UCSD Cognitive Science

Adobe

Trimming and Improving Skip-thought Vectors

--Representing sentences as vectors

Shuai Tang (唐帅)

Why?

Sentence $\longrightarrow$ Vector

Why?

Sentence ⟶ Vector

We communicate in sentences,
and they convey our thoughts.

Why?

Sentence $\longrightarrow$ Vector

Vector is an efficient type of representation for machines to operate on.

Why?

Sentence $\longrightarrow$ Vector

If we convert a sentence into a vector that **captures the meaning** of the sentence, then Google can do much better searches; they can search based on what's being said in a document. (Hinton, 2015)

Natural Reasoning

Machine Learning

Sentence $\longrightarrow$ Vector

Learn from data!

Supervised Learning

Unsupervised Learning

Supervised Learning

movies that are highly rated in last year

strongly related

somehow related

best movies of 2016

top 100 movies of all time

Goodfellow, Bengio & Courville. Deep Learning, 2017

Supervised Learning

labels

strongly related

somehow related

Goodfellow, Bengio & Courville. Deep Learning, 2017
Photo credit: Google Image

Unsupervised Learning

Sentence ⟶ Vector

Learn from data!

Without labels!

Goodfellow, Bengio & Courville. Deep Learning, 2017

Existing Models

- Bag-of-words (BOW)
- Continuous Bag-of-words (CBOW)/ Skip-gram
- Sequence to Sequence (Seq2Seq)
- Skip-thought

Existing Models

- **Bag-of-words (BOW)**
  - **Harris, Word1954**
- Continuous Bag-of-words (CBOW)/ Skip-gram
- Sequence to Sequence (Seq2Seq)
- Skip-thought

Bag-of-words model (BOW)

- Corpus
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Dictionary
  - {i, love, you, however, don’t, me, it, is, a, sad, story}
- Representations
  - [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
  - [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0]
  - [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1]

Bag-of-words model (BOW)

- Corpus
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Dictionary
  - {i, love, you, however, don’t, me, it, is, a, sad, story}
- Representations
  - [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
  - [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0]
  - [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1]

Bag-of-words model (BOW)

- Corpus
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Dictionary
  - {i, love, you, however, don’t, me, it, is, a, sad, story}
- Representations
  - [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
  - [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0]
  - [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1]

Bag-of-words model (BOW)

- Corpus
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Dictionary
  - {i, love, you, however, don’t, me, it, is, a, sad, story}
- Representations
  - [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
  - [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0]
  - [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1]

Fast!

Bag-of-words model (BOW)

- Corpus
  - i love you.
  - however, you don't love me.
  - it is a sad story.
- Dictionary
  - {i, love, you, however, don't, me, it, is, a, sad, story}
- Representations
  - [1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]
  - [0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0]
  - [0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1]

Existing Models

- Bag-of-words (BOW)
- **Continuous Bag-of-words (CBOW)/ Skip-gram**
  - **Mikolov et al., NIPS2013**
- Sequence to Sequence (Seq2Seq)
- Skip-thought

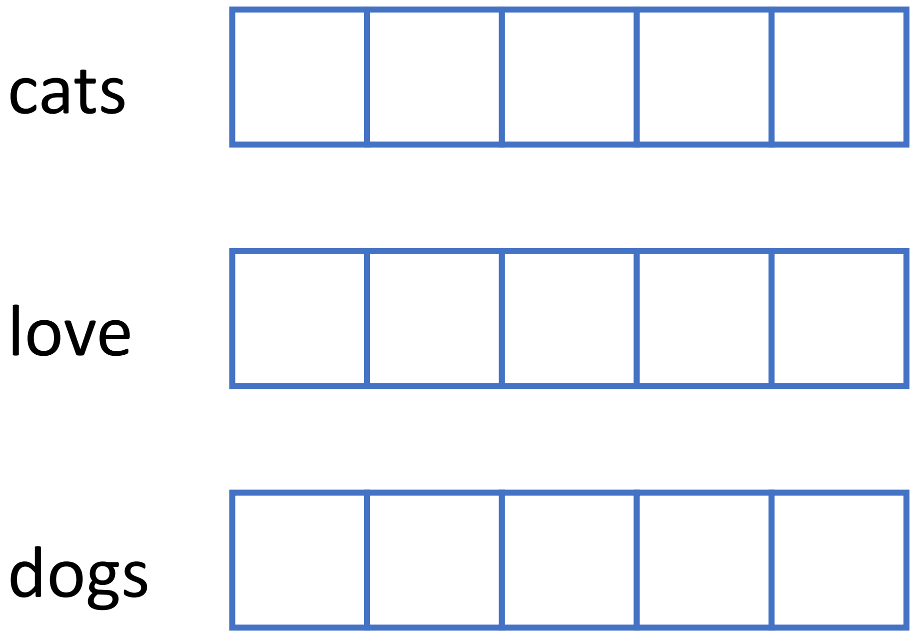
Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)

cats

love

dogs

Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)



Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)

cats	0.4	-0.5	0	-0.1	0.2
love	0	0.1	0.9	-0.3	-0.4
dogs	0.5	-0.4	0.1	-0.2	0.3

Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)

cats	0.4	-0.5	0	-0.1	0.2
love	0	0.1	0.9	-0.3	-0.4
dogs	0.5	-0.4	0.1	-0.2	0.3
cats love dogs	0.30	-0.27	0.33	-0.20	0.03

Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)

cats	0.4	-0.5	0	-0.1	0.2
love	0	0.1	0.9	-0.3	-0.4
dogs	0.5	-0.4	0.1	-0.2	0.3
cats love dogs	0.30	-0.27	0.33	-0.20	0.03

Fixed Manually

Continuous BOW/ Skip-gram (Mikolov et al. NIPS2013)

dogs love cats

0.30	-0.27	0.33	-0.20	0.03

Same!

cats love dogs

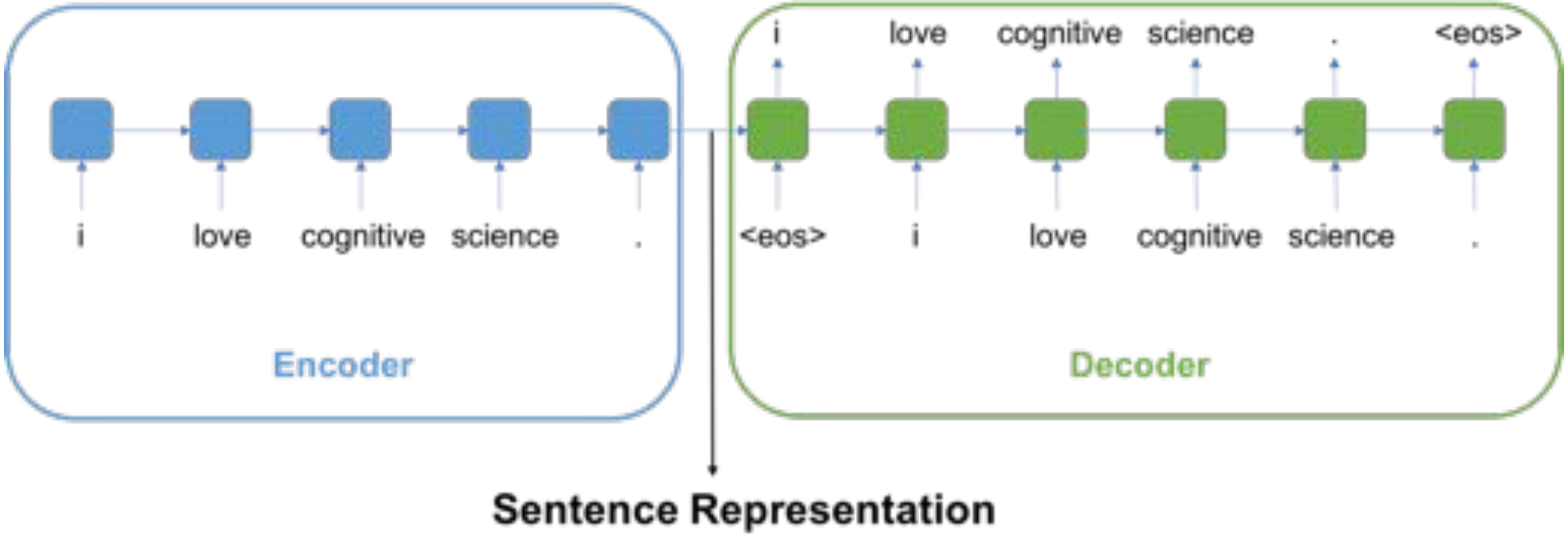
0.30	-0.27	0.33	-0.20	0.03

Existing Models

- Bag-of-words (BOW)
- Continuous Bag-of-words (CBOW)/ Skip-gram
- **Sequence to Sequence (Seq2Seq)**
  - **Sutskever, Vinyals & Le (NIPS2014)**
  - **Dai & Le (NIPS2015)**
- Skip-thought

