SSMBA: Self-Supervised Manifold Based Data Augmentation for Improving Out-of-Domain Robustness

집현전 중급반
https://github.com/jiphyeonjeon

발표자 : 박동주
https://github.com/toriving

About

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SSMBA: Self-Supervised Manifold Based Data Augmentation for Improving Out-of-Domain Robustness

Nathan Ng
University of Toronto
Vector Institute

Kyunghyun Cho
New York University

Marzyeh Ghassemi
University of Toronto
Vector Institute

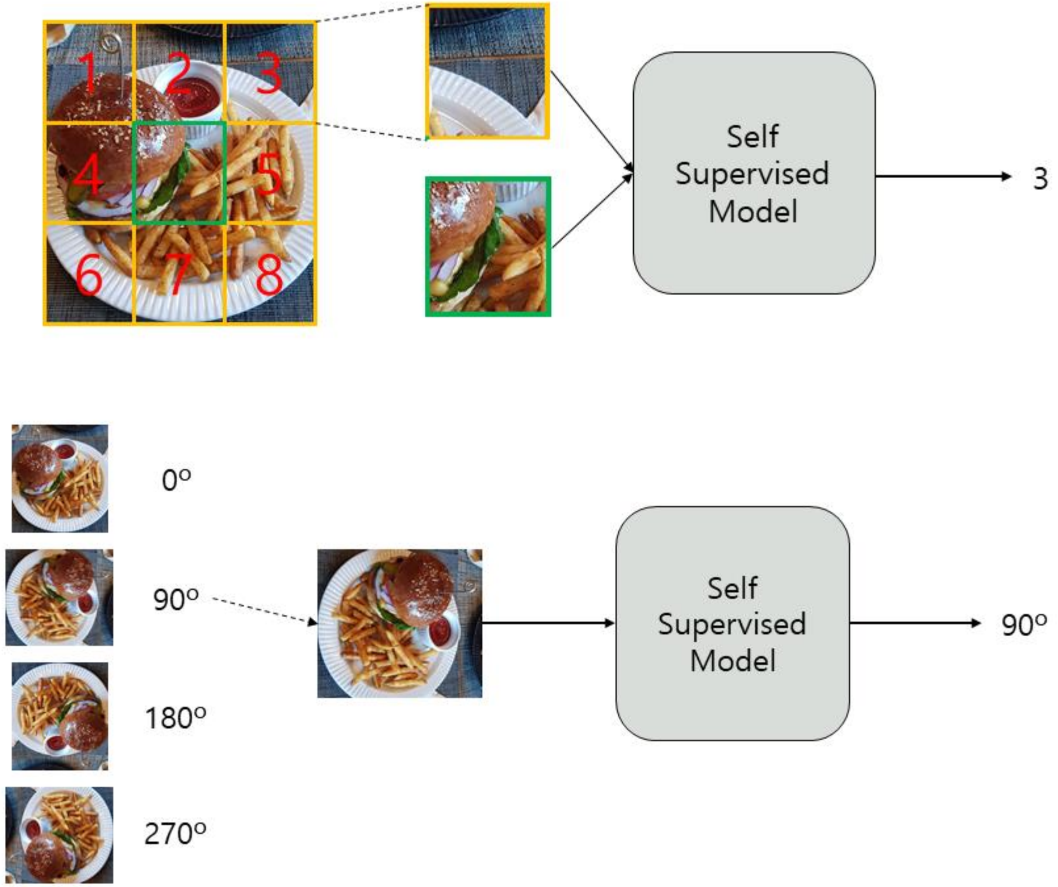
EMNLP2020 – Long paper

Topic : Data augmentation

Paper : https://www.aclweb.org/anthology/2020.emnlp-main.97.pdf
Code : https://github.com/nng555/ssmba

