

Reproducibility Challenge:

Imputing Out-of-Vocabulary Embeddings with LOVE Makes Language Models Robust with Little Cost

11/29/2022

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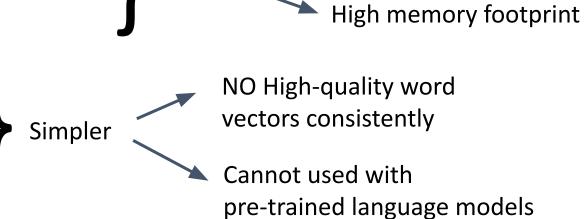


Introduction - Why Love

 In general, model performance deteriorates with unseen words (e.g. typos, slang, rare words ...)

Solution:

- → word embeddings on sub-word tokens
 - FastText
 - BERT
- → MIMICK-like language models
 - MIMICK
 - BoS
 - KVQ-FH

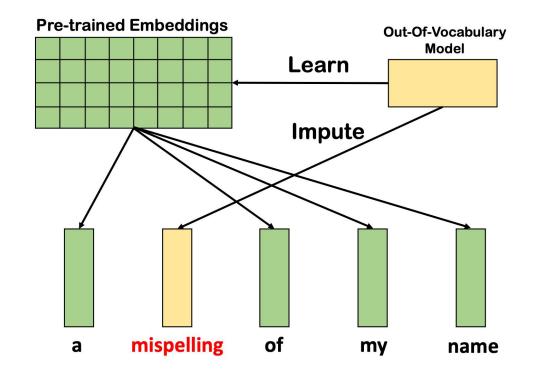




Pre-training from scratch

Introduction - What is Love

- LOVE uses a novel type of data augmentation and hard negative generation
- Produces high-quality word representations robust to character perturbations
- LOVE is lightweight compared to FastText and BERT
- LOVE can be used in a plug-and-play fashion with FastText and BERT
 - → Increase Robustness





Introduction - Love Performance on intrinsic task

 Intrinsic evaluations measure syntactic or semantic relationships between words directly

	paramet	ters			Word Si	milarity			Word	Avg	
	embedding	others	RareWord	SimLex	MTurk	MEN	WordSim	SimVerb	AP	BLESS	150
FastText (2017)	969M		48.1	30.4	66.9	78.1	68.2	25.7	58.0	71.5	55.9
MIMICK (2017)	9M	517K	27.1	15.9	32.5	36.5	15.0	7.5	59.3	72.0	33.2
BoS (2018)	500M	_	44.2	<u>27.4</u>	<u>55.8</u>	<u>65.5</u>	<u>53.8</u>	<u>22.1</u>	41.8	39.0	<u>43.7</u>
KVQ-FH (2019)	12M	-	<u>42.4</u>	20.4	55.2	63.4	53.1	16.4	39.1	42.5	41.6
LOVE	6.3M	200K	42.2	35.0	62.0	68.8	55.1	29.4	<u>53.2</u>	<u>51.5</u>	49.7



Introduction - Love Performance on extrinsic task

- Extrinsic evaluations measure the performance of word embeddings as input features to a downstream task
 - Named Entity Recognition (NER)
 - Text Classification

	paramet	ers	SST	SST2		MR		CoNLL-03		BC2GM	
	embedding	others	original	+typo	original	+typo	original	+typo	original	+typo	
FastText (2017)	969M	-	82.3	60.5	73.3	62.2	86.4	66.3	71.8	53.4	69.5
Edit Distance	969M	1-1	-:	67.4	-	68.3	-	76.2		66.6	-:
MIMICK (2018)	9M	517K	69.7	62.3	73.6	61.4	68.0	65.2	56.6	56.7	64.2
BoS (2018)	500M	-	<u>79.7</u>	<u>72.6</u>	73.6	69.5	79.5	68.6	66.4	61.5	71.5
KVQ-FH (2019)	12M	-	77.8	71.4	72.9	66.5	73.1	70.4	46.2	53.5	66.5
LOVE	6.3M	200K	81.4	73.2	74.4	<u>66.7</u>	<u>78.6</u>	<u>69.7</u>	<u>64.7</u>	63.8	71.6



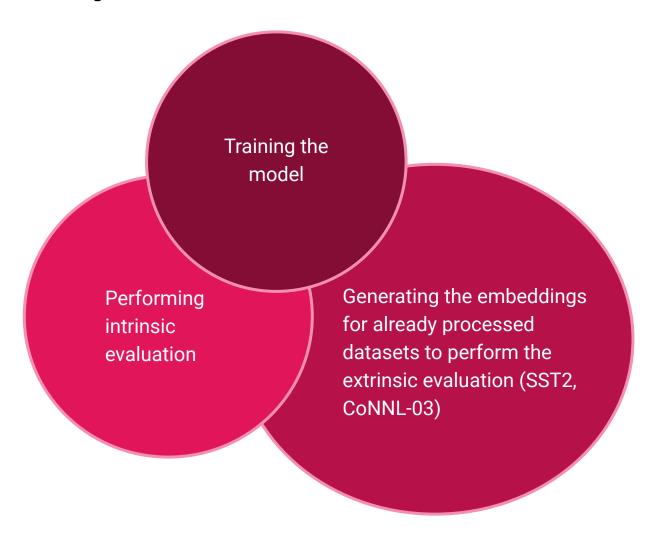
Introduction - LOVE performance on Extrinsic Task

