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

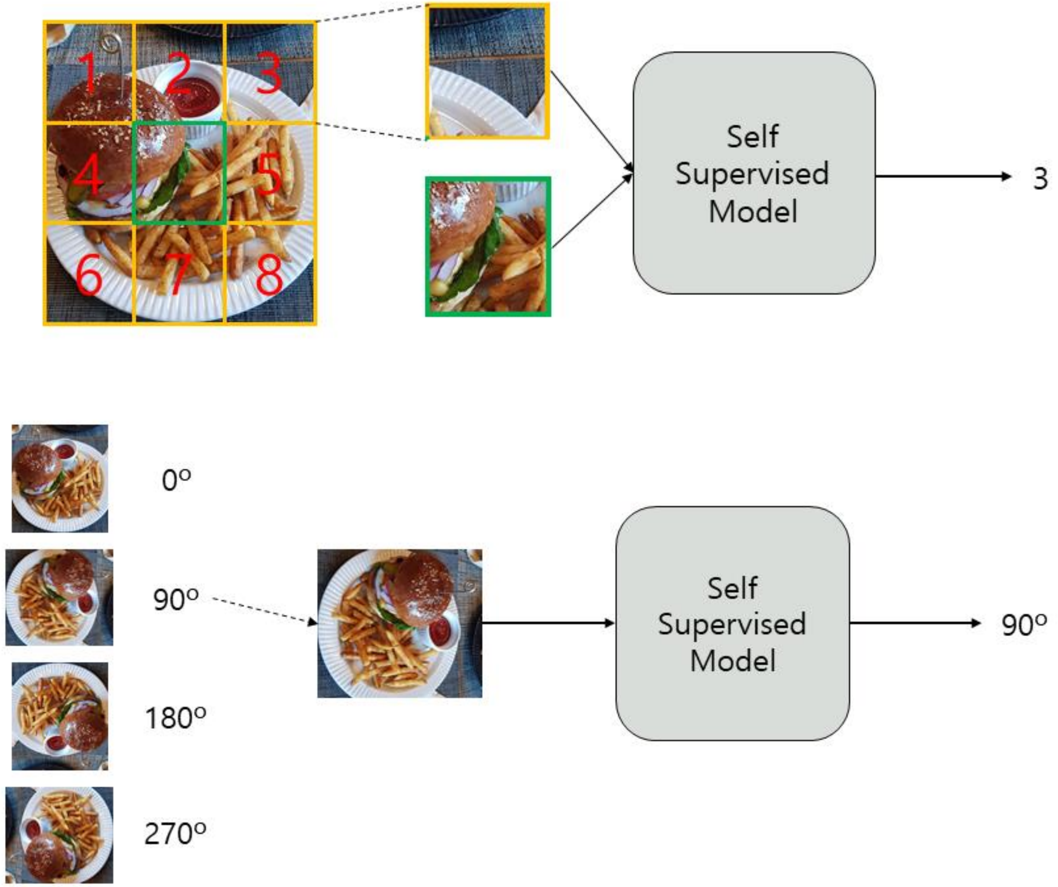
EMNLP2020 – Long paper

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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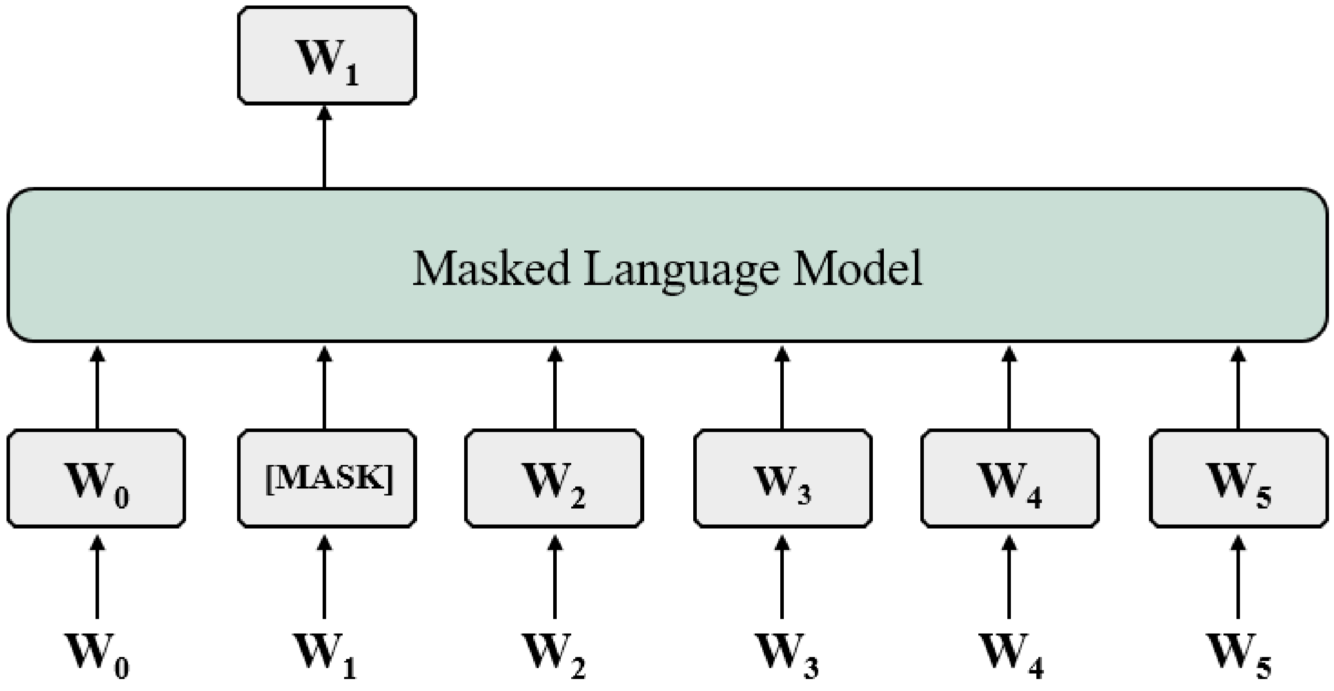
Natural Language Processing