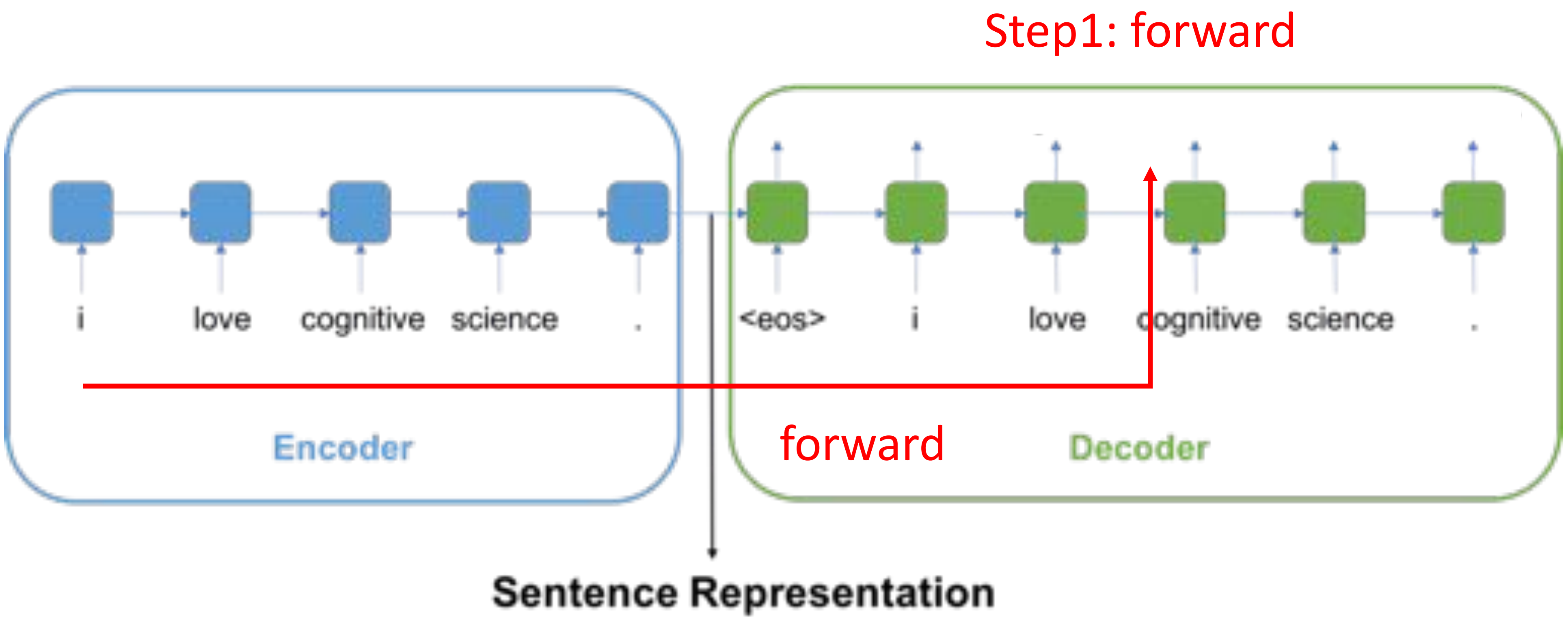
Sequence to Sequence (Dai & Le, NIPS2015)

- With Recurrent Neural Networks



Sequence to Sequence (Dai & Le, NIPS2015)

- Each training iteration…

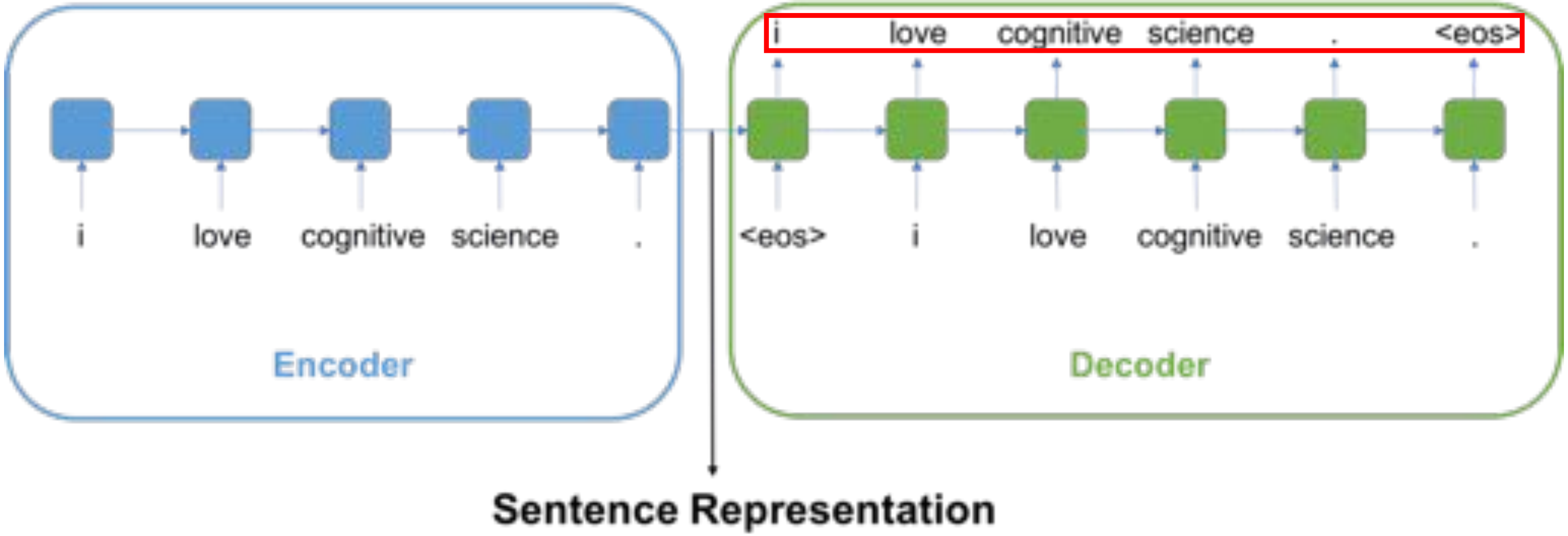


Goodfellow, Bengio & Courville. Deep Learning, 2017

Sequence to Sequence (Dai & Le, NIPS2015)

- Each training iteration…

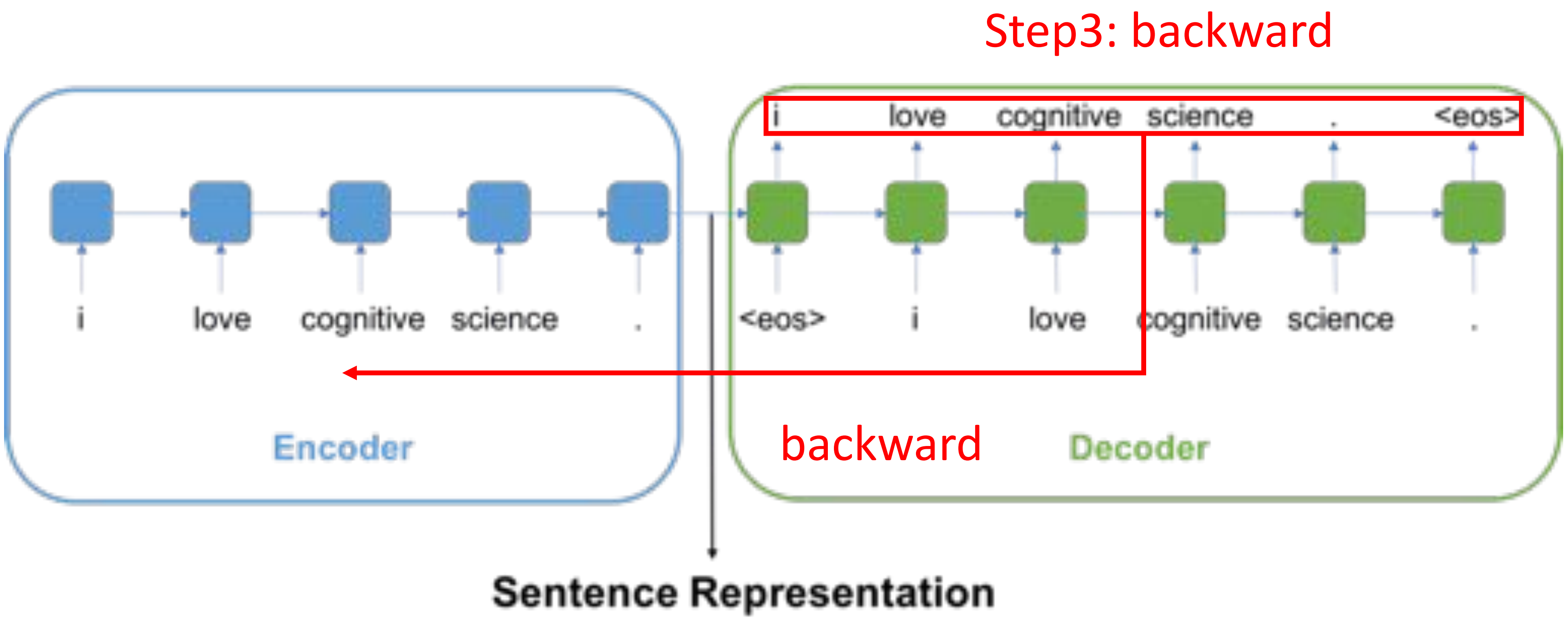
Step2: objective



Goodfellow, Bengio & Courville. Deep Learning, 2017

Sequence to Sequence (Dai & Le, NIPS2015)