- Introducing OCR typos increase the robustness of the model
- LOVE degrades performance on original datasets only marginally

			SST	2			CoNLL-03						
Typo Probability	original	10%	30%	50%	70%	90%	original	10%	30%	50%	70%	90%	Avg
Static Embeddings													
FastText FastText + LOVE	82.3 82.1	68.2 79.8	59.8 74.9	56.7 74.2	57.8 68.8	60.3 67.2	86.4 86.3	81.6 84.7	78.9 81.8	73.9 77.5	70.2 73.1	63.4 71.3	70.0 76.8
				Dyna	mical Er	nbedding	gs						
BERT BERT + LOVE	91.5 91.5	88.2 88.3	78.9 83.7	74.7 77.4	69.0 72.7	60.1 63.3	91.2 89.9	89.8 88.3	86.2 86.1	83.4 84.3	79.9 80.8	76.5 78.3	80.7 82.1



Ease of reproduction





Extent of reproduction

We were **able** to reproduce the following analysis:

- Intrinsic Evaluation
 - 6 out of 8 Datasets → Word similarity tasks
- Extrinsic Evaluation
 - 4 out of 4 Datasets → Both NER and Text Classification
- Extrinsic Evaluation in a plug-and-play fashion
 - Only for FastText+Love for both SST2 and CoNLL-03 datasets



Extent of reproduction

We were **unable** to reproduce the following tasks:

- Intrinsic Evaluation
 - 2 out of 8 Datasets (AP and BLESS) → Word Cluster tasks
- Extrinsic Evaluation in a plug-and-play fashion
 - BERT+Love for both SST2 and CoNLL-03 datasets
- Demonstration of effectiveness of the architecture (Ablation study)
 - Varying input method, encoder and loss function
- The performance of mimicking BERT (Replacement strategy)

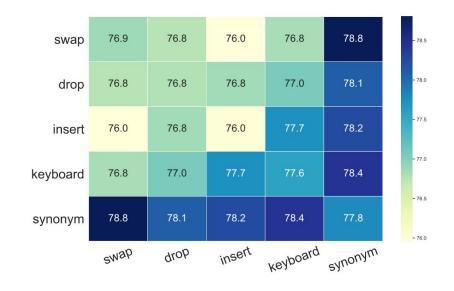


Extent of reproduction

What we were **unable** to reproduce:

- Performances of different augmentations on RareWord
- Performances of different augmentations on SST2







Results - intrinsic evaluation

Our Results:

RareWord	SimLex	MTurk	MEN	WordSim	SimVerb	
42.65	35.02	63.77	68.4	55.89	28.72	

Author's Results:

	paramet	ters			Word Si	milarity			Word	l Cluster	Avg
	embedding	others	RareWord	SimLex	MTurk	MEN	WordSim	SimVerb	AP	BLESS	
FastText (2017)	969M	-	48.1	30.4	66.9	78.1	68.2	25.7	58.0	71.5	55.9
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LOVE	6.3M	200K	42.2	35.0	62.0	68.8	55.1	29.4	<u>53.2</u>	<u>51.5</u>	49.7



Results - extrinsic evaluation

Our Results:

SST2	SST2+typo	MR	MR+typo	CoNLL-03	CoNLL-03+typo	BC2GM	BC2GM+typo
79.96	71.21	73.92	66.17	83.41	66.17	54.09	25.95

Author's Results:

	paramet	ters	SST	SST2		MR		L-03	BC2GM		Avg
	embedding	others	original	+typo	original	+typo	original	+typo	original	+typo	
FastText (2017)	969M	×-	82.3	60.5	73.3	62.2	86.4	66.3	71.8	53.4	69.5
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Results - robustness evaluation

Extrinsic Evaluation Love+FastText on SST2

Our Results:

original	10%	30%	50%	70%	90%
79.96	78.69	78.09	73.75	71.21	69.67

Extrinsic Evaluation Love+FastText on CoNLL-03

original	10%	30%	50%	70%	90%	
83.4	80.33	76.21	72.19	66.17	63.1	

Author's Results:

	CoNLL-03												
Typo Probability	original	10%	30%	50%	70%	90%	original	10%	30%	50%	70%	90%	Avg
Static Embeddings													
FastText FastText + LOVE	82.3 82.1	68.2 79.8	59.8 74.9	56.7 74.2	57.8 68.8	60.3 67.2	86.4 86.3	81.6 84.7	78.9 81.8	73.9 77.5	70.2 73.1	63.4 71.3	70.0 76.8



Key findings

- How to use LOVE+FastText in a plug-and-play fashion
- The model outperformed MIMICK-like models in intrinsic evaluation tasks and in extrinsic evaluation for SST2 and MR datasets
- Probabilities of word augmentation
 - Not specified the probability used for each specific word augmentation
 - Size of the synonym file from which synonym augmentation was extracted





Thank you!

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