Data Augmentation – Computer Vision

Original

Blur

Noise

Translation

Horizontal flip

Vertical flip

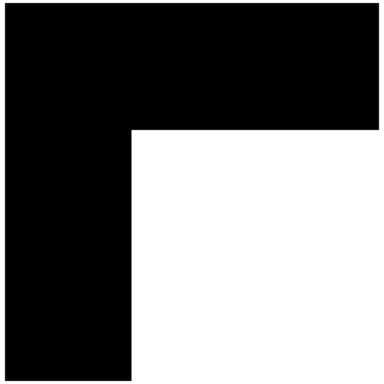
Rotation

Data Augmentation – Computer Vision

255	255	255
0	0	255
0	0	255

Rotation

255	255	255
255	0	0
255	0	0



Data Augmentation – Computer Vision

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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

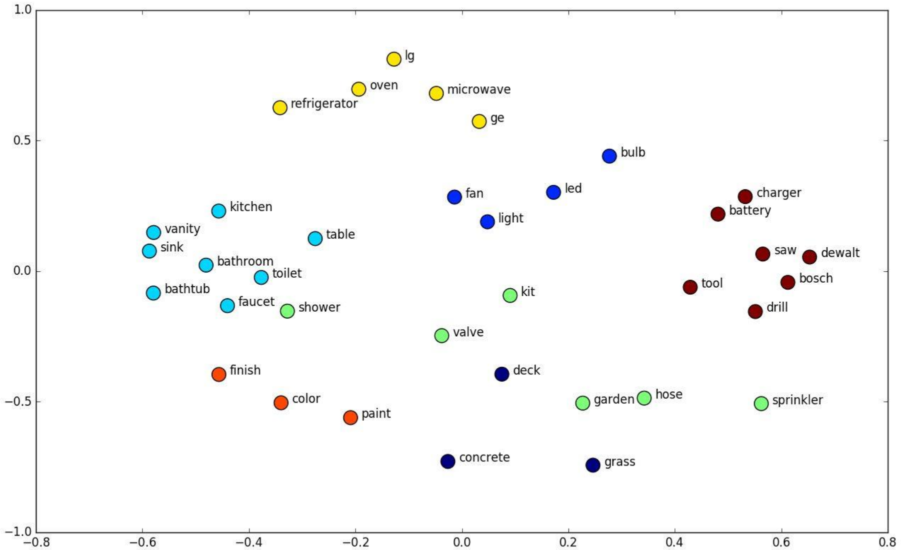
I go to ????? by bus

Data Augmentation – Natural Language Processing

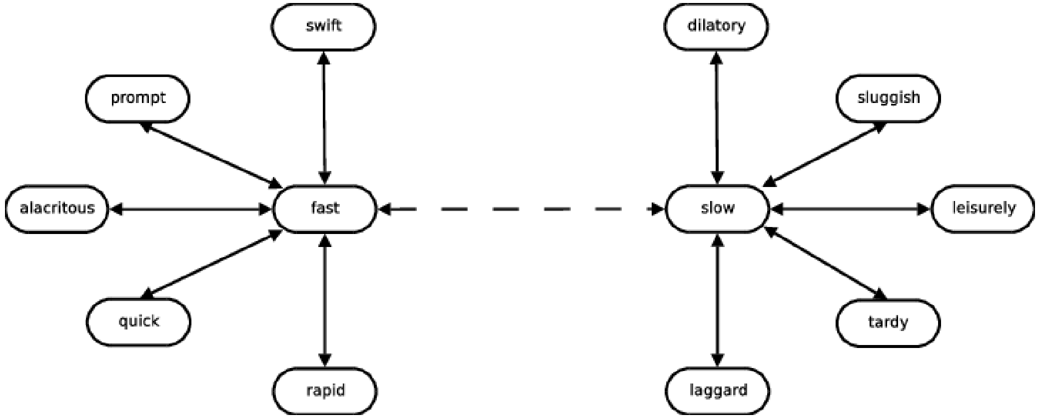
255	255	255
0	0	255
0	0	255

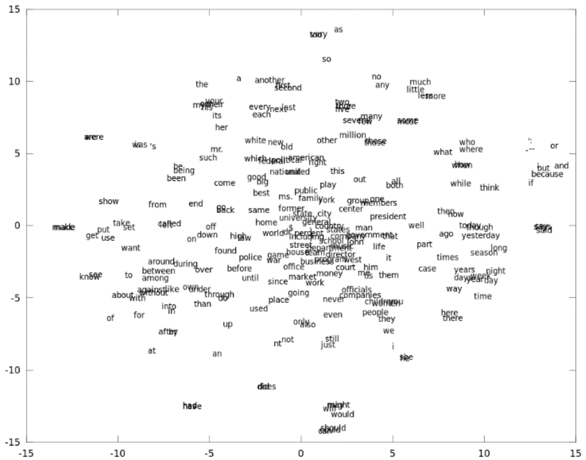
$$W(\text{“cat”}) = (0.2,\ \text{-}0.4,\ 0.7,\ \ldots)$$