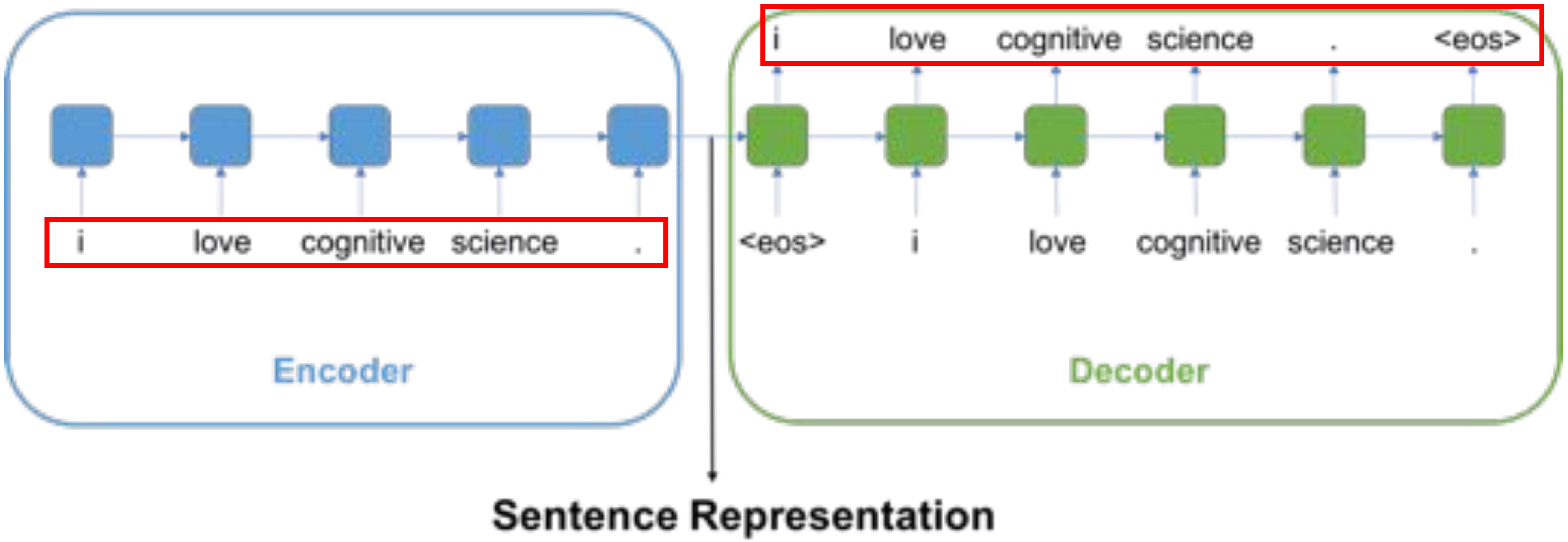
- Each training iteration…



Goodfellow, Bengio & Courville. Deep Learning, 2017

Sequence to Sequence (Dai & Le, NIPS2015)

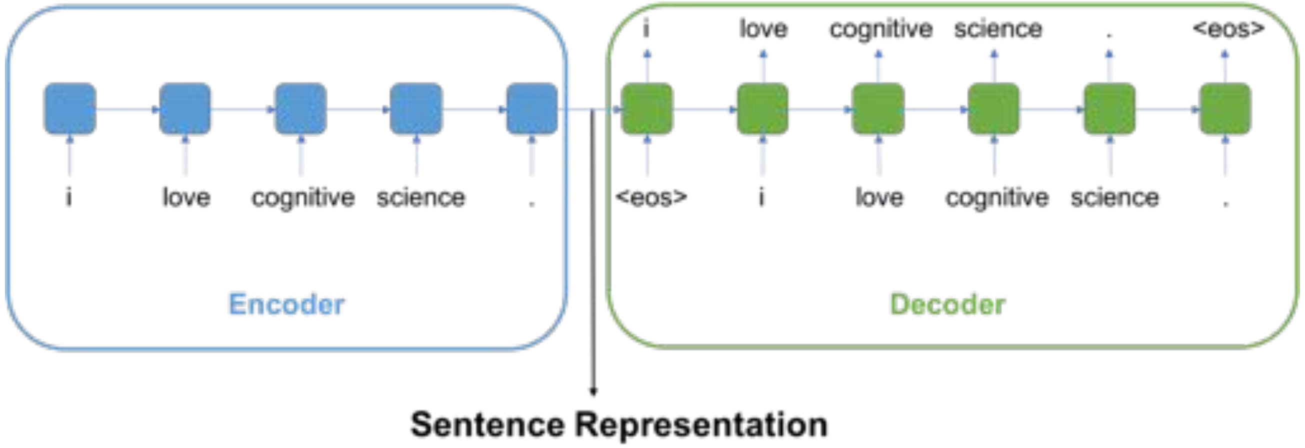
- With Recurrent Neural Networks



Sequence to Sequence (Dai & Le, NIPS2015)

- Pros:
  - Word-order information is utilized in training.

- Cons:
  - Training is slow.



Existing Models

- Bag-of-words (BOW)
- Continuous Bag-of-words (CBOW)/ Skip-gram
- Sequence to Sequence (Seq2Seq)
- **Skip-thought**
  - **Kiros et al., NIPS2015**

Trimming and Improving Skip-thought Vectors

- **Skip-thought**
  - **Kiros et al., NIPS2015**
- Our hypotheses to improve skip-thought
- Comparison between our trimmed skip-thought model and the skip-thought model
- Conclusion

Skip-thought (Kiros et al., NIPS2015)

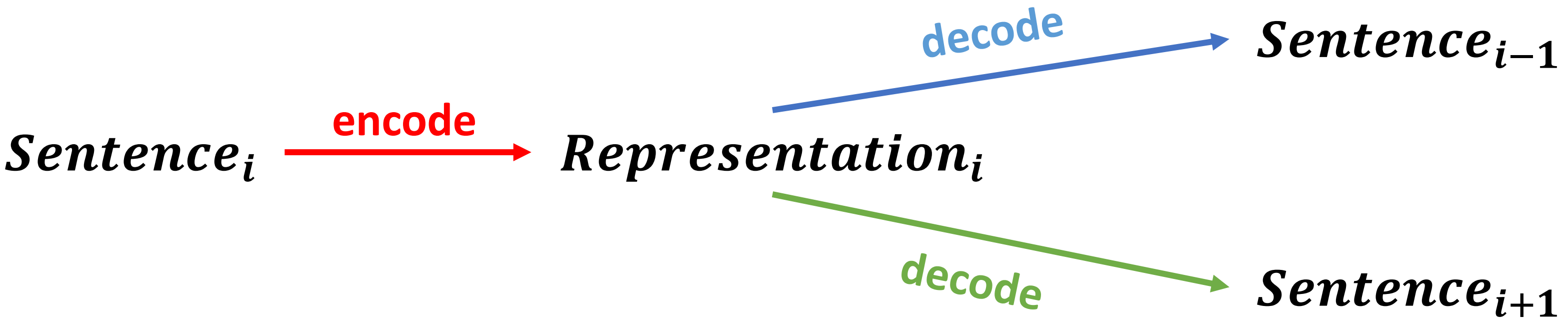
- Skip-thought model is for learning a generic sentence **encoder** .

Encoder - Decoder

$$\textbf{Sentence} \xrightarrow{encode} \textbf{Representation} \xrightarrow{decode} \textbf{Sentences}$$

Skip-thought (Kiros et al., NIPS2015)

- The skip-thought model learns to encode a sentence, and decode its surrounding two sentences, instead of itself.