Self-Supervised Learning – Computer Vision

Input image



Self-Supervised Learning – Natural Language Processing

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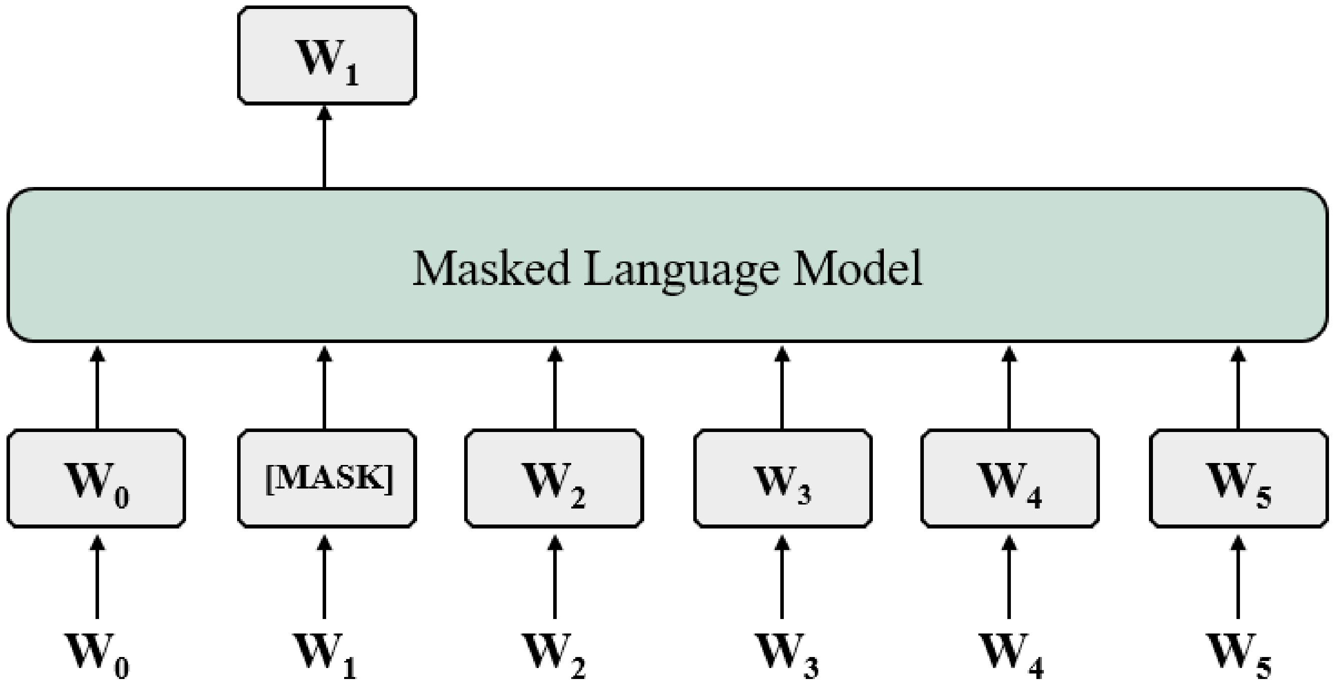
Natural Language Processing