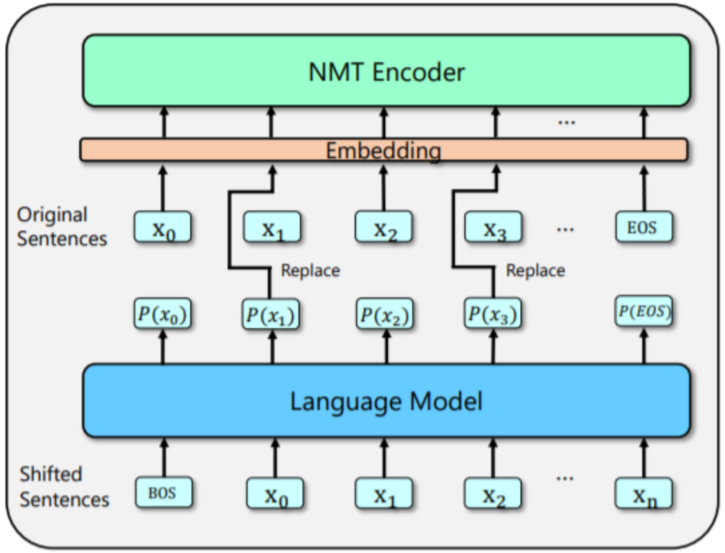
$$W(\text{“mat”}) = (0.0,\ 0.6,\ \text{-}0.1,\ \ldots)$$



Data Augmentation – Natural Language Processing







Introduction

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Introduction

- 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

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- 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.

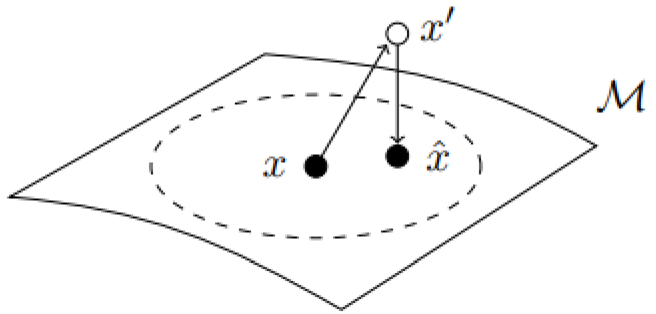


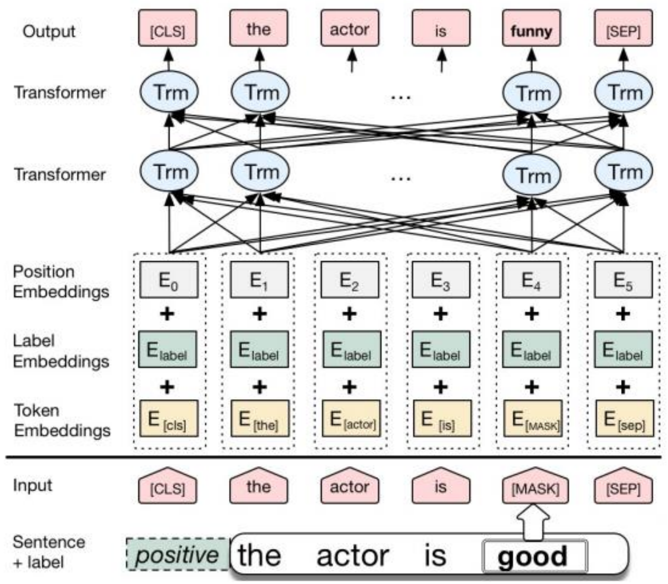
Figure 1: SSMBA moves along the data manifold $\mathcal{M}$ by using a corruption function to perturb an example x off the data manifold, then using a reconstruction function to project it back on.