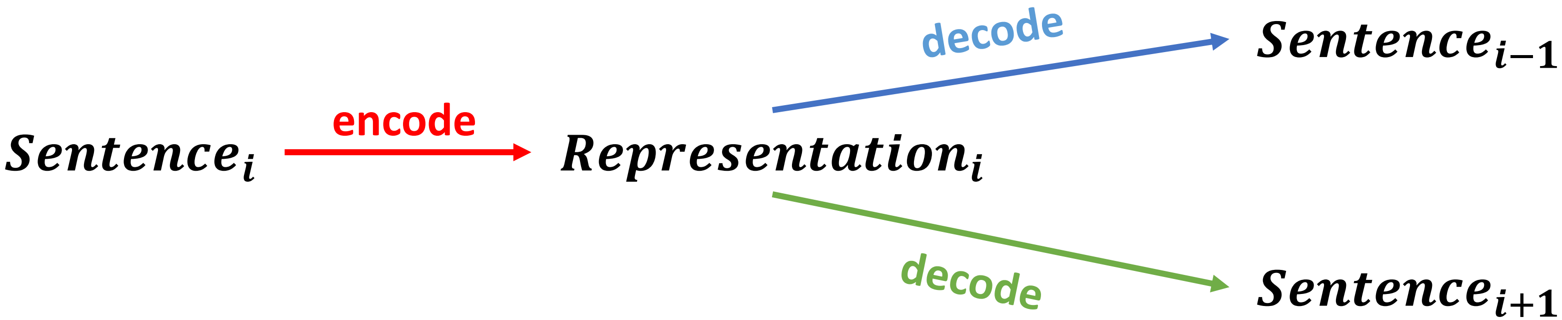


The context in which words and sentences are understood plays an important role in human comprehension.
(Altmann & Steedman, 1988; Binder & Desai, 2011)

Skip-thought (Kiros et al., NIPS2015)

- The model contains
  - an encoder
  - a previous decoder
  - a next decoder

3 **parametric** functions needs to be learned



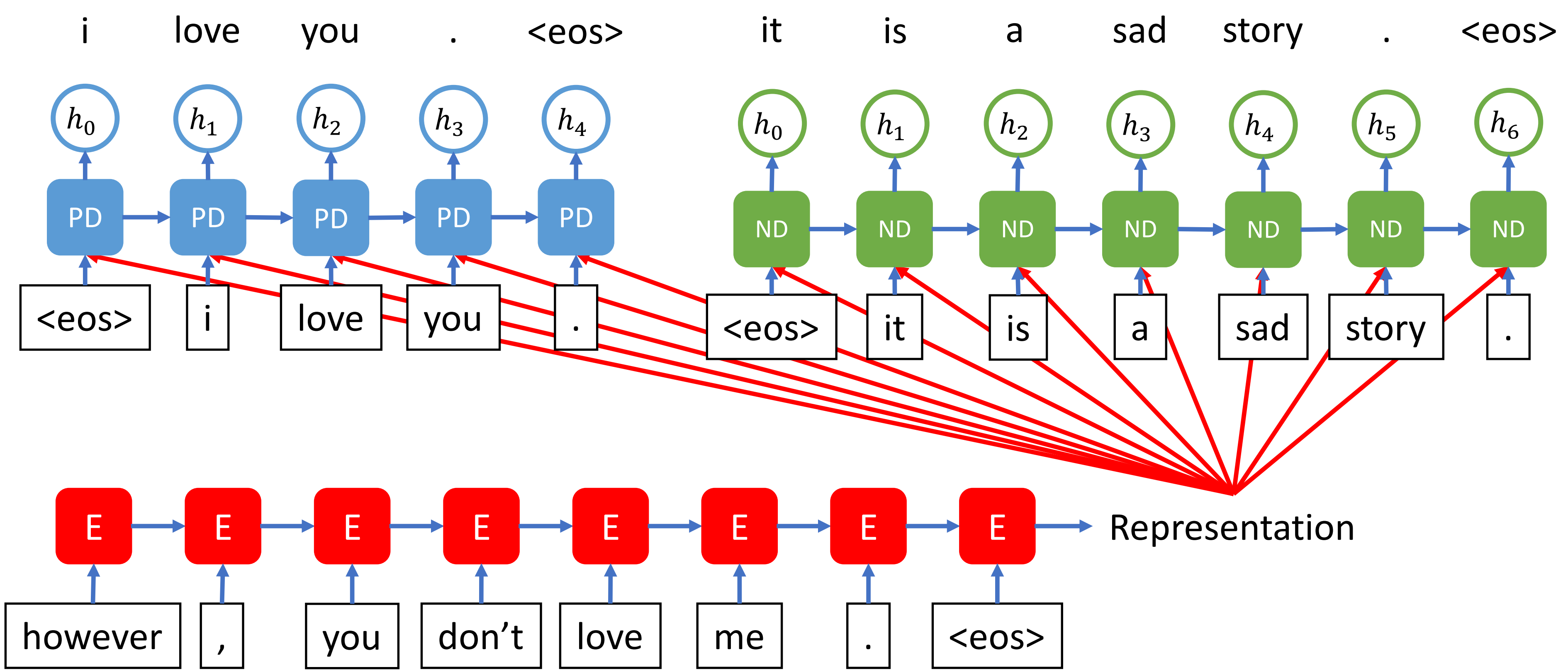
Skip-thought (Kiros et al., NIPS2015)

- Given a sentence tuple
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Detailed encoding schemes
  - Uni-skip/ Bi-skip/ Combine-skip

Skip-thought (Kiros et al., NIPS2015)

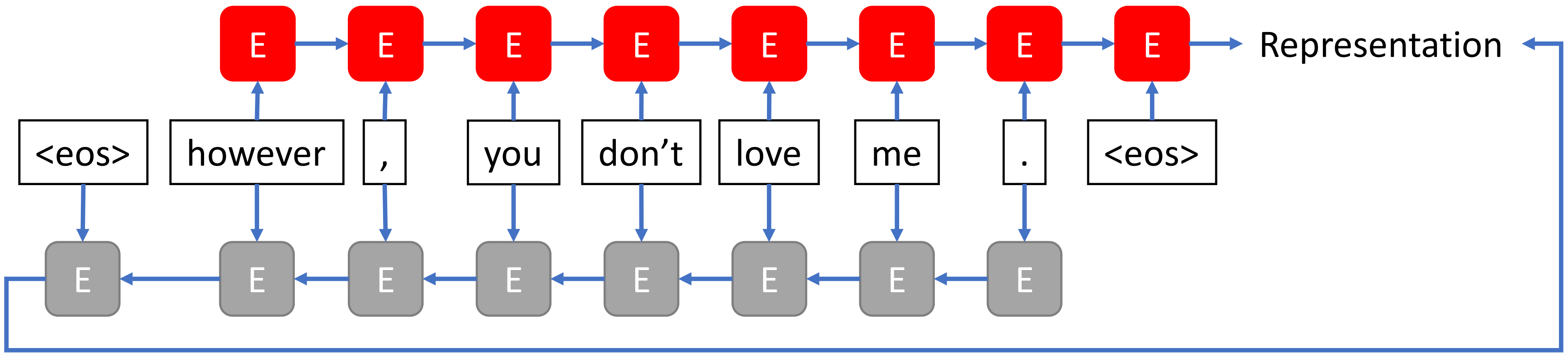
- Given a sentence tuple
  - i love you.
  - however, you don’t love me.
  - it is a sad story.
- Detailed encoding schemes
  - Uni-skip/ Bi-skip/ Combine-skip