Data Augmentation – Computer Vision

Original

Blur

Noise

Translation

Horizontal flip

Vertical flip

Rotation

Data Augmentation – Computer Vision

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255	255	255
0	0	255
0	0	255

Rotation

255	255	255
255	0	0
255	0	0

Data Augmentation – Computer Vision

Data Augmentation – Natural Language Processing

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vertical-flip

brighten

coarse-salt

I go to school by bus

I go to school by bus

I go to ????? by bus

Data Augmentation – Natural Language Processing

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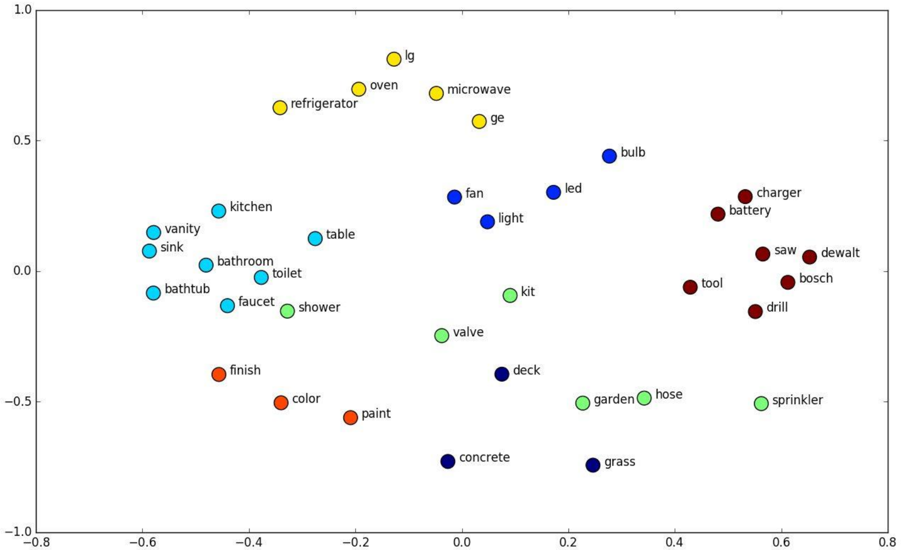
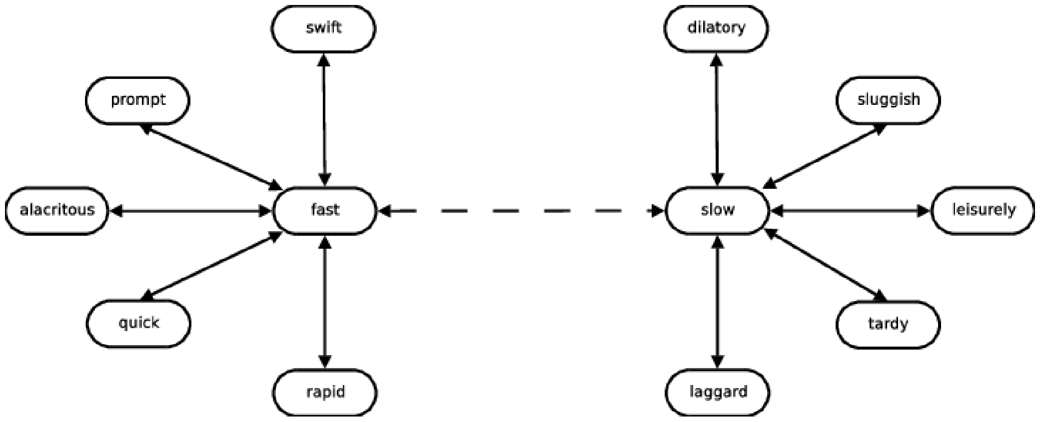
255	255	255
0	0	255
0	0	255

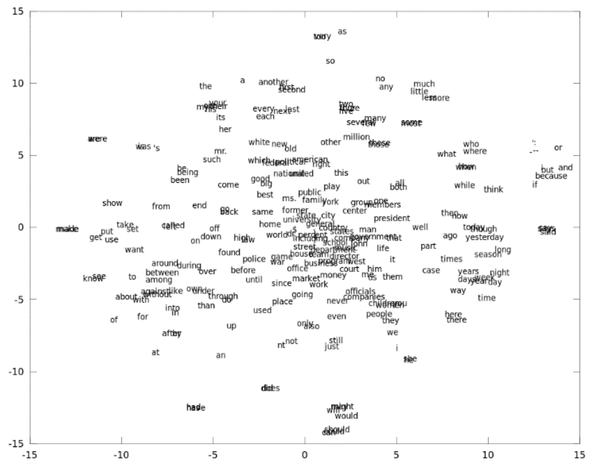
$$W(\text{``cat''}) = (0.2,\ \text{-}0.4,\ 0.7,\ \dots)$$

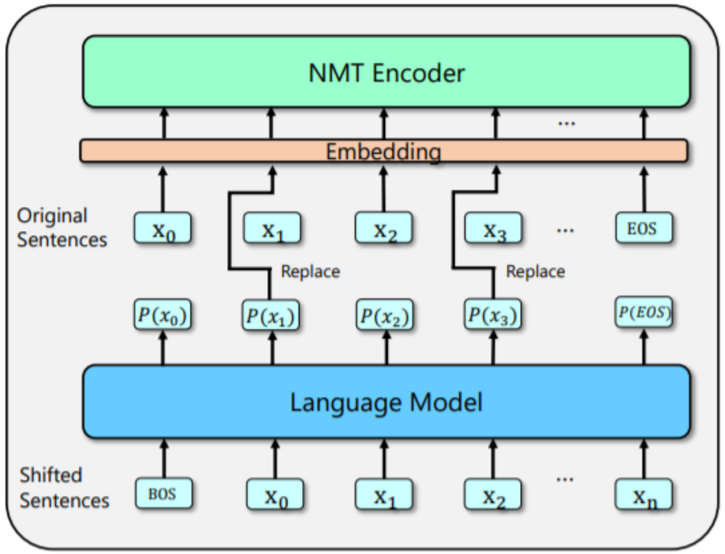
$$W(\text{``mat''}) = (0.0,\ 0.6,\ \text{-}0.1,\ \dots)$$



Data Augmentation – Natural Language Processing







Introduction

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- Training distributions often do not cover all of the test distributions we would like a supervised classifier or model to perform well on.

