Cross-domain Soft Patterns for Sentiment Analysis

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Abstract

This report describes experiments

1 Introduction

The objective of domain adaptation techniques is to adapt a hypothesis trained on a source data distribution so that it can perform well on a related target distribution. These techniques have been applied to a variety of NLP tasks such as sentiment analysis (Blitzer et al., 2007; McAuley and Leskovec, 2013; McAuley et al., 2015; Ruder and Plank, 2018), style transfer in text generation (Fu et al., 2018; Yang et al., 2018; Peng et al., 2018), textual and visual question answering (Chao et al., 2018; Zhao and Liu, 2018), and machine translation (Etchegoyhen et al., 2018; Britz et al., 2017), to name a few.

In the case of sentiment analysis of user reviews, the idea is to leverage large amounts of data available for certain product categories and domain adaptation techniques

what is sent analizis

why is domain adp important for sent analisis

In this report, we focus on unsupervised domain adaptation for the task of sentiment analysis, transfering from a single source domain into a single target domain.

what we are introducing build upon —

on what data, which domains, method, contributions?

2 Related Work

sopa does well on sent analisis on one-domain

how prev work struggled because of vocabulary mismatch

sopa's flexibility to match patterns with * or missing elements –¿ chance to explicitly model vocab mismatch

3 Domain Adaptation with Soft Patterns

explain training proc here

4 Experimental Setup

We build upon the implementation of SoPa introduced by Schwartz et al. (2018).[1] All models are implemented in PyTorch[2].

4.1 Dataset

We use the provided dataset, a balanced subset of the reviews data extracted by McAuley et al. (2015). The data consists of users reviews on two domains –movies and TV, and games–, extracted from Amazon. We use Movies & TV category as source domain and Games as target domain. We extract a development subset from the source domain and further divide the target domain's data into unlabeled, development, and test splits. Table 1 presents the sizes of each split considered in the experiments.

4.2 Training of source domain

We use pre-trained 300-dimensional GloVe 840B embeddings Pennington et al. (2014) normalized to unit length. Training was performed using Adam (Kingma and Ba, 2014) as optimizer.

For hyper-parameter tunning, we resort to a subset of the training and development source data, consisting of 10,000 and 5,000 instances, respectively. These subsets were sampled following a uniform distribution without replacement. We use a Tree-structured Parzen Estimator (TPE) optimization model over 30 iterations[3]. Table 2 shows the range of hyper-paramter values explored and their optimal values.

[1] https://github.com/Noahs-ARK/soft_patterns

[2] https://pytorch.org/

[3] We use HyperOpt library (http://hyperopt.github.io/hyperopt/)

Domain	Train	Dev	Test	Unlabeled
Movies & TV (src)	89,998	17,999	10,000	-
Games (tgt)	-	5,000	11,142	5,000

Table 1: Size of data splits in source (src) and target (tgt) domains.

Hyper-parameter	Range	Optimal
Patterns	{6:10, 5:10, 4:10, 3:10, 2:10}, {6:10, 5:10, 4:10}	{6:10, 5:10, 4:10}
Learning rate	10^{-9}–10^{-2}	0.00015
Dropout	0–0.2	0.0017
MLP hid. dim.	100–300	100
Batch size	10–64	20

Table 2: Range and optimal values of hyper-parameters tuned.

4.3 Self-training of target domain

5 Results and Discussion

References

John Blitzer, Mark Dredze, and Fernando Pereira. 2007. Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In *Proceedings of the 45th annual meeting of the association of computational linguistics*, pages 440–447.

Denny Britz, Quoc Le, and Reid Pryzant. 2017. Effective domain mixing for neural machine translation. In *Proceedings of the Second Conference on Machine Translation*, pages 118–126.

Wei-Lun Chao, Hexiang Hu, and Fei Sha. 2018. Cross-dataset adaptation for visual question answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5716–5725.

Thierry Etchegoyhen, Anna Fernández Torné, Andoni Azpeitia, Eva Martínez Garcia, and Anna Matamala. 2018. Evaluating domain adaptation for machine translation across scenarios. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC-2018)*.

Zhenxin Fu, Xiaoye Tan, Nanyun Peng, Dongyan Zhao, and Rui Yan. 2018. Style transfer in text: Exploration and evaluation. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

Julian McAuley and Jure Leskovec. 2013. Hidden factors and hidden topics: understanding rating dimensions with review text. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 165–172. ACM.

Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 43–52. ACM.

Nanyun Peng, Marjan Ghazvininejad, Jonathan May, and Kevin Knight. 2018. Towards controllable story generation. In *Proceedings of the First Workshop on Storytelling*, pages 43–49, New Orleans, Louisiana. Association for Computational Linguistics.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 1532–1543.

Sebastian Ruder and Barbara Plank. 2018. Strong baselines for neural semi-supervised learning under domain shift. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1044–1054.

Roy Schwartz, Sam Thomson, and Noah A Smith. 2018. Sopa: Bridging cnns, rnns, and weighted finite-state machines. In *Proceedings of ACL*.

Zichao Yang, Zhiting Hu, Chris Dyer, Eric P Xing, and Taylor Berg-Kirkpatrick. 2018. Unsupervised Text Style Transfer using Language Models as Discriminators. In S Bengio, H Wallach, H Larochelle, K Grauman, N Cesa-Bianchi, and R Garnett, editors, *Advances in Neural Information Processing Systems 31*, pages 7287–7298. Curran Associates, Inc.

Helen Jiahe Zhao and Jiamou Liu. 2018. Finding answers from the word of god: Domain adaptation for neural networks in biblical question answering. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.