ESimCSE: Enhanced Sample Building Method for Contrastive Learning of Unsupervised Sentence Embedding

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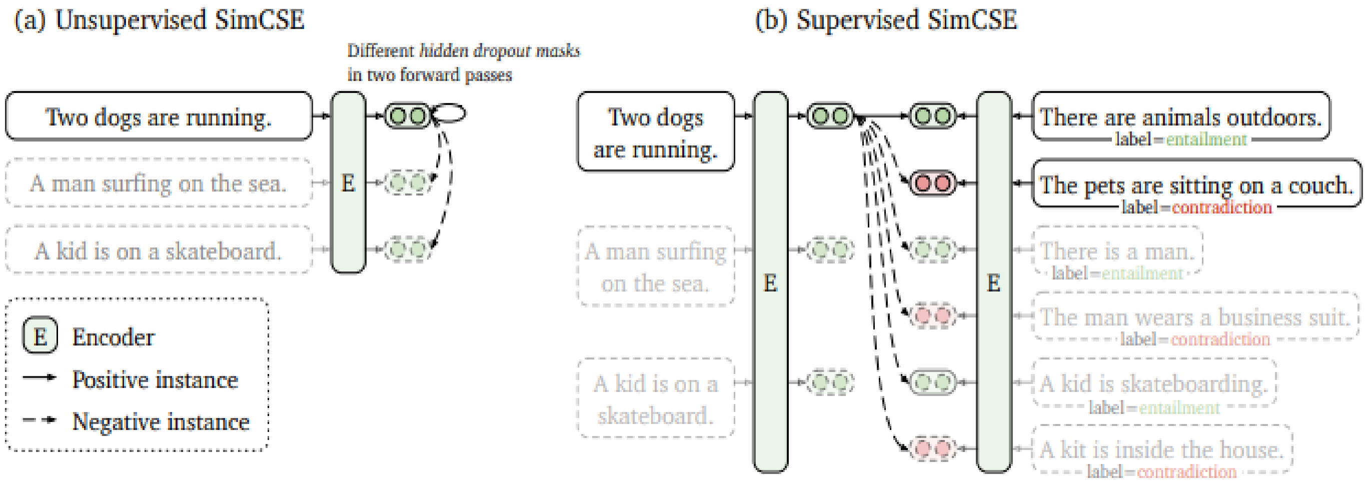
ESimCSE Outline

- **SimCSE의 샘플 구축 방법에서 발생한 문제에 대한 개선 방법 제안**

- Negative pair 수를 늘리기 위해 Momentum Contrast method 사용 제안

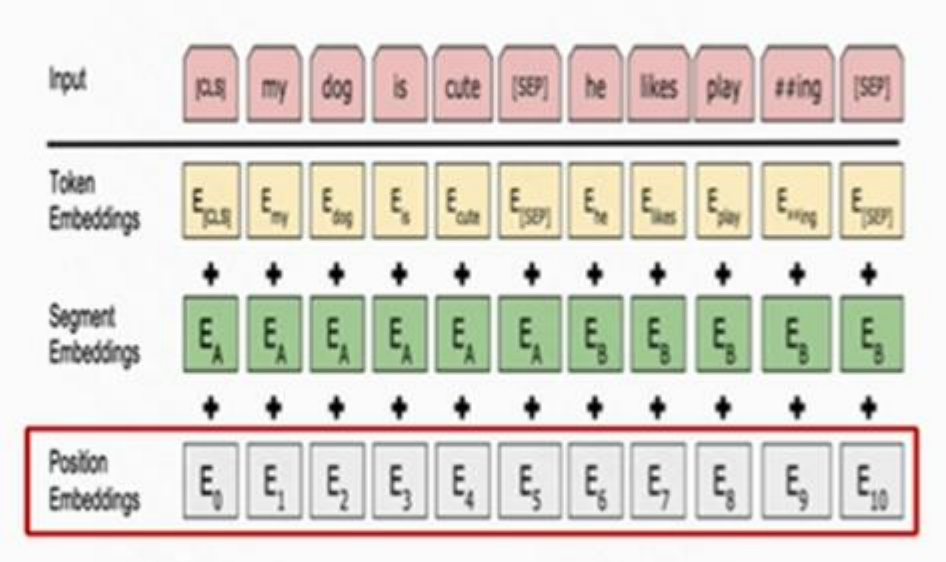
1. Introduction

SimCSE



$$\ell_i = -\log \frac{e^{\mathrm{sim}(\mathbf{h}_i^{z_i}, \mathbf{h}_i^{z'_i})/\tau}}{\sum_{j=1}^{N} e^{\mathrm{sim}(\mathbf{h}_i^{z_i}, \mathbf{h}_j^{z'_j})/\tau}}, \qquad (4)$$

SimCSE 샘플 구축에 대한 문제점



Length Diff	Avg. Similarity Diff
> 3	16.34
≤ 3	**18.18** (+1.84)

Table 1: The average similarity difference between the model (SimCSE-BERT) predictions and the normalized ground truths.