- Therefore, a key challenge in training machine learning models in these settings is ensuring they are robust to unseen examples.

- If data concentrates on a low-dimensional manifold then these synthetic examples should lie in a manifold neighborhood of the original examples.

- However, in domains such as natural language, it is much more difficult to find a set of invariances that preserves meaning or semantics.

Introduction

- Self-Supervised Manifold Based Data Augmentation (SSMBA): a data augmentation method for generating synthetic examples in domains where the data manifold is difficult to heuristically characterize.

- Motivation : Denoising auto-encoders
    - Corruption fuction : Stochastically perturb examples *off* the data manifold
    - Reconstruction function : Project them *back* on.

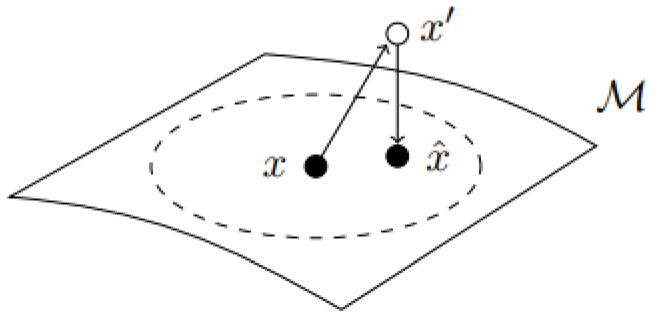


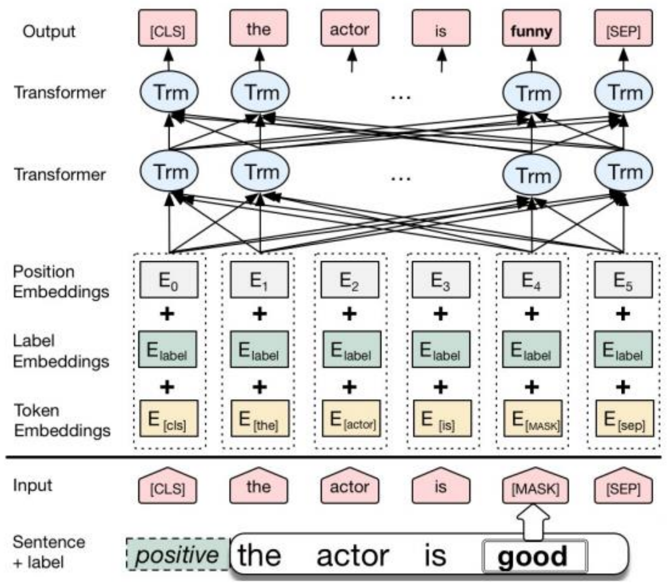
Figure 1: SSMBA moves along the data manifold $\mathcal{M}$ by using a corruption function to perturb an example x off the data manifold, then using a reconstruction function to project it back on.

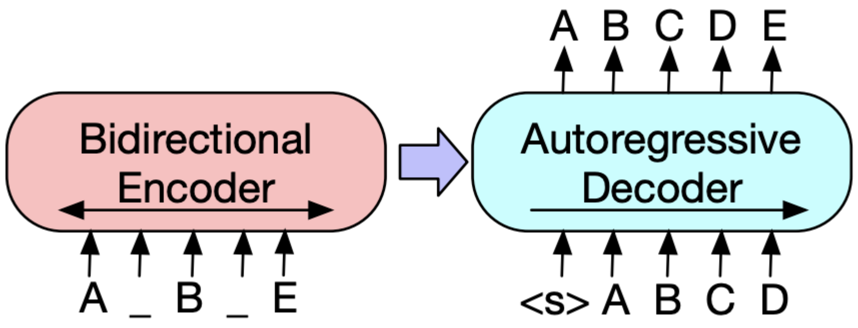
Background and Related Work

Data Augmentation in NLP

- Existing work on improving generalization has focused on data augmentation, where synthetically generated training examples are used to augment an existing dataset.

- It is hypothesized that these examples induce robustness to local perturbations, which has been shown to be effective in semi-supervised and self-supervised settings.