Uni-Skip

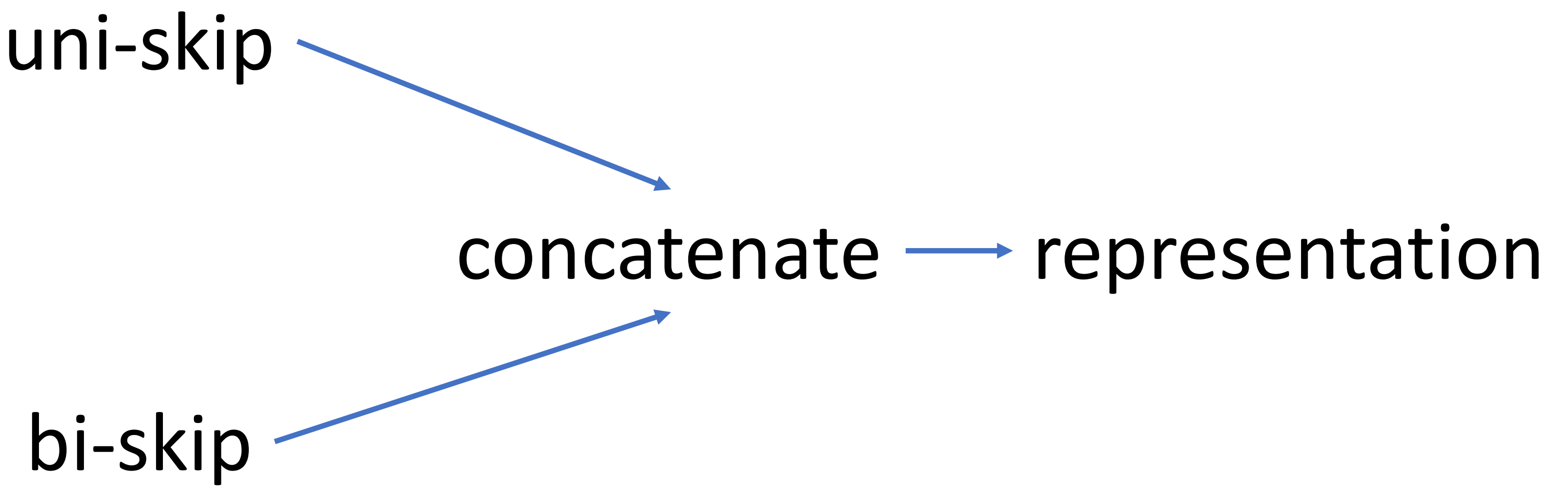


i love you . <eos>
it is a sad story . <eos>
h_0 h_1 h_2 h_3 h_4
h_0 h_1 h_2 h_3 h_4 h_5 h_6
PD PD PD PD PD
ND ND ND ND ND ND ND
<eos> i love you .
<eos> it is a sad story .
E E E E E E E E
Representation
however , you don’t love me . <eos>

Bi-Skip



Combine-Skip



Trimming and Improving Skip-thought Vectors

- Skip-thought (Kiros et al., NIPS2015)
- Our hypotheses to improve skip-thought
  - **Neighborhood hypothesis**
  - Average+Max Connection
  - Word Vectors Initialization
- Comparison between our trimmed skip-thought model and the skip-thought model
- Conclusion

Neighborhood Hypothesis

- Does this model really need a previous decoder and a next decoder?
- Hypothesis: Given the current sentence, inferring the previous sentence and inferring the next sentence both provide same supervision power.

Neighborhood Hypothesis

- Skip-thought model

$$\mathit{Sentence}_i \xrightarrow{\text{encode}} \mathit{Representation}_i \xrightarrow{\text{decode}} \mathit{Sentence}_{i-1}$$

$$\mathit{Representation}_i \xrightarrow{\text{decode}} \mathit{Sentence}_{i+1}$$

- Neighborhood Hypothesis

$$\mathit{Sentence}_i \xrightarrow{\text{encode}} \mathit{Representation}_i \xrightarrow{\text{decode}} \mathit{Sentence}_{i-1}$$

$$\mathit{Representation}_i \xrightarrow{\text{decode}} \mathit{Sentence}_{i+1}$$

Neighborhood Hypothesis

- Can we further simplify the skip-thought model?

Yes!

Neighborhood Hypothesis

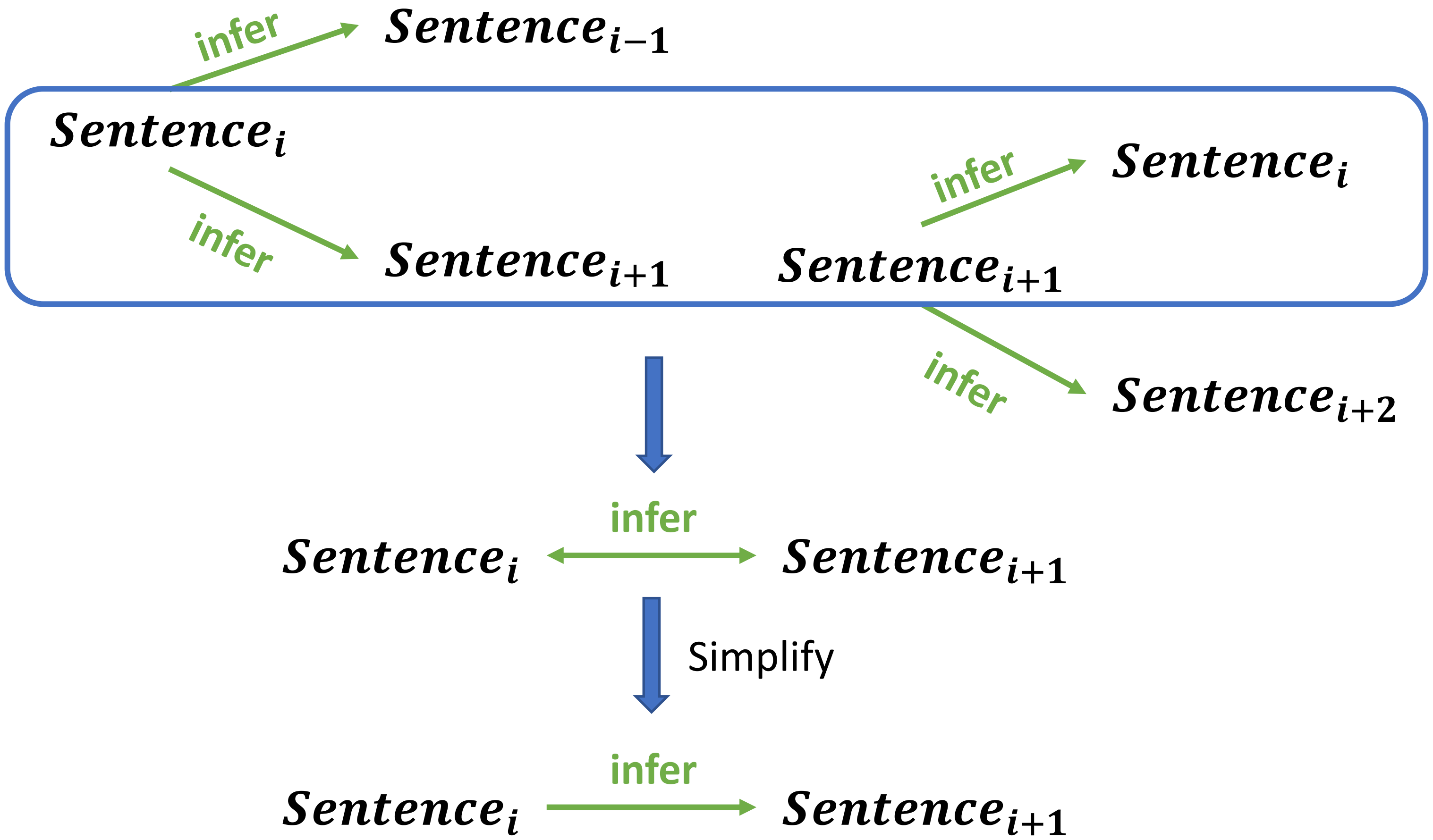
$$\boldsymbol{Sentence_i} \xrightarrow{\text{infer}} \boldsymbol{Sentence_{i-1}}$$

$$\boldsymbol{Sentence_i} \xrightarrow{\text{infer}} \boldsymbol{Sentence_{i+1}}$$

$$\boldsymbol{Sentence_{i+1}} \xrightarrow{\text{infer}} \boldsymbol{Sentence_i}$$

$$\boldsymbol{Sentence_{i+1}} \xrightarrow{\text{infer}} \boldsymbol{Sentence_{i+2}}$$

Neighborhood Hypothesis



Neighborhood Hypothesis

- Skip-thought Model

$$\begin{tikzcd} & & \boldsymbol{Sentence_{i-1}} \\ \boldsymbol{Sentence_i} \arrow[r, "\text{encode}"] & \boldsymbol{Representation_i} \arrow[ur, "\text{decode}"] \arrow[dr, "\text{decode}"'] & \\ & & \boldsymbol{Sentence_{i+1}} \end{tikzcd}$$

- Our **Trimmed** Skip-thought Model

$$\boldsymbol{Sentence_i} \xrightarrow{\text{encode}} \boldsymbol{Representation_i} \xrightarrow{\text{decode}} \boldsymbol{Sentence_{i+1}}$$