Word Repetition

- 문장 길이 편향을 완화하기 위한 방법

Method	Text	Similarity
original sentence	I like this apple because it looks so fresh and it should be delicious.	1.0
random insertion	I **don't** like this apple because **but** it looks so **not** fresh and it should be **dog** delicious.	0.69
random deletion	I like this ~~apple~~ because it looks so ~~fresh~~ and it should be ~~delicious~~.	0.32
word repetition	I like **like** this apple because it looks so **so** fresh and **and** it should be delicious.	0.99
word repetition	I **I** like this apple **apple** because it looks **looks** so fresh **fresh** and it should be delicious **delicious**.	0.98

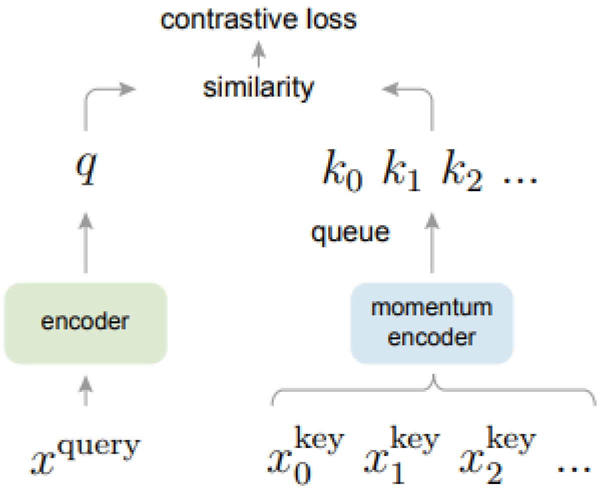
Table 2: An example of semantic similarity after different methods change a sentence's length.

$$dup\_len \in [0, max(2, int(dup\_rate * N))] \quad (3)$$

$$dup\_set = uniform([1, N], num = dup\_len) \quad (4)$$

Momentum Contrast

- 대조 학습은 이론적으로 negative pair가 많을 수록 좋음.
- 그러나 큰 배치 크기가 항상 더 좋은 선택은 아님.
- SimCSE BERT base 경우 배치 크기가 커질 수록 성능이 저하 됨.



$$\theta_{\mathrm{m}} \leftarrow \lambda\theta_{\mathrm{m}} + (1-\lambda)\theta_{\mathrm{e}} \tag{5}$$