Background and Related Work

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VRM and the Manifold Assumption

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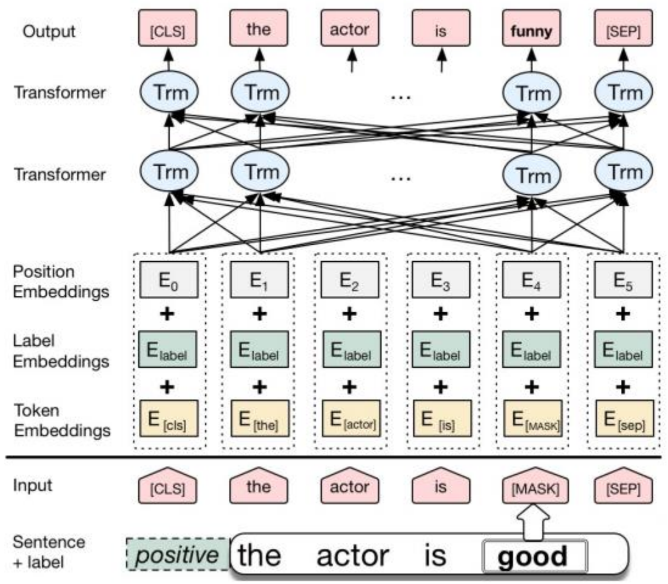

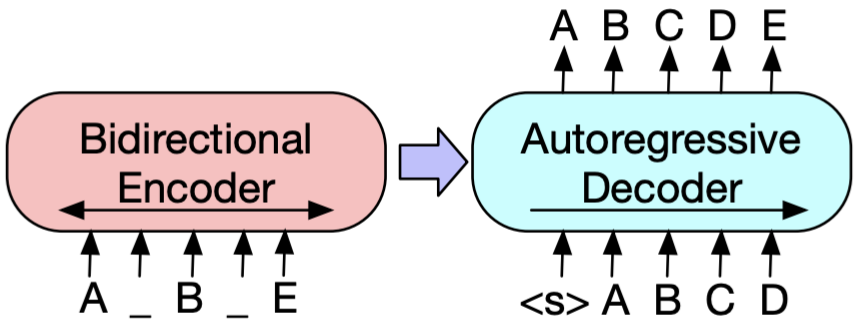

Background and Related Work

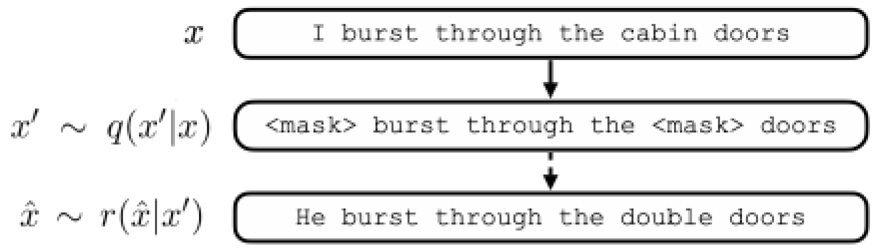

Figure 2: To sample from an MLM DAE, we apply the MLM corruption q to the original sentence then reconstruct the corrupted sentence using our DAE r.

Data Augmentation – Natural Language Processing

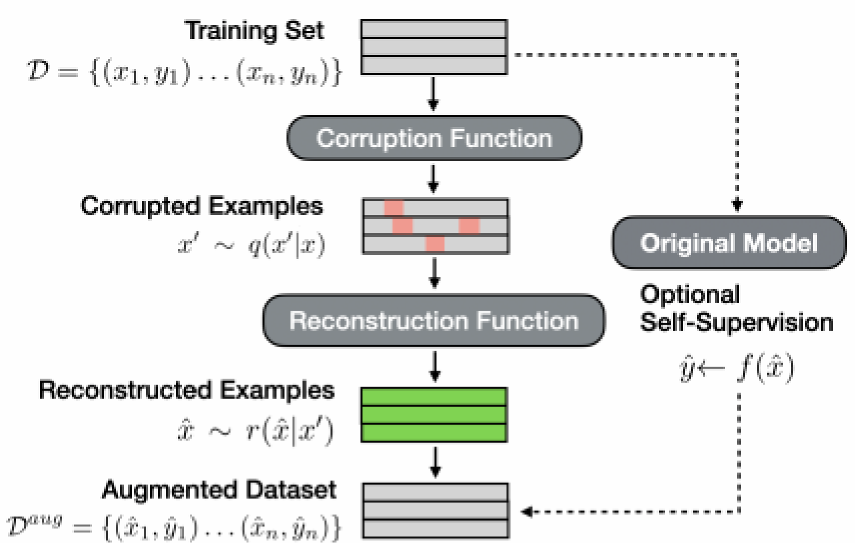

Figure 3: SSMBA generates synthetic examples by corrupting then reconstructing the original training inputs. To form the augmented dataset, corresponding outputs are preserved from the original data or generated from a supervised model f trained on the original data.

