0.0250	0.0153	0.0000	0.0007	0.0004
+french	0.6040	0.6516	0.6253	0.6159	0.8274	0.7399	0.1645	0.2533	0.2068	0.1572	0.2090	0.1773	<u>0.1947</u>	<u>0.2036</u>	0.1862	0.0086	<u>0.0365</u>	<u>0.0250</u>	0.0000	0.0000	0.0000
+german	0.5987	0.6553	0.6275	<u>0.6257</u>	0.8363	<u>0.7487</u>	0.1770	0.2876	0.2329	<u>0.1875</u>	<u>0.2350</u>	<u>0.2056</u>	<u>0.1467</u>	0.1715	0.1474	0.0033	0.0272	0.0167	0.0013	0.0018	0.0016
+spanish	0.6000	0.6581	0.6278	0.6319	<u>0.8354</u>	0.7501	0.1908	0.2853	0.2389	0.1638	0.2266	0.1947	<u>0.1914</u>	<u>0.1922</u>	0.1803	0.0007	0.0157	0.0108	0.0000	0.0003	0.0003
+all	0.5865	0.6566	0.6254	0.6319	0.8239	0.7435	0.1993	0.2919	0.2445	0.1921	0.2386	0.2076	0.2487	0.2741	0.2481	0.0013	0.0355	0.0197	<u>0.0007</u>	0.0003	0.0004
semeval-15-restaurant																					
none	0.7000	0.6897	0.6757	0.3327	0.5248	0.4343	0.2320	0.3549	0.2925	0.1872	0.3133	0.2500	0.0560	0.0493	0.0485	0.0080	0.0410	0.0244	0.0000	0.0005	0.0005
+chinese	0.6661	0.6928	0.6699	0.3723	0.5287	0.4596	0.1968	0.3408	0.2647	0.1760	0.2783	0.2261	0.0624	0.0717	0.0637	0.0112	<u>0.0575</u>	0.0354	0.0016	0.0028	0.0022
+farsi	<u>0.6742</u>	0.6707	0.6608	0.3703	0.5386	0.4592	0.1840	0.3494	0.2689	0.1776	0.2834	0.2303	0.0560	0.0823	0.0722	0.0096	0.0400	0.0253	0.0000	0.0002	0.0002
+arabic	0.6661	0.6898	0.6671	<u>0.4139</u>	<u>0.5683</u>	<u>0.4939</u>	0.2000	0.3654	0.2887	0.1568	0.2956	0.2269	0.0592	0.0649	0.0577	0.0000	0.0271	0.0160	0.0000	0.0000	0.0000
+french	0.6565	0.7030	0.6734	0.4040	0.5584	0.4883	<u>0.2512</u>	<u>0.3577</u>	0.3032	0.1968	<u>0.3048</u>	0.2481	<u>0.0720</u>	<u>0.0837</u>	<u>0.0733</u>	0.0176	0.0551	<u>0.0377</u>	0.0000	0.0008	0.0006
+german	0.6710	0.6927	0.6721	0.3980	0.5505	0.4787	0.2416	0.3648	0.2976	0.1808	0.2691	0.2242	0.0560	0.0717	0.0603	0.0048	0.0542	0.0324	0.0000	0.0061	0.0036
+spanish	0.6645	0.7099	0.6769	0.3921	0.5663	0.4842	0.2224	0.3737	0.3035	0.2000	0.2975	0.2466	0.0464	0.0531	0.0458	0.0192	0.0314	0.0246	0.0000	0.0000	0.0000
+all	0.6613	0.7182	0.6823	0.5980	0.7861	0.7096	0.2592	0.3744	0.3104	0.2128	0.2986	0.2515	0.2192	0.2470	0.2263	0.0224	0.0731	0.0478	0.0016	0.0008	0.0010
semeval-16-restaurant																					
none	0.6844	0.6911	0.6806	0.4193	0.5496	0.4912	0.1699	0.2828	0.2248	0.0828	<u>0.1600</u>	<u>0.1204</u>	0.0226	0.0430	0.0352	0.0097	0.0389	0.0250	0.0022	0.0008	0.0009
+chinese	0.6700	0.7062	0.6864	0.5659	0.6904	0.6371	0.1538	0.2781	0.2173	<u>0.0968</u>	0.1446	0.1189	0.0624	0.0891	0.0769	0.0129	0.0262	0.0196	0.0000	0.0014	0.0008
+farsi	0.6811	0.6915	0.6783	<u>0.5733</u>	0.7259	0.6634	0.1398	0.2716	0.2068	0.0731	0.1425	0.1063	0.0839	<u>0.1230</u>	<u>0.1023</u>	0.0129	0.0592	0.0393	0.0000	0.0005	0.0003
+arabic	0.6744	0.6849	0.6736	0.5630	0.7378	0.6661	0.1785	0.2879	0.2279	0.0645	0.1456	0.1062	0.0774	0.1118	0.0924	0.0151	0.0316	0.0223	0.0000	0.0013	0.0008
+french	0.6811	0.6963	0.6834	0.5763	<u>0.7541</u>	0.6796	0.2118	<u>0.2919</u>	0.2451	0.0871	0.1473	0.1159	0.0602	0.1082	0.0868	0.0075	0.0451	0.0287	<u>0.0011</u>	<u>0.0016</u>	<u>0.0011</u>
+german	0.6856	0.6891	0.6806	0.5719	0.7481	<u>0.6764</u>	0.1312	0.2715	0.2060	0.0860	0.1514	0.1188	0.0602	0.1009	0.0793	0.0086	0.0303	0.0227	<u>0.0011</u>	0.0022	0.0018
+spanish	0.6656	0.6951	0.6784	0.5600	0.7467	0.6697	<u>0.1957</u>	0.2935	<u>0.2408</u>	0.1054	0.1718	0.1372	0.0656	0.1107	0.0879	<u>0.0140</u>	0.0372	0.0279	0.0000	0.0014	0.0007
+all	0.6622	<u>0.6992</u>	0.6774	0.5304	0.7141	0.6375	0.1591	0.2694	0.2130	0.0774	0.1410	0.1070	0.2097	0.2607	0.2272	0.0151	0.0487	0.0304	0.0000	0.0009	0.0006