ESimCSE

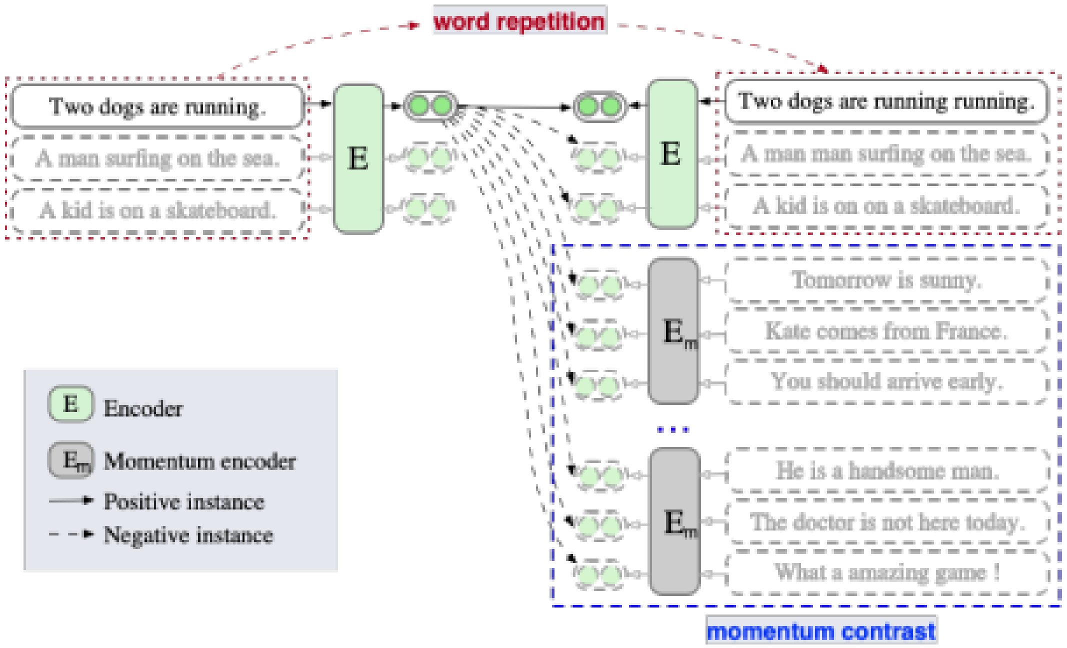


Figure 1: The schematic diagram of the ESimCSE method.

$$\ell_i = -\log \frac{e^{\mathrm{sim}(\mathbf{h}_i, \mathbf{h}_i^+)/\tau}}{\sum_{j=1}^{N} e^{\mathrm{sim}(\mathbf{h}_i, \mathbf{h}_j^+)/\tau} + \sum_{m=1}^{M} e^{\mathrm{sim}(\mathbf{h}_i, \mathbf{h}_m^+)/\tau}} \tag{6}$$

Training

- Model: BERT, RoBERTa
- Dataset: 영어 위키피디아에서 무작위로 추출한 100만개 문장을 사용하여 학습
- Optimizer: Adam
- Batch size = 64
- Temperature: 0.05
- learning rate
  - BERT base: 3e-5
  - 이 외: 1e-5
- dropout
  - base: p=0.1
  - large: p=0.15
- momentum λ: 0.995

Sentence embedding performance

Model	STS12	STS13	STS14	SICK15	STS16	STS-B	SICK-R	Avg.
IS-BERT$_{base}$ △	56.77	69.24	61.21	75.23	70.16	69.21	64.25	66.58
CT-BERT$_{base}$ △	61.63	76.80	68.47	77.50	76.48	74.31	69.19	72.05
ConSERT$_{base}$ ♡	64.64	78.49	69.07	79.72	75.95	73.97	67.31	72.74
BERT$_{base}$-flow◇	63.48	72.14	68.42	73.77	75.37	70.72	63.11	69.57
SG-OPT-BERT$_{base}$ ♠	66.84	80.13	71.23	81.56	77.17	77.23	68.16	74.62
Mirror-BERT$_{base}$ ♯	69.10	81.10	73.00	81.90	75.70	78.00	69.10	75.40
SimCSE-BERT$_{base}$ ♣	68.40	82.41	74.38	80.91	78.56	76.85	72.23	76.25
ESimCSE-BERT$_{base}$	**73.40**	**83.27**	**77.25**	**82.66**	**78.81**	**80.17**	**72.30**	**78.27**
ConSERT$_{large}$ ♡	70.69	82.96	74.13	82.78	76.66	77.53	70.37	76.45
BERT$_{large}$-flow◇	65.20	73.39	69.42	74.92	77.63	72.26	62.50	70.76
SG-OPT-BERT$_{large}$ ♠	67.02	79.42	70.38	81.72	76.35	76.16	70.20	74.46
SimCSE-BERT$_{large}$ ♣	70.88	84.16	76.43	**84.50**	**79.76**	79.26	73.88	78.41
ESimCSE-BERT$_{large}$	**73.21**	**85.37**	**77.73**	84.30	78.92	**80.73**	**74.89**	**79.31**
Mirror-RoBERTa$_{base}$ ♯	66.60	82.70	74.00	82.40	79.70	79.60	69.70	76.40
SimCSE-RoBERTa$_{base}$ ♣	**70.16**	81.77	73.24	81.36	**80.65**	80.22	68.56	76.57
ESimCSE-RoBERTa$_{base}$	69.90	**82.50**	**74.68**	**83.19**	80.30	**80.99**	**70.54**	**77.44**
SimCSE-RoBERTa$_{large}$ ♣	72.86	83.99	75.62	84.77	**81.80**	81.98	71.26	78.90
ESimCSE-RoBERTa$_{large}$	**73.20**	**84.93**	**76.88**	**84.86**	81.21	**82.79**	**72.27**	**79.45**

Table 3: Sentence embedding performance on 7 semantic textual similarity (STS) test sets. ♣ : results from official published model by (Gao et al., 2021).♡ : results from (Yan et al., 2021). ♠ : results from (Kim et al., 2021). ◇ : results from (Li et al., 2020). △ : results are reproduced and reevaluated by (Gao et al., 2021). ♯ : results from (Liu et al., 2021)

Performance on Transfer Tasks

Model	MR	CR	SUBJ	MPQA	SST	TREC	MRPC	Avg.
SimCSE ♣	81.18	**86.46**	94.45	**88.88**	85.50	89.80	74.43	85.81
ESimCSE	**81.32**	86.22	**94.74**	88.74	**85.50**	**91.00**	**74.90**	**86.06**

Table 11: Results on transfer tasks of different sentence embedding models, in terms of accuracy. ♣ : results from (Gao et al., 2021).