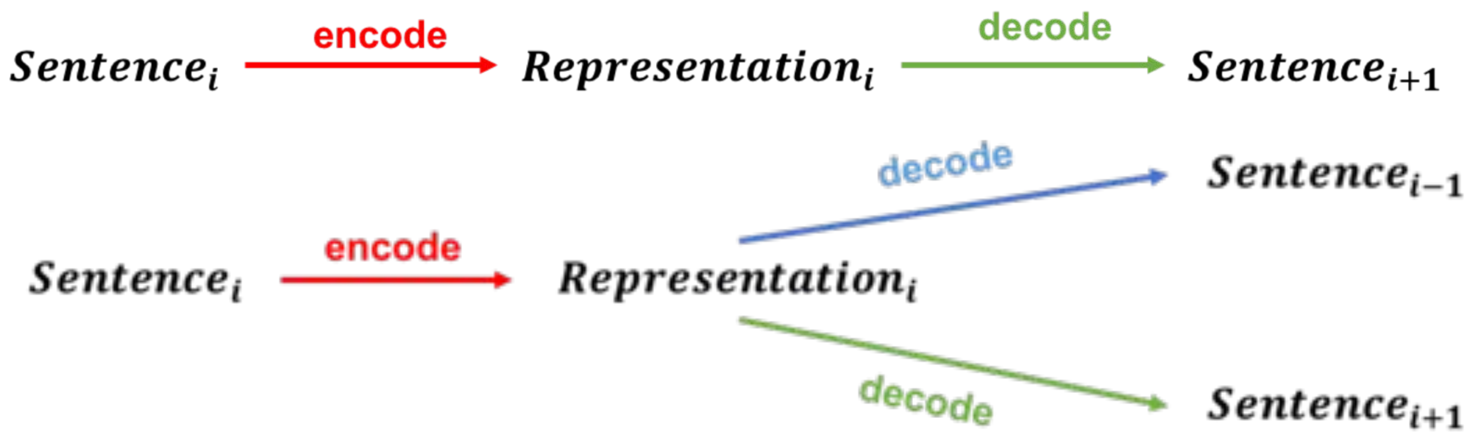
Neighborhood Hypothesis

- **BookCorpus** dataset (Zhu et al., ICCV2015)
  - 74 million contiguous sentences from 7,000 books

Encoder - Decoder

- Then, the sentence **encoder** was evaluated on 7 natural language processing (NLP) tasks.

Neighborhood Hypothesis

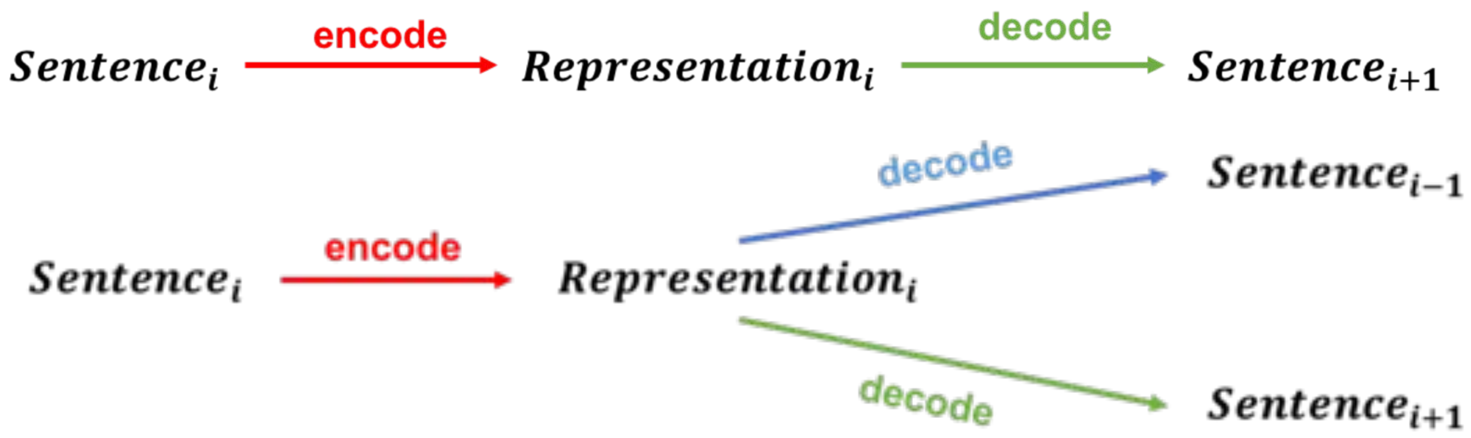


Relationship of sentence pair

Classification on single sentence

Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Plain Connection										
bi-T-skip	word2vec	0.8408	0.7649	0.2994	75.3 / **83.0**	76.1	80.3	92.3	87.5	86.6
uni-T-skip		0.8349	0.7629	0.3084	73.7 / 81.9	75.7	82.1	91.3	87.4	86.4
C-T-skip		**0.8518**	**0.7808**	**0.2802**	**75.7 / 83.0**	76.8	**83.2**	**92.8**	**88.4**	87.5
bi-skip	word2vec	0.8385	0.7618	0.3028	73.9 / 82.0	75.7	81.4	92.1	87.2	88.4
uni-skip		0.8344	0.7586	0.3098	73.6 / 81.6	76.2	81.8	92.2	87.6	87.0
C-skip		0.8492	0.7738	0.2844	74.6 / 82.3	**77.0**	83.0	92.7	87.9	**89.2**

Neighborhood Hypothesis



Relationship of sentence pair

Classification on single sentence

Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Plain Connection										
bi-T-skip	word2vec	0.8408	0.7649	0.2994	75.3 / **83.0**	76.1	80.3	92.3	87.5	86.6
uni-T-skip		0.8349	0.7629	0.3084	73.7 / 81.9	75.7	82.1	91.3	87.4	86.4
C-T-skip		**0.8518**	**0.7808**	**0.2802**	**75.7 / 83.0**	76.8	**83.2**	**92.8**	**88.4**	87.5
bi-skip	word2vec	0.8385	0.7618	0.3028	73.9 / 82.0	75.7	81.4	92.1	87.2	88.4
uni-skip		0.8344	0.7586	0.3098	73.6 / 81.6	76.2	81.8	92.2	87.6	87.0
C-skip		0.8492	0.7738	0.2844	74.6 / 82.3	**77.0**	83.0	92.7	87.9	**89.2**

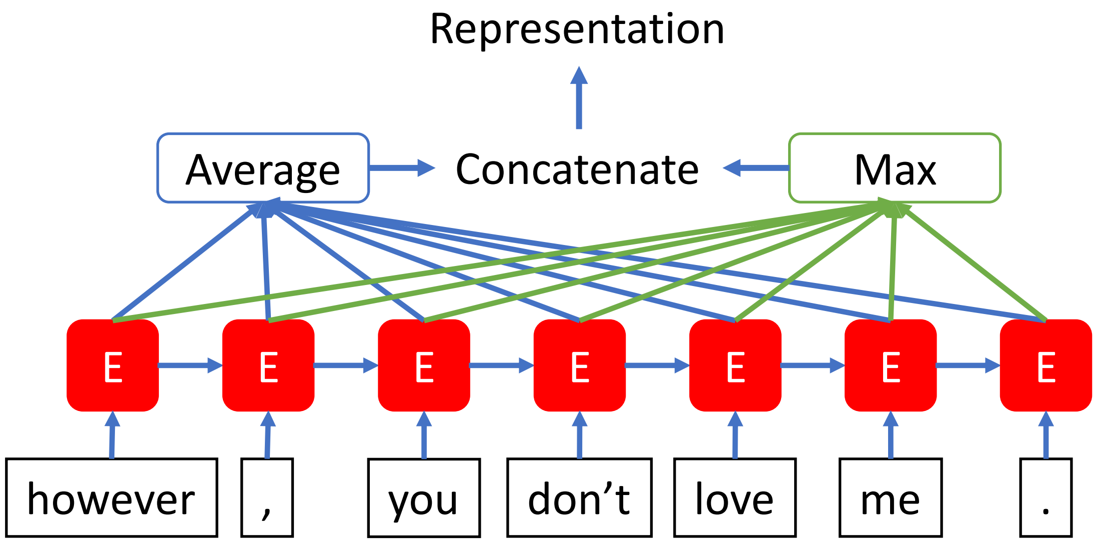
Trimming and Improving Skip-thought Vectors

- Skip-thought
- Our hypotheses to improve skip-thought
  - Neighborhood hypothesis
  - **Average+Max Connection**
  - Word Vector Initialization
- Comparison between our trimmed skip-thought model and the skip-thought model
- Conclusion