random review from the test set, we removed the aspect terms from the review (synthetically make it latent) and used our model to predict the review’s latent aspect. We evaluate the baselines on a randomly increasing percentage of latent aspects in the test set from 0% (all aspects are explicit) to 100% (all aspects are latent).

4.2 Results

In response to RQ1, i.e., whether augmentation via language backtranslation improves the performance of aspect detection methods, from Table 3, all baselines, including random, could generally improve upon augmentation across datasets and domains. Specifically, the best results were when the training sets were augmented from *all* languages (+all).

On a per-language basis, we can further observe that backtranslation augmentation via languages in the same family as english like spanish, german, or french generally yielded runner-up results. However, there are inconsistencies like backtranslation augmentation via arabic that obtain the competitor results in semeval-15-laptop using cat baseline. Further, from a row-wise view, baseline methods have different performance gains from review augmentation. For instance, a poor method before augmentation like ctm can boost its performance by augmentation and become one of the best methods among unsupervised baselines as opposed to neurallda’s marginal performance gain. With respect to the state-of-the-art methods, bert-tfm’s gain is limited since it identifies an aspect term within the elements of an input sequence solely overlooking other possible candidate aspect terms.

In contrast, cat is unsupervised and can select aspect terms from a global vocabulary set, hence benefiting substantially from augmentation. In general, unsupervised baselines enhanced their performance through augmentation in any language of choice across all domains and datasets. Last, when it comes to comparing neural vs. traditional topic modelings, neural models like ctm utilized augmentation more effectively compared to non-neural models such as loclda and btm.

To answer RQ2, i.e., whether backtranslation augmentation improves the performance of aspect detection methods when aspects are latent. Figure 2 shows the performance gain of models when their training sets were augmented by +all languages compared to no augmentation. As seen, while there is a general declining trend as more aspects in the test set become latent, selected models, specifically unsupervised ones such as cat and ctm, show strong positive performance gain in terms of pr1 and ndcg5 to predict latent aspects. Interestingly, augmentation via backtranslation helps cat and ctm up to +15% improvements in challenging scenarios where 70% of reviews contain latent aspects.

Regarding RQ3, i.e., if the impact of augmentation across datasets from different domains is consistent, from Table 3, we see that backtranslation augmentation via all languages (+all) generally improved the performance in restaurant and laptop reviews in *all* semeval datasets, which implies the domain-agnostic synergy of backtranslation augmentation in aspect detection.

5 CONCLUSION AND FUTURE WORK

We presented augmentation via backtranslation for the task of aspect detection. Our experiments on backtranslation via six natural languages from varying language families demonstrate the synergistic impact of backtranslation augmentation across aspect detection methods and domains, including restaurant and laptop, esp., in reviews where aspects happen to be latent. Our future research includes experiments on *i*) datasets of unsolicited reviews from social media, which are short and informal, and *ii*) backtranslation augmentation via low-resource languages.

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