Synthetic Examples Improve Cross-Target Generalization: A Study on Stance Detection on a Twitter Corpus

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Abstract

Cross-target generalization is a known problem in stance detection (SD), where systems tend to perform poorly when exposed to targets unseen during training. Given that data annotation is expensive and time-consuming, finding ways to leverage abundant unlabeled in-domain data can offer great benefits. In this paper, we apply a weakly supervised framework to enhance cross-target generalization through synthetically annotated data. We focus on Twitter SD and show experimentally that integrating synthetic data is helpful for cross-target generalization, leading to significant improvements in performance, with gains in $F_1$ scores ranging from $+3.4$ to $+5.1$.

1 Introduction

Stance Detection (SD) is a widely investigated task (Mohammad et al., 2017), which constitutes an important component of many complex NLP problems, ranging from fake news detection to rumor verification (Vlachos and Riedel, 2014; Baly et al., 2018; Zubiaga et al., 2018b). Since from early works (Agrawal et al.), research on SD focused on user-generated content, ranging from blogs and commenting sections on websites (Hercig et al.), to Reddit or Facebook posts (Klenner et al.) and, above all, Twitter data (Inkpen et al., 2017; Zubiaga et al., 2018a).

Recently, Conforti et al. (2020) released Will-They-Won’t-They (WT–WT), a very large corpus of stance-annotated tweets discussing five US mergers and acquisitions (M&A) operations spanning over two industries: healthcare and entertainment. M&A is a general term that refers to the process in which the ownership of companies are transferred. Such process has many stages that range from informal talks to the closing of a deal, and discussions may not be publicly disclosed until a formal agreement is signed (Bruner and Perella, 2004): in this sense, the analysis of the evolution of opinions and concerns expressed by users about a possible M&A operation, from early stage discussion to the signing of the merger (or its rejection), is a process similar to rumor verification, a widely studied field (Zubiaga et al., 2018a). Interestingly, Conforti et al. (2020) observed a consistent drop in performance when a system trained on mergers in one industry is tested on data discussing a merger in a different industry. Such a performance drop when testing conditions deviate from training conditions is a known problem in Stance Detection (SD) (Aker et al.).

In this paper, we investigate the impact of using synthetically annotated data to improve zero-shot cross-target generalization in Twitter SD:

(1) We investigate a weakly supervised framework for SD, which integrates synthetically annotated data to improve performance on new targets; as to our knowledge, we are the first to use synthetically annotated data for SD;

(2) We test our framework on Twitter SD and prove that it successfully improves cross-target generalization on new, unseen targets;

(3) We extend the WT–WT corpus with additional annotated tweets discussing M&A operations in one additional domain, which we release for future research on cross-target generalization¹.

2 Cross-Target Generalization with Synthetically Annotated Samples

Given an in-domain (ID) test set and a gold out-of-domain (OOD) train set, we augment the corpus with synthetically labeled ID data (Figure 1):

1. We train a SD system on the gold OOD data.
2. We crawl for a large amount of unlabeled ID data and label it with the system trained in 1, obtaining silver, synthetically annotated data.

¹https://github.com/cambridge-wtwt/
3. We train a new system on both gold OOD and synthetic ID data: in this way, the system is exposed to a gold signal from the OOD data and to a noisy but ID signal from silver data.

4. We predict the ID test data with the system trained in 3.

Comparison with previous work on Data Augmentation and Domain Adaptation.

Note that this framework differs from data augmentation (DAug) strategies adopted to supply for small training data, like in question answering (Kafle et al.), machine translation (Fadaee et al.) distillation (Tang et al., 2019), or for adversarial sample generation (Jia and Liang, 2017). Such techniques, inspired by DAug in speech recognition and computer vision (Chatfield et al., 2014), work by deformating gold samples to generate new artificial samples (for example, by random token masking, or POS- or semantics-based token replacement). Our approach differs in a number of aspects:

1. In DAug the goal is to enlarge a set of initial ID data; here, we assume we don’t have any ID training data, but only OOD;
2. For this reason, while DAug helps to cope with data sparsity, our approach is also useful for domain shifts;
3. In DAug, sample generation might introduce two kinds of noise: it can lead to mismatches between the new samples and the associated labels, and also produce ungrammatical samples; in our approach, the system is always exposed to well-structured input: the only noise are potential errors in synthetic labeling.