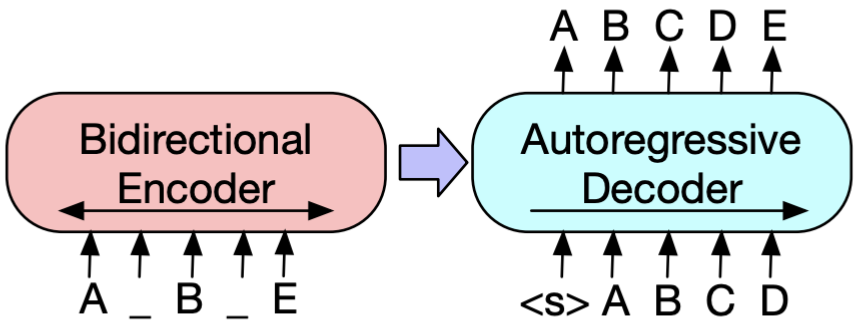
Background and Related Work

1. 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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1. VRM and the Manifold Assumption

- Vicinal Risk Minimization (VRM) formalizes data augmentation as enlarging the training set support by drawing samples from a vicinity of existing training examples.

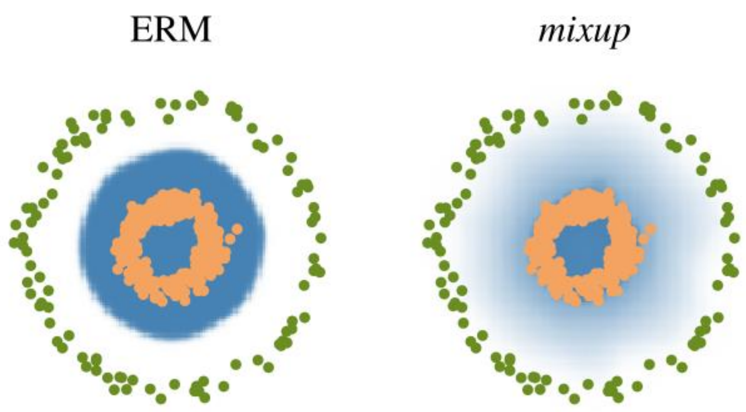
- Expected risk : $R(f) = \int \ell(f(x), y) \mathrm{d}P(x, y).$

- Empirical risk : $R_\delta(f) = \int \ell(f(x), y) \mathrm{d}P_\delta(x, y) = \frac{1}{n} \sum_{i=1}^{n} \ell(f(x_i), y_i).$

$$P_\delta(x, y) = \frac{1}{n} \sum_{i=1}^{n} \delta(x = x_i, y = y_i)$$

- Vicinal risk : $R_\nu(f) = \frac{1}{m} \sum_{i=1}^{m} \ell(f(\tilde{x}_i), \tilde{y}_i).$

$$P_\nu(\tilde{x}, \tilde{y}) = \frac{1}{n} \sum_{i=1}^{n} \nu(\tilde{x}, \tilde{y} | x_i, y_i)$$



Background and Related Work

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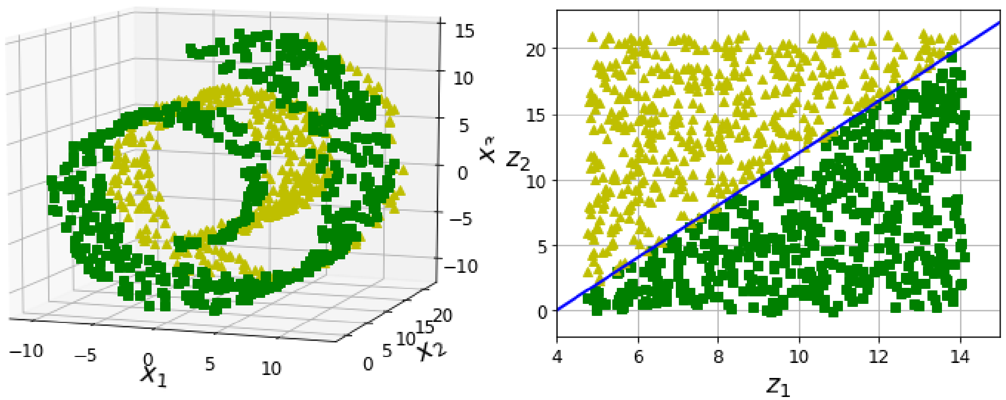
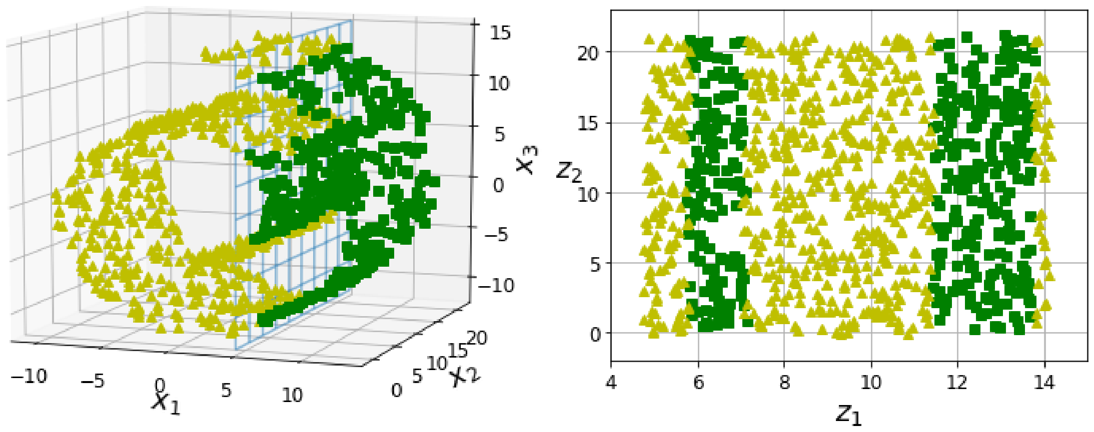
2. VRM and the Manifold Assumption