Data Augmentation – Natural Language Processing

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Algorithm 1 SSMBA

Require: perturbation function q
reconstruction function r
Input: Dataset $\mathcal{D} = \{(x_1, y_1) \dots (x_n, y_n)\}$
number of augmented examples m
function SSMBA($\mathcal{D}$, m)
    train a model f on $\mathcal{D}$
    for $(x_i, y_i) \in \mathcal{D}$ **do**
        for $j \in 1 \dots m$ **do**
            sample perturbed $x'_{ij} \sim q(x'|x_i)$
            sample reconstructed $\hat{x}_{ij} \sim r(\hat{x}|x'_{ij})$
            generate $\hat{y}_{ij} \leftarrow f(\hat{x}_{ij})$ or preserve the original y_i
        end for
    end for
    let $\mathcal{D}^{aug} = \{(\hat{x}_{ij}, \hat{y}_{ij})\}_{i=1\dots n, j=1\dots m}$
    augment $\mathcal{D}' \leftarrow \mathcal{D} \cup \mathcal{D}^{aug}$
    return $\mathcal{D}'$
end function

Data Augmentation _Natural Language Processing

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Dataset	Domain	n	l	Train	Test
AR-Clothing	*	4	35	25k†	2k
AR-Full	*	10	67	25k†	2k
Yelp	*	4	138	25k†	2k
Movies	SST2	-	11	66k	1k
	IMDb	-	296	46k	2k
MNLI	*	10	36	80k	1k
ANLI	R1	-	92	17k	1k
	R2	-	90	46k	1k
	R3	-	82	100k	1k
IWSLT	-	1	24	160k	7k
OPUS	Medical	5	15	1.1m	2k
de-rm	Law	-	22	100k	2k
	Blogs	-	25	-	2k

Table 1: Dataset summary statistics. n: number of domains. l: average tokenized input length. A * in the domain column indicates that the statistics are identical across domains within that dataset. Training sets marked with a † are sampled randomly from a larger dataset. Refer to Appendix A for more information.

Data Augmentation – Natural Language Processing

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		AR-Full		AR-Clothing		Movies		Yelp		Average	
Model	Augmentation	ID	OOD	ID	OOD	ID	OOD	ID	OOD	ID	OOD
RNN	None	69.46	66.32	69.25	67.80	90.74	71.94	62.51	61.28	70.16	66.17
	EDA	67.32	64.47	66.87	65.21	88.43	68.3	58.39	57.19	67.56	63.55
	CBERT	69.94	66.77	69.56	68.10	**91.01**	72.11	63.17	61.75	70.17	66.57
	UDA	69.92	66.97	69.98	68.24	90.05	69.73	63.40	62.13	70.64	66.53
	SSMBA	**70.38** *†	**67.41** *†	**70.19**	**68.60** *†	89.61	**73.20**	**63.85**	**62.83** *†	**70.96**	**67.31**
CNN	None	70.67	67.64	70.14	68.52	92.92	72.11	65.13	64.46	71.68	67.63
	EDA	68.52	66.03	67.76	66.17	91.22	74.20	60.99	59.88	69.13	65.65
	CBERT	70.62	67.70	70.13	68.23	92.92	71.56	65.09	64.19	71.65	67.49
	UDA	70.80	68.06	70.29	68.70	92.63	72.55	65.22	64.32	71.77	67.89
	SSMBA	**71.10** *	**68.18** *	**70.74**	**69.04** *	**92.93**	**74.67**	**65.59**	**64.81** *†	**72.11**	**68.33**

Table 2: Average in-domain (ID) and out-of-domain (OOD) accuracy (%) for models trained on sentiment analysis datasets. Average performance across datasets is weighted by number of domains contained in each dataset. Accuracies marked with a $*$ and $\dagger$ are statistically significantly higher than unaugmented models and the next best model respectively, both with $p < 0.01$.