Our approach fits into the broad family of weakly- and semi-supervised frameworks which have been adopted to tackle domain adaptation (DAda) problems (Søgaard, 2013). In recent literature, such methods have been applied with mixed success to many tasks, ranging from named entity recognition (Fries et al., 2017) to relation extraction (Mintz et al., 2009), tagging (Plank et al., 2014), parsing (McClosky et al., 2010), and sentiment analysis (Blitzer et al., 2007; Ruder and Plank, 2018; Ratner et al., 2020). In this paper, we propose to apply weakly supervision to SD, by adopting the extremely simple and inexpensive framework described above.

3 Related Work on Stance Detection

SD is a widely investigated field in NLP. Starting from Mohammad et al. (2017), research in SD focused on the analysis of Twitter posts. Another research direction explored the classification of Twitter users with respect to given topics, like political independence (Darwish et al., 2019). Work on other types of user-generated data includes SD on parenting blogs (Skeppstedt et al., 2017), political posts on newspapers websites (Hanselowski et al., 2018), posts on online debate forums on various topics (Hasan and Ng, 2014) and posts on wordpress blogs (Simaki et al., 2017). SD has been also integrated into Fake News Detection (Pomerleau and Rao, 2017) and constitutes an important step in the rumor verification pipeline (Zubiaga et al., 2018b): in this framework, popular shared tasks focused on SD of rumors tweets (Gorrell et al., 2018) and Reddit posts (Gorrell et al., 2018). These works analyze tweets in a tree-shaped stream (Zubiaga et al., 2015). Note that SD constitutes a related but different task than sentiment analysis (Mohammad et al., 2017): the latter focuses on the polarity expressed w.r.t. a topic, while the former aims to determine the text’s orientation w.r.t. the topic. Consider the following tweet:

#Cancer patients will suffer if CVSHealth buys Aetna CVS #PBM has resulted in delays in therapy, switches, etc all documented. Terrible!

The sentiment of the tweet w.r.t. the target is negative: the user believes that the merger would harm patients; however, its stance is comment, as it is
not stating that the merger is going to happen or to be rejected, but is talking about its consequences.

4 Experimental Setup

Data. We consider the following data (Table 1-2):

- **Annotated data.** The WT–WT corpus constitutes our primary source of labeled data, which we extend with gold-annotated tweets discussing a merger in the defense industry, following the same procedure as in Conforti et al. (2020). Each \{tweet, merger\} sample is annotated with a label from support, comment, refute and unrelated, which expresses its stance w.r.t the likelihood of the merger to happen.

- **Unlabeled data.** We crawl for 16 additional mergers, obtaining 134,922 unlabeled tweets.

Models and Hyperparameters. We employ a multi-layer perceptron (MLP) classifier, which takes as input the concatenation of the tweet’s and the target’s TF-IDF representations and their cosine similarity. This simple model achieved good results on SD (Riedel et al., 2017) and is relatively stable over parameter selection. Hyperparameters used are listed in Table 6 (Appendix B) for replication.

### Synthetic Label Generation.

We train a system on the gold train set (total 30,367 samples). We use early stopping with a patience of 5 over the