- The manifold assumption states that high dimensional data concentrates around a low-dimensional manifold.

- This assumption allows us to define the vicinity of a training example as its manifold neighborhood, the portion of the neighborhood that lies on the data manifold.



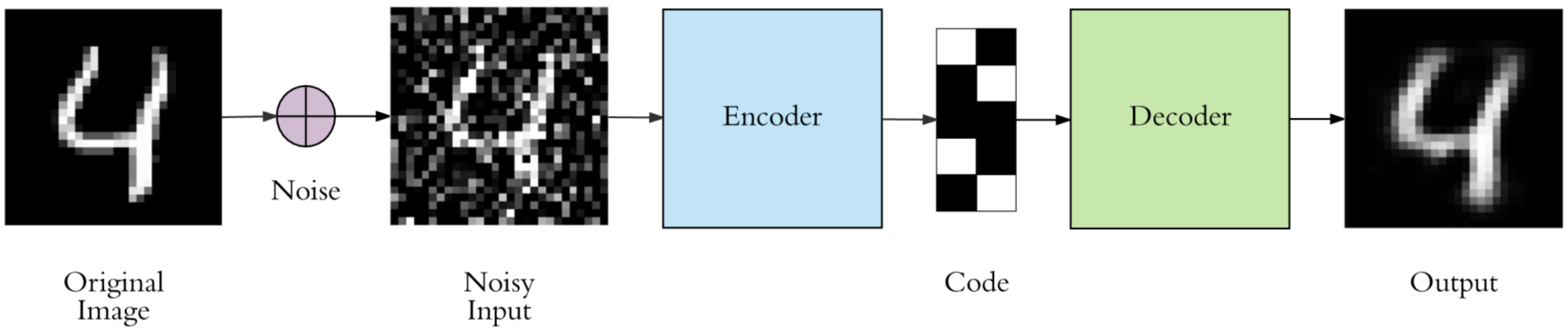


3. Sampling from Denoising Autoencoders

- A denoising autoencoder (DAE) is an autoencoder trained to reconstruct a clean input x from a stochastically corrupted one $x' \sim q(x'|x)$ by learning a conditional distribution $P_\theta(x|x')$

- Sample from a DAE by successively corrupting and reconstructing an input using the following pseudo-Gibbs Markov chain:

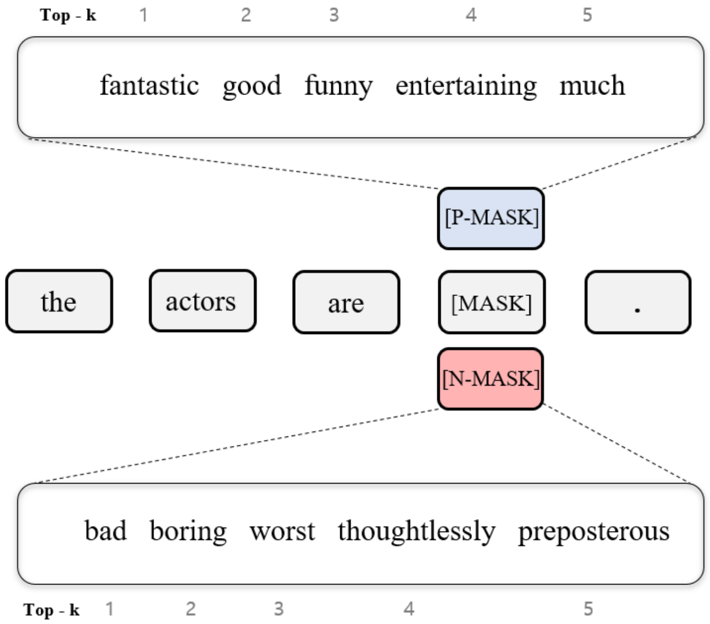
$$x'_t \sim q(x'|x_{t-1}),\ x_t \sim P_\theta(x|x'_t).$$



Background and Related Work

4. Masked Language Models

- Recent advances in unsupervised representation learning for natural language have relied on pretraining models on a masked language modeling (MLM) objective.