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	MNLI		ANLI	
Augmentation	ID	OOD	ID	OOD
None	84.29	80.61	42.54	**43.80**
EDA	83.44	80.34	45.59	42.77
CBERT	84.24	80.34	46.68	43.53
UDA	84.24	80.99	45.85	42.89
SSMBA	**85.71**	**82.44***†	**48.46***†	**43.80**

Table 3: Average in-domain and out-of-domain accuracy (%) for RoBERTa models trained on NLI tasks. Accuracies marked with a $*$ and $\dagger$ are statistically significantly higher than unaugmented models and the next best model respectively, both with $p < 0.01$.

System	BLEU
ConvS2S (Edunov et al., 2018)	32.2
Transformer (Wu et al., 2019a)	34.4
DynamicConv (Wu et al., 2019a)	35.2
Transformer (ours)	34.70
+ Word Dropout	34.43
+ RAML	35.00
+ SwitchOut	35.28
+ SSMBA	**36.10***†

Table 4: Results on IWSLT de→en for models trained with different data augmentation methods. Scores marked with a $*$ and $\dagger$ are statistically significantly higher than baseline transformers and the next best model, both with $p < 0.01$.

Data Augmentation – Natural Language Processing

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	OPUS		de→rm	
Augmentation	ID	OOD	ID	OOD
None	**56.99**	10.24	51.53	12.23
Word Dropout	56.26	10.15	50.23	12.23
RAML	56.76	10.10	51.52	12.49
SwitchOut	55.50	9.27	51.34	13.59
SSMBA	54.88	**10.65**	**51.97**	**14.67***†

Table 5: Average in-domain and out-of-domain BLEU for models trained on OPUS (de→en) and de→rm data. Scores marked with a $*$ and $\dagger$ are statistically significantly higher than baseline transformers and the next best model, both with $p < 0.01$.

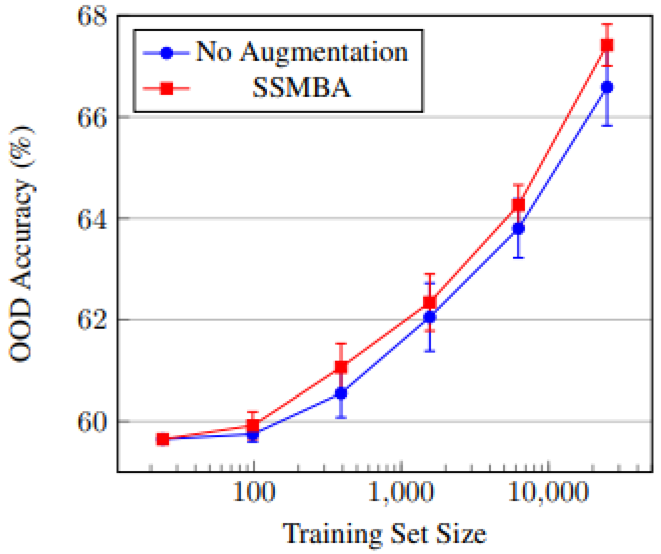

Figure 4: OOD accuracy of models trained on successively subsampled datasets. The full training set contains 25k examples. Error bars show standard deviation in OOD accuracy across models.

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	Distil	Base	Large
OOD Accuracy Boost (%)	0.73	0.78	0.78

Table 6: Boost in OOD accuracy (%) of models trained with SSMBA augmented data generated with different reconstruction functions.

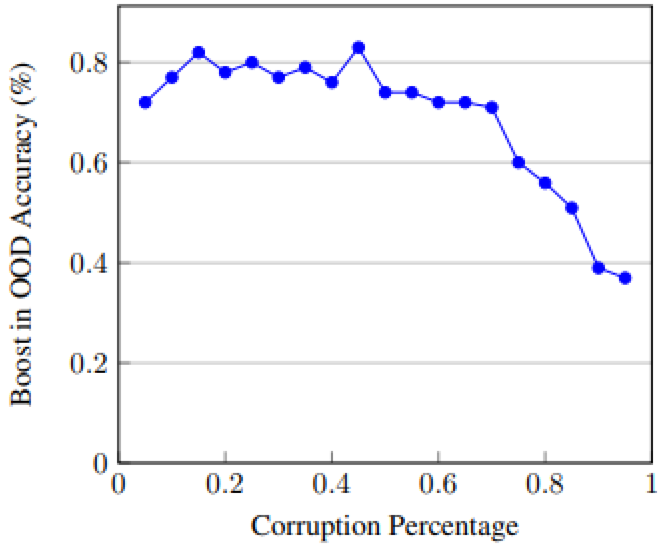

Figure 5: Boost in OOD accuracy (%) of models trained with SSMBA augmentation applied with different percentages of corrupted tokens.