| M&A buyer | target | industry | crawl start-end dates | samples | outcome | labels |
|-----------|--------|----------|-----------------------|---------|---------|--------|
| ABT_STJ   | Abbott Lab. | St. Jude | pharma               | 09/12/14 | 12,829  | success | yes |
| AVGQ_QCOM | Broadcom | Qualcomm | broadband            | 09/09/14 | 22,667  | success | yes |
| BMY_CELEG | Celgene  | pharma   | 04/03/13              | 10/07/19 | 3,940   | failure | no  |
| CHTR_TWC  | Charter Com | Time W. Cable | broadband | 01/01/14 | 13,061  | success | no  |
| CLN_HUN   | Clariant  | Huntsman | chemicals            | 01/01/17 | 836     | failure | no  |
| CMSA_TWC  | Comcast   | Time W. Cable | broadband | 01/04/13 | 23,672  | failure | no  |
| CTL_LVLT  | CenturyLink | Level 3 | technology          | 01/01/16 | 1,524   | success | no  |
| DELL_EMCE | Dell      | EMC      | technology           | 11/06/14 | 7,978   | success | no  |
| HAL_BHGE  | Halliburton | Baker Hughes | oil industry | 01/12/13 | 6,386   | failure | no  |
| IBM_RHT   | IBM       | Red Hat  | technology           | 01/03/18 | 16,106  | success | no  |
| MDFT_COV  | Medtronic | Covidien | pharma               | 01/05/14 | 5,608   | success | no  |
| MSFT_LNKD | Microsoft | LinkedIn | pharma               | 06/01/16 | 15,107  | success | no  |
| TMUS_S    | T-Mobile  | Sprint   | broadband            | 01/04/17 | 24,559  | success | no  |
| VIBAB_CBS | Viacom    | CBS Corp | entertainment        | 01/09/16 | 12,934  | success | no  |
| VPS_AGNC  | Abbott    | Allergan | pharma               | 01/09/12 | 2,740   | success | no  |
| WATSR_CRX | Actavis   | Warner Chilcott | pharma | 01/04/13 | 613     | success | no  |

Table 1: M&A operations considered in this work. Operations before the horizontal line are unlabeled. Operations followed by: * are part of the WT–WT corpus; â are used for testing. Note that some companies (WATS, AETNA and CI) appear in different operations.

| Train Set | Sup | Rel | Com | Unr |
|-----------|-----|-----|-----|-----|
| –         | 14.52 | 11.87 | 37.43 | 36.16 |

Table 2: Label distribution of: the training set, the test sets and the synthetically labeled data. The second column reports the merger’s outcome (Success/Fail/Tbd). See Appendix A for a complete list of companies.


Table 3: Results of SD on the three test sets (one ID and two OOD), when selecting synthetic data of different types; as recommended when dealing with unbalanced class distribution (Hanselowski et al., 2018), we report on macro-averaged precision, recall and $F_1$ score; the last four columns report on single label accuracy.

Table 4: Results of SD on the OOD test sets, selecting synthetic data annotated with different stances (3rd col).

heldout data. The system achieved an $F_1$ score of 78.33 on the heldout data. Then, the unla-

beld data is annotated using the trained system. The predicted label distribution reflects the actual 

merger output (Table 2). Refer to Table 5 (Ap-

pendix A) for qualitative examples of correctly 

and wrongly synthetically annotated samples.

5 Experiments and Discussion

Baseline. Table 3 reports on results without using any synthetic data. As expected, we observe a no-

table gap in generalization performance between the ID healthcare test set and the OOD test sets.

Experiment I. To understand the impact of including different types of synthetic data during training, we consider three settings:

(1) related mergers: adding synthetic data from mergers which are ID w.r.t. the considered test set (we select ID mergers for each test set according to similarities between industries, see Appendix A);

(2) succeeded mergers: adding data from mergers which were successful: such mergers tend to better 

match the distribution of the test mergers, as all of 

them succeeded;

(3) all mergers: adding data from all synthet-

ically annotated mergers: this last setting was implemented to test whether synthetically anno-

tated data, even if not perfectly ID w.r.t. the test-

set, could have a positive regularization function 

beyond DA (as hypothesized by Sennrich et al. 

2016) in the context of Machine Translation).

For experiments, we randomly add synthetic sam-

ples with a proportion of 50% w.r.t. the train set 

to account for uncertainty, we use sample 

weighting for synthetic samples: sup, ref and com 

are weighted 0.6, while unr are weighted 0.2 (after 

qualitative analysis, we found them to be noisier).