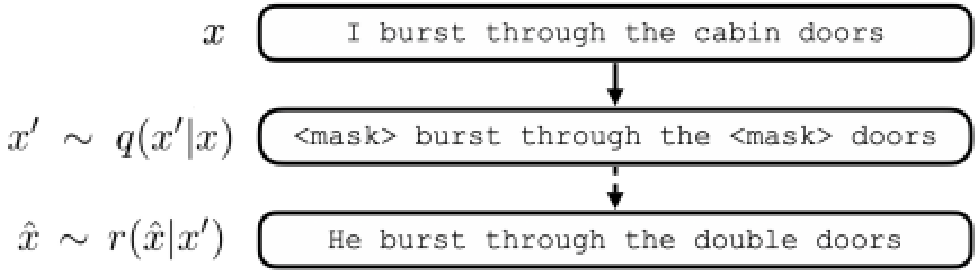


Figure 2: To sample from an MLM DAE, we apply the MLM corruption q to the original sentence then reconstruct the corrupted sentence using our DAE r.

SSMBA: Self-Supervised Manifold Based Augmentation

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Algorithm

- Assume the input points concentrate around an underlying lower dimensional data manifold M.
- q is corruption function, $x' \sim q(x'|x)$ such that x' no longer lies on M.
- r is reconstruction function, $\hat{x} \sim r(\hat{x}|x')$ such that $\hat{x}$ lies on M.
- $(x_i, y_i) \in D$ → $x_i' \sim q(x'|x_i)$ → $\hat{x}_{ij} \sim r(\hat{x}|x_i')$

- Label of $\hat{y}_{ij}$
  - Preserving y_i
  - Getting *soft label* via teacher model
  - Getting *hard label* via teacher model

- q : Maksed Language Model
- r : Pre-trained BERT

Algorithm 1 SSMBA

Require: perturbation function q
reconstruction function r
Input: Dataset $\mathcal{D} = \{(x_1, y_1) \ldots (x_n, y_n)\}$
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 $j \in 1 \ldots m$ **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 $\mathcal{D}^{aug} = \{(\hat{x}_{ij}, \hat{y}_{ij})\}_{i=1\ldots n, j=1\ldots m}$
  augment $\mathcal{D}' \leftarrow \mathcal{D} \cup \mathcal{D}^{aug}$
  return $\mathcal{D}'$
end function

SSMBA: Self-Supervised Manifold Based Augmentation

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Contribution

- SSMBA does not rely on task-specific knowledge, requires no dataset-specific fine-tuning, and is applicable to any supervised natural language task.

- SSMBA requires only a pair of functions q and r used to generate data.

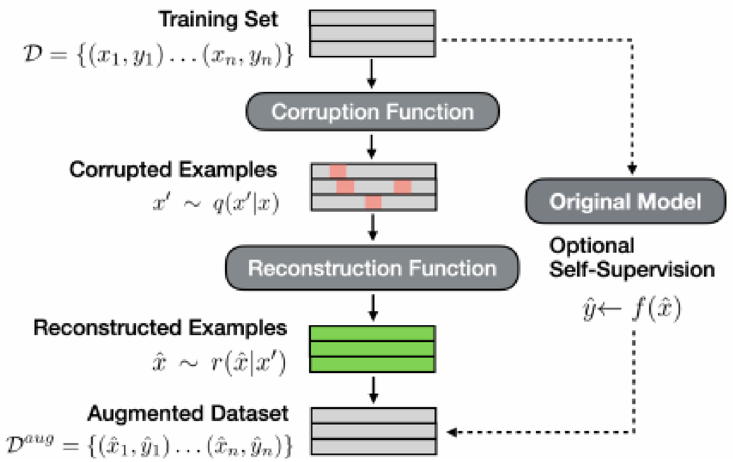

Figure 3: SSMBA generates synthetic examples by corrupting then reconstructing the original training inputs. To form the augmented dataset, corresponding outputs are preserved from the original data or generated from a supervised model f trained on the original data.

Datasets

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Setiment Analysis

- Amzon Review Dataset (1 to 5 rating)
  - AR-Full : contains reviews from the 10 largest categories
  - AR-Clothing : contains reviews in the clothing category seperated into subcategories by metadata

- Movies dataset
  - SST2 : contains movie review excerpts
  - IMDb dataset : contains full length movie reviews

- Yelp Review Dataset : contains restaurant reviews with associated business metadata (1 to 5 star rating)

Datasets

Natural Language Inference

- MNLI : corpus of NLI data from 10 distinct genres of written and spoken English.
- ANML : corpus of NLI data designed adversarially by humans such that state-of-the-art models fail to classify examples correctly.