Sentence embedding performance

Model	LD	STS12	STS13	STS14	SICK15	STS16	STS-B	SICK-R	Avg.
SimCSE	> 3	8.93	15.74	11.90	19.68	28.91	21.33	7.86	16.34
	≤ 3	9.29	22.81	19.53	19.92	24.08	22.12	9.53	18.18
ESimCSE	> 3	13.48	23.73	17.14	25.98	34.71	26.22	10.44	21.67
	≤ 3	12.52	28.56	24.13	24.17	29.32	25.63	12.35	22.38

Table 7: The difference between the model predicted cosine similarity and the true label on each dataset's test set. "LD" is short for length difference.

Word Repetition vs Momentum Contrast

Model	STS-B
SimCSE ♣	82.45
+ word repetition	84.09 (+1.64)
+ momentum contrast	83.98 (+1.53)
ESimCSE	**84.85** (+2.40)

Table 4: Improvement on STS-B development sets that word repetition or momentum contrast brings to SimCSE. ♣ : results from official published model by (Gao et al., 2021).

Effect of Sentence-Length-Extension Method

Length-extension Method	STS-B
+Inserting Stop-words	81.72
+Inserting [MASK]	83.08
+Inserting Masked Prediction	84.18
+Word Repetition	84.40
+Sub-word Repetition	**84.85**

Table 5: Effects of sentence-length-extension method.

Batching Sentences of Similar Length in Training

- We divide the training set into two coarse-grained buckets based on whether the sentence length is greater than buc_len, where $buc\_len \in [3, 8]$;
- We divide the training set by sentence length into 6 fine-grained buckets: $\{\leq 3, 4, 5, 6, 7, \geq 8\}$, which we use $buc\_len = 3 \sim 8$ for short.

buc_len	wr	3	4	5
STS-B	84.09	81.92	82.00	82.66
buc_len	6	7	8	$3 \sim 8$
STS-B	82.00	82.13	83.00	82.18

Table 6: Effects of different bucket lengths buc_len. "wr" means using word repetition method instead of bucketing sentences. "$3 \sim 8$" means fine-grained buckets setting: $\{\leq 3, 4, 5, 6, 7, \geq 8\}$.

Will Word Repetition Bring New Bias?

1. We randomly select a sentence as a query, such as q = "I like **this** apple because it **looks very** fresh"
2. We use the query to randomly recall a candidate sentence with 13%-17% overlap tokens, such as s1 = "**This** is a very tall tree and it **looks like** a giant"
3. We apply the word-repetition operation on the overlap tokens in the candidate sentence and produce a word-repeated sentence, such as s2 = "**This this** is a **very very** tall tree and it **looks looks** like a giant."
4. We calculate the similarity of <q, s1 >and <q, s2 >and compare them.

Model	**Sim <q,s1 >**	**Sim <q,s2 >**
SimCSE	26.39	27.07(**+0.68**)
ESimCSE	36.82	36.87(**+0.05**)

Table 8: Effect of repeated words on the average similarity of two sets

Effect of Hyperparameters

- Repetition Rate

dup_rate	0.08	0.12	0.16	0.2
STS-B	83.5	83.62	82.01	83.01
dup_rate	0.24	0.28	0.32	0.36
STS-B	84.24	82.96	**84.85**	83.84

Table 9: Effects of repetition rate dup_rate.

- Momentum Queue Size

Queue Size	**STS-B**
$1 \times batch\_size$	83.83
$1.5 \times batch\_size$	83.81
$2 \times batch\_size$	83.03
$2.5 \times batch\_size$	**84.85**
$3 \times batch\_size$	82.66

Table 10: Effects of queue size of momentum contrast.

결론

- SimCSE 문장 길이에 대한 편향 존재 확인
- 단어 반복 데이터 증강을 통해 편향 개선 및 성능 향상
- 모코를 이용하여 성능 향상

감사합니다.