Data Augmentation – Natural Language Processing

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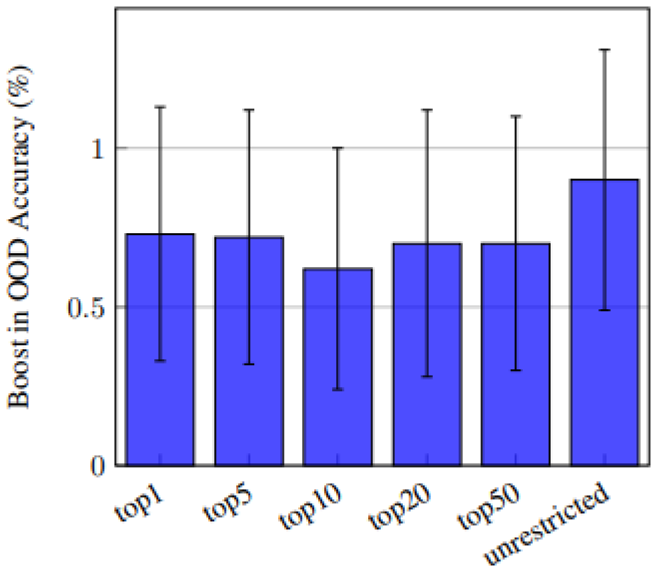

Figure 6: Boost in OOD accuracy (%) of models trained with SSMBA augmentation using different sampling methods. Error bars show standard deviation in OOD accuracy across models.

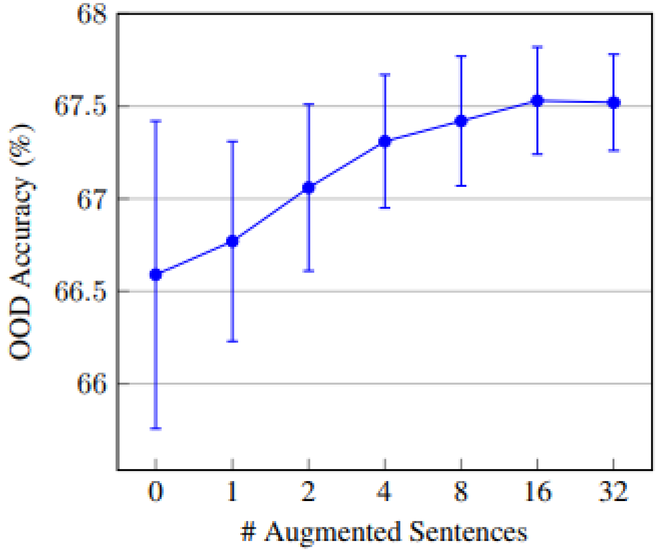

Figure 7: OOD accuracy (%) of models trained with different amounts of SSMBA augmentation. 0 augmentation corresponds to a baseline model. Error bars show standard deviation in OOD accuracy across models.

Data Augmentation – Natural Language Processing

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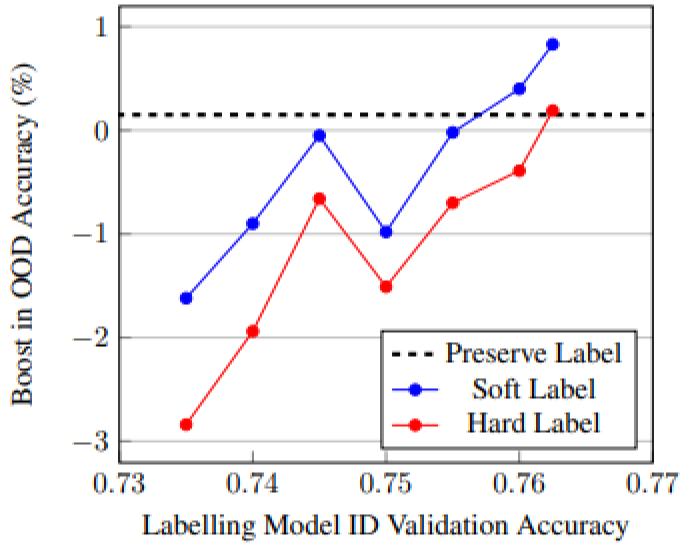

Figure 8: Boost in OOD accuracy (%) of models trained with augmented data labelled with different supervision models and label generation methods.