Machine Translation

- IWSLT14 (de → en)
- OPUS (OOD)
- Allegra corpus

Datasets

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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.

Experimental Setup

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1. **Model Types**

- Sentiment analysis : LSTMs and CNNs
- NLI : fine-tuned RoBERTa_base
- MT : Transformers

Experimental Setup

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2. SSMBA Settings

- q : MLM corruption function.

- Tune the corruption percentage.

- r
    - Sentiment analysis and NLI : RoBERTa_base
    - MT : pre-trained German BERT model

- Generate 5 augmented examples using unrestricted sampling.

- For translation experiments, target side translations are generated with beam search with width 5

Experimental Setup

3. Baselines

- Sentiment analysis and NLI tasks
  - Easy Data Augmentation (EDA)
  - Conditional Bert Contextual Augmentation (CBERT)
  - Unsupervised Data Augmentation (UDA) : Back translation

- MT tasks
  - Word dropout : randomly chooses word in the source sentence to set to zero embeddings
  - Reward Augmented Maximum Likelihood (RAML) : noisy target sentences
  - SwitchOut : noise function similar to RAML to both the source and target side

Results

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1. Sentiment Analysis

Model	Augmentation	AR-Full ID	AR-Full OOD	AR-Clothing ID	AR-Clothing OOD	Movies ID	Movies OOD	Yelp ID	Yelp OOD	Average ID	Average 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 $p < 0.01$.

Results

2. Natural Language Inference

	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 $p < 0.01$.

Results

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3. Machine Translation

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 $p < 0.01$.

	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 $p < 0.01$.

Analysis and Discussion

Settings

Baby domain within the AR-Clothing dataset

- Relatively small size (25k sentences)
- # of OOD domains is 3
- CNN model
- 45% corruption
- Restricted sampling
- Self-supervised soft labeling
- Generating 5 synthetic examples for each training example

Analysis and Discussion

1. Training Set Size

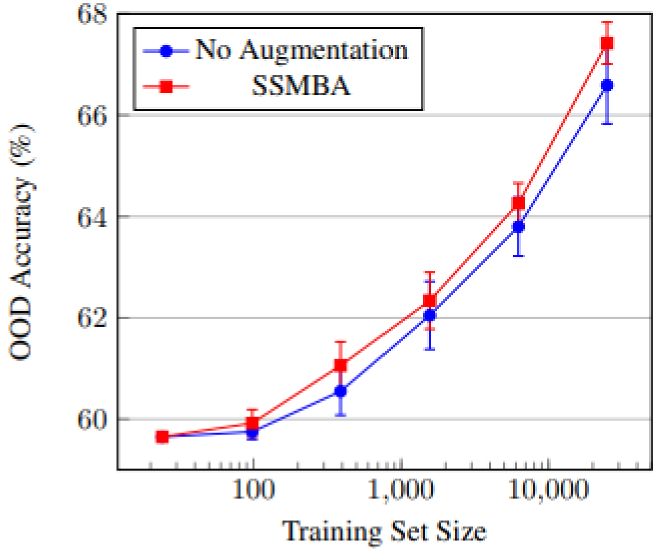

Figure 4: OOD accuracy of models trained on successively subsampled datasets. The full training set contains 25k examples. Error bars show standard deviation in OOD accuracy across models.

Analysis and Discussion

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2. Reconstruction Model Capacity

	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.

Analysis and Discussion

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3. Corruption Amount

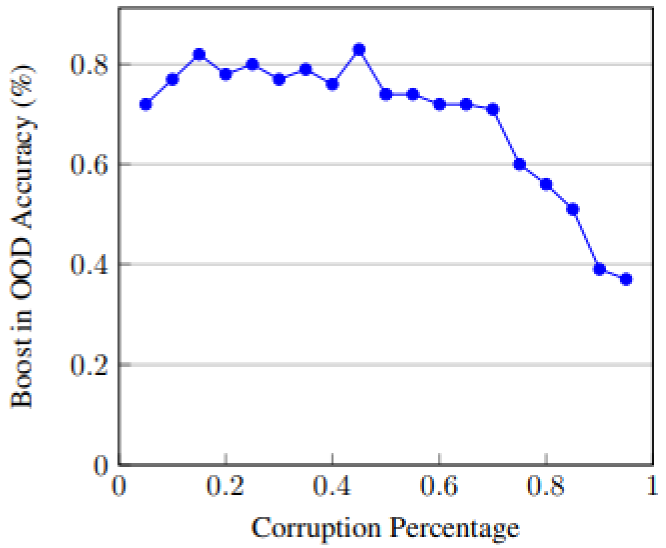

Figure 5: Boost in OOD accuracy (%) of models trained with SSMBA augmentation applied with different percentages of corrupted tokens.