Results in Table 3 show that adding synthetic 

samples leads to improvements in generalization 

over OOD test sets in all considered settings (up

184
to +3.4 in $F_1$ score for $\text{FOXA\_DIS}$ and up to +5.1 for $\text{UTX\_COL}$; note that results on $\text{UTX\_COL}$ without synthetic data were significantly lower than on $\text{FOXA\_DIS}$). This is in line with previous results on semi-supervised learning investigating other tasks, such as sentiment analysis (Blitzer et al., 2007) or text categorization (Ando and Zhang, 2005). Interestingly, synthetic samples didn’t bring any improvement to the ID test set; moreover, best results overall were obtained with the related merger setting: this seems to indicate that synthetic data act as a powerful domain adaptation technique rather than as a regularizer alone, this is in line with findings in Machine Translation (Edunov et al., 2018).

**Experiment II.** We consider the best performing setting, related mergers, and perform a second set of experiments to understand the impact of adding synthetic samples belonging to different stances; we consider: only $\text{unr}$; only $\text{com}$; only $\text{unr+com}$; $\text{sup+ref+com}$; $\text{sup+ref}$; and finally adding samples from all stances. Differences in performance between settings are negligible (Table 4). Concerning single labels, synthetic samples had the most significant impact on $\text{unr}$ not only for OOD test sets (up to +39.7 in accuracy for $\text{FOXA\_DIS}$ and +4.5 for $\text{UTX\_COL}$), but even for ID (+18.44).

**Experiment III.** We run a final set of experiments to investigate the relation between performance and the amount of synthetic data considered. For both operations (Figure 2), we observe that improvements in $F_1$ score are supported by a rise in recall which reaches a plateau around 30% and, for $\text{UTX\_COL}$, in precision.

### 6 Conclusions and Future Work

We investigated an inexpensive framework to integrate unlabeled ID data to improve cross-target SD. We studied Twitter SD and showed, through a comprehensive set of experiments, that it is a promising strategy. We reserve to study its applicability to other domains in future work.

### Acknowledgments

We thank the anonymous reviewers for their efforts and for the constructive suggestions. We gratefully acknowledge funding from the Keynes Fund, University of Cambridge (grant no. JHOQ). CC is grateful to NERC DREAM CDT (grant no. 1945246) for partially funding this work. CG and FT are thankful to the Cambridge Endowment for Research in Finance (CERF).

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Appendix A: Details on Data

Table 5 reports examples of correctly and wrongly synthetically labeled samples.

Appendix B: Details on Modeling

For each test set, we include synthetically annotated tweets from a number of related mergers. Related mergers have been manually selected by an expert in the Economics domain, based on industry similarity.

| M&A          | correct | predicted | tweet text                                                                 |
|--------------|---------|-----------|-----------------------------------------------------------------------------|
| IBM_RHT      | support | support   | IBM Completes Red Hat Deal the Largest Software Acquisition Ever <URL> via Barronsonline |
| AVGO_QCOM    | refute  | refute    | EU’s $1.2-Billion Fine Against Qualcomm Might Complicate Broadcom’s Bid <URL> |
| MSFT_LNKD    | comment | comment   | Bill Gates believes #Microsoft Can Make #LinkedIn as Successful as #Facebook <URL> |
| DELL_EMC     | unrelated| unrelated | Synnex reaches agreement with Dell for Canadian distribution <URL>            |
| DELL_EMC     | comment | support   | The largest tech deal in history is like mating elephants? Really. #dellme <URL> |
| IBM_RHT      | comment | unrelated | IBM and Red Hat Explained #ibm – <URL>                                     |
| MDT_COV      | support | refute    | Medtronic’s proposed $43B acquisition of Covidien has cleared all anti-trust hurdles worldwide <URL> |
| MSFT_LNKD    | comment | unrelated | How Microsofis bid for LinkedIn sets a standard for every business to copy <URL> |
| DELL_EMC     | support | unrelated | Dell to acquire EMC in $67 billion record tech deal <URL> #CloudComputing     |
| MDT_COV      | support | comment   | Medtronic is still in on Covidien buyout – MassDevice <URL>                 |

Table 5: Examples of correctly and wrongly synthetically annotated tweets.