Analysis and Discussion

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4. Sample Generation Methods

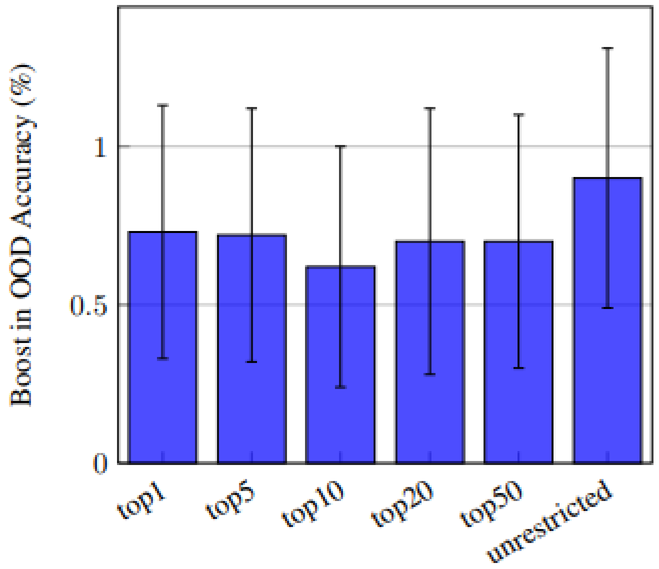

Figure 6: Boost in OOD accuracy (%) of models trained with SSMBA augmentation using different sampling methods. Error bars show standard deviation in OOD accuracy across models.

Analysis and Discussion

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5. Amount of Augmentation

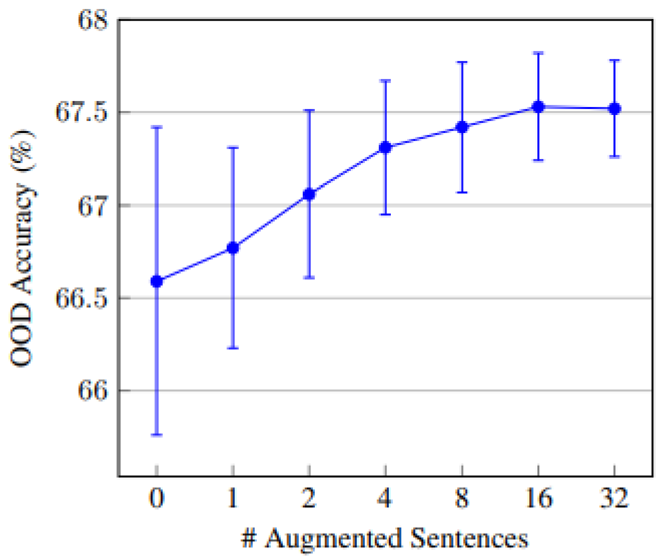

Figure 7: OOD accuracy (%) of models trained with different amounts of SSMBA augmentation. 0 augmentation corresponds to a baseline model. Error bars show standard deviation in OOD accuracy across models.

Analysis and Discussion

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6. Label Generation

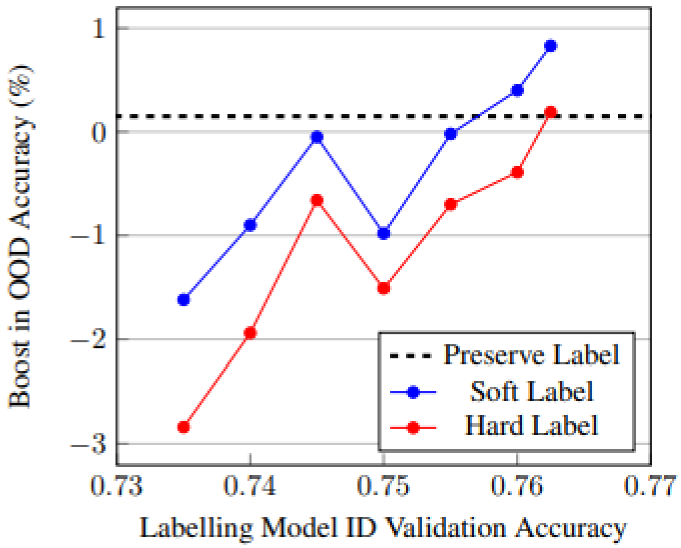

Figure 8: Boost in OOD accuracy (%) of models trained with augmented data labelled with different supervision models and label generation methods.

Conclusion

- Defines Corruption Function and Reconstruction Function to augment data via Denoising Auto-Encoder method.

- MLM as corruption function and RoBERTa / Bert as reconstruction function.

- The difference from previous similar methodologies is that the reconstruction function is not fine-tuned.

- Labeling of augmented data via Self-Supervision

- Performance is improved even for out-of-domain (OOD) data

End Of Document

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Thank you

Reference

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