Average+Max Connection

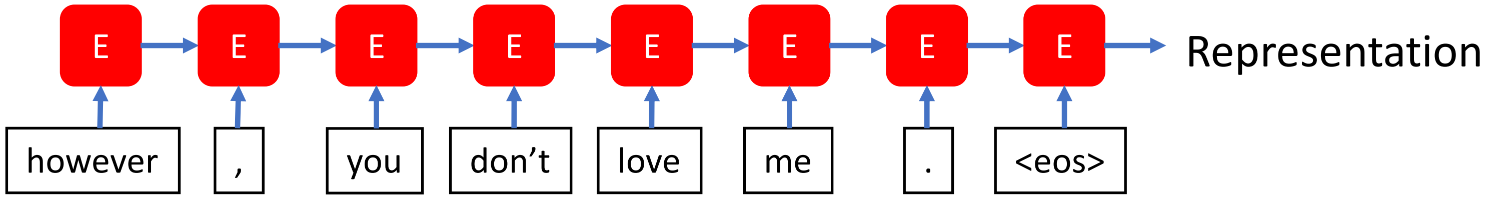
- Plain Connection (Kiros et al., NIPS2015)

- Average+Max Connection (Chen et al., arXiv2017)

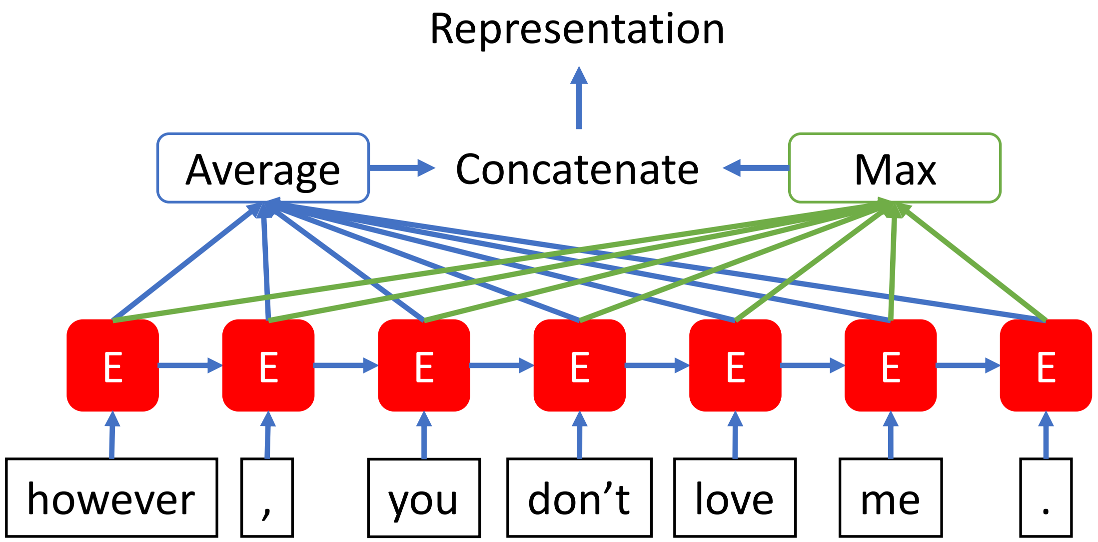


Average+Max Connection

- Plain Connection (Kiros et al., NIPS2015)



- Average+Max Connection (Chen et al., arXiv2017)



Average+Max Connection

- The average+max connection was proposed for **supervised** tasks, and specifically for Stanford Natural Language Inference corpus.
  - (Chen et al., arXiv2017; Bowman et al., EMNLP2015)

supervised → **unsupervised**

- We hypothesize that, our trimmed skip-thought model could also **benefit** from the average+max connection .

Average+Max Connection

- The average+max connection was proposed for **supervised** tasks, and specifically for Stanford Natural Language Inference corpus.
  - (Chen et al., arXiv2017; Bowman et al., EMNLP2015)

supervised → **unsupervised**

- We hypothesize that, our trimmed skip-thought model could also **benefit** from the average+max connection .

Average+Max Connection

		Relationship of sentence pair				Classification on single sentence				
Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Plain Connection										
bi-T-skip	word2vec	0.8408	0.7649	0.2994	75.3 / **83.0**	76.1	80.3	92.3	87.5	86.6
uni-T-skip		0.8349	0.7629	0.3084	73.7 / 81.9	75.7	82.1	91.3	87.4	86.4
C-T-skip		0.8518	0.7808	0.2802	**75.7 / 83.0**	**76.8**	**83.2**	**92.8**	**88.4**	87.5
Average+Max Connection										
bi-T-skip	word2vec	0.8463	0.7744	0.2894	73.3 / 81.6	74.4	78.6	91.3	86.2	88.8
uni-T-skip		0.8466	0.7705	0.2884	74.0 / 81.7	73.0	78.6	91.3	85.2	88.4
C-T-skip		**0.8598**	**0.7892**	**0.2654**	75.0 / 82.2	75.1	80.0	92.2	87.2	**90.0**

Average+Max Connection

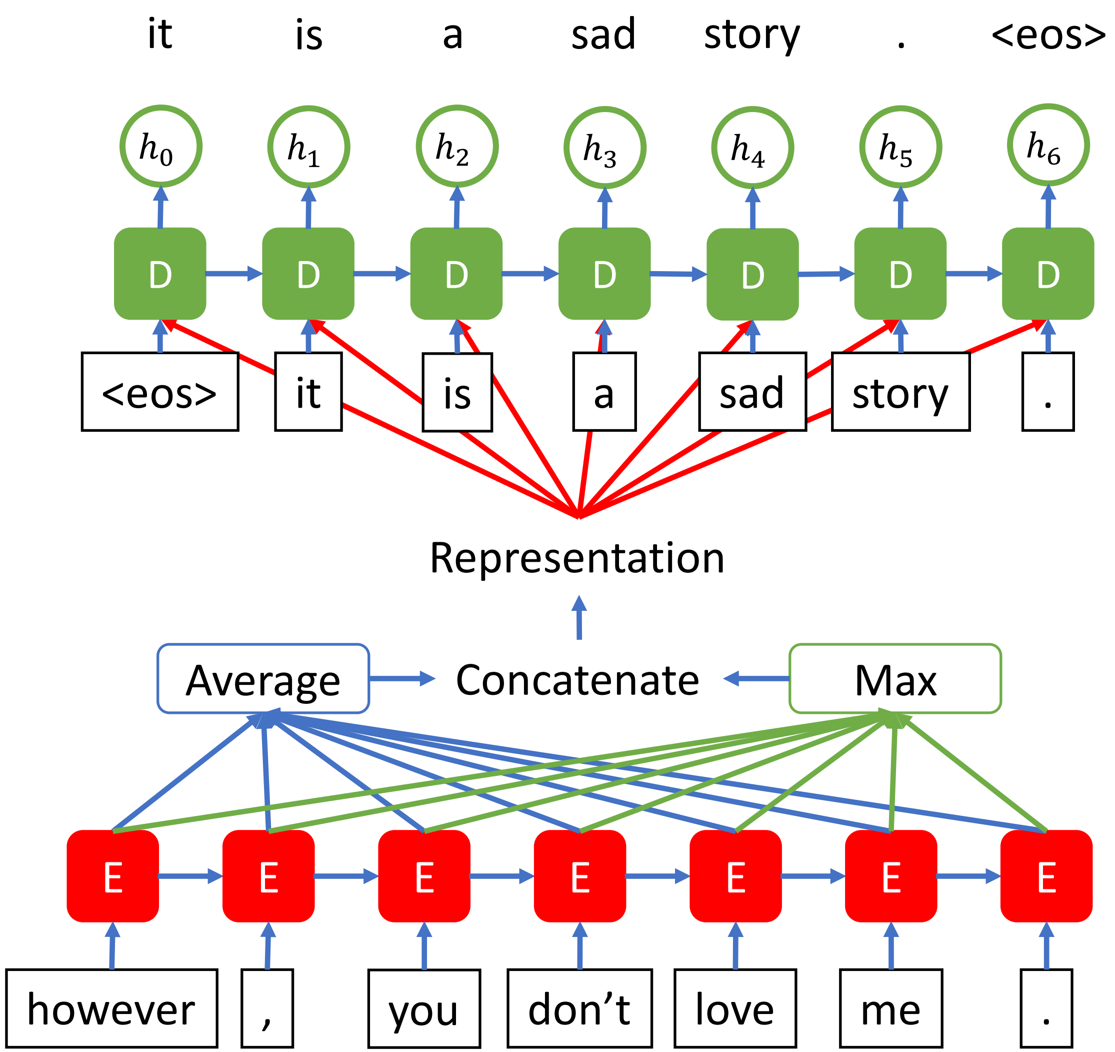
Relationship of sentence pair | Classification on single sentence

Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Plain Connection										
bi-T-skip	word2vec	0.8408	0.7649	0.2994	75.3 / **83.0**	76.1	80.3	92.3	87.5	86.6
uni-T-skip	word2vec	0.8349	0.7629	0.3084	73.7 / 81.9	75.7	82.1	91.3	87.4	86.4
C-T-skip	word2vec	0.8518	0.7808	0.2802	**75.7 / 83.0**	**76.8**	**83.2**	**92.8**	**88.4**	87.5
Average+Max Connection										
bi-T-skip	word2vec	0.8463	0.7744	0.2894	73.3 / 81.6	74.4	78.6	91.3	86.2	88.8
uni-T-skip	word2vec	0.8466	0.7705	0.2884	74.0 / 81.7	73.0	78.6	91.3	85.2	88.4
C-T-skip	word2vec	**0.8598**	**0.7892**	**0.2654**	75.0 / 82.2	75.1	80.0	92.2	87.2	**90.0**

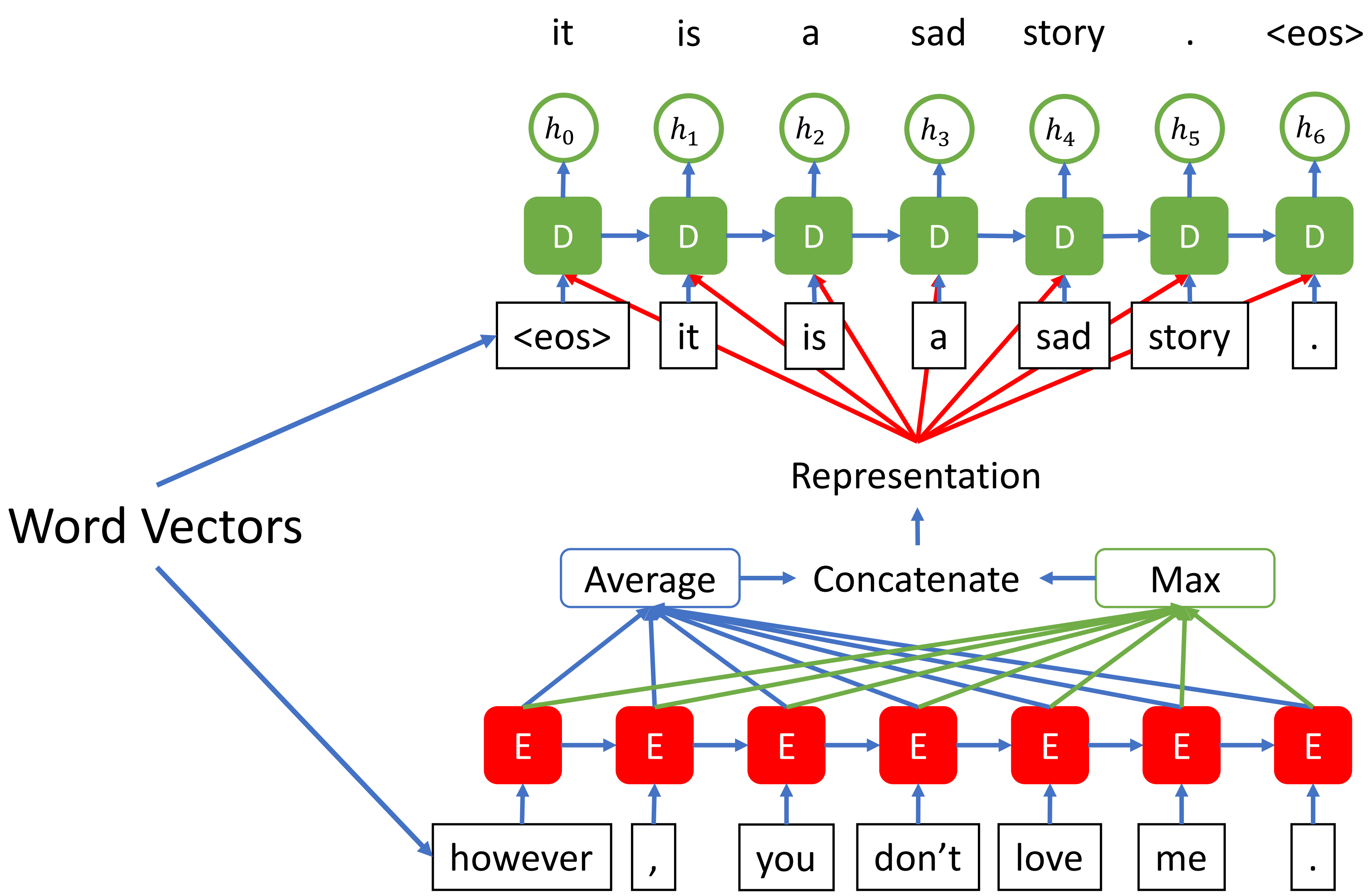
Trimming and Improving Skip-thought Vectors

- Skip-thought
- Our hypotheses to improve skip-thought
  - Neighborhood hypothesis
  - Average+Max Connection
  - **Word Vectors Initialization**
- Comparison between our trimmed skip-thought model and the skip-thought model
- Conclusion

Word Vectors Initialization



Word Vectors Initialization



Word Vectors Initialization

- Pretrained word vectors usually help the deep learning models to perform better on **supervised** tasks. (Collobert et al., JMLR2011)
  - word2vec (Mikolov et al., NIPS2013)
  - GloVe (Pennington et al., EMNLP2014)

- We hypothesize that, initializing our model with **pretrained word vectors** could also help the model to learn better sentence representation.

Word Vectors Initialization

- Pretrained word vectors usually help the deep learning models to perform better on **supervised** tasks. (Collobert et al., JMLR2011)
  - word2vec (Mikolov et al., NIPS2013)
  - GloVe (Pennington et al., EMNLP2014)

- We hypothesize that, initializing our model with **pretrained word vectors** could also help the model to learn better sentence representation.

Word Vectors Initialization

- Based on our trimmed skip-thought model with Average+Max connection, we implement models with 3 initializations.

Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Average+Max Connection										
bi-T-skip	random	0.8336	0.7612	0.3112	73.2 / 81.3	69.7	76.0	89.6	83.5	86.6
uni-T-skip	random	0.8293	0.7555	0.3180	72.5 / 81.0	67.3	74.9	89.0	81.1	83.6
C-T-skip	random	0.8458	0.7755	0.2902	74.7 / 82.1	70.4	76.7	90.4	83.8	84.8
bi-T-skip	GloVe	0.8444	0.7739	0.2922	75.1 / 82.4	74.4	79.5	90.9	85.3	87.6
uni-T-skip	GloVe	0.8485	0.7711	0.2854	73.7 / 81.8	74.6	78.8	91.1	86.2	87.0
C-T-skip	GloVe	0.8596	**0.7903**	0.2665	**75.4 / 82.6**	**75.6**	**80.4**	91.9	87.0	89.0
bi-T-skip	word2vec	0.8463	0.7744	0.2894	73.3 / 81.6	74.4	78.6	91.3	86.2	88.8
uni-T-skip	word2vec	0.8466	0.7705	0.2884	74.0 / 81.7	73.0	78.6	91.3	85.2	88.4
C-T-skip	word2vec	**0.8598**	0.7892	**0.2654**	75.0 / 82.2	75.1	80.0	**92.2**	**87.2**	**90.0**

Word Vectors Initialization

Relationship of sentence pair

Classification on single sentence

Model	WE	SICK			MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
		r	ρ	MSE						
Average+Max Connection										
bi-T-skip	random	0.8336	0.7612	0.3112	73.2 / 81.3	69.7	76.0	89.6	83.5	86.6
uni-T-skip	random	0.8293	0.7555	0.3180	72.5 / 81.0	67.3	74.9	89.0	81.1	83.6
C-T-skip	random	0.8458	0.7755	0.2902	74.7 / 82.1	70.4	76.7	90.4	83.8	84.8
bi-T-skip	GloVe	0.8444	0.7739	0.2922	75.1 / 82.4	74.4	79.5	90.9	85.3	87.6
uni-T-skip	GloVe	0.8485	0.7711	0.2854	73.7 / 81.8	74.6	78.8	91.1	86.2	87.0
C-T-skip	GloVe	0.8596	**0.7903**	0.2665	**75.4 / 82.6**	**75.6**	**80.4**	91.9	87.0	89.0
bi-T-skip	word2vec	0.8463	0.7744	0.2894	73.3 / 81.6	74.4	78.6	91.3	86.2	88.8
uni-T-skip	word2vec	0.8466	0.7705	0.2884	74.0 / 81.7	73.0	78.6	91.3	85.2	88.4
C-T-skip	word2vec	**0.8598**	0.7892	**0.2654**	75.0 / 82.2	75.1	80.0	**92.2**	**87.2**	**90.0**

Furthermore…

- We wonder if adding more parameters could improve our model.

Furthermore…

- Double-sized encoder gave us further improvement.

Relationship of sentence pair: SICK, MSRP. Classification on single sentence: MR, CR, SUBJ, MPQA, TREC.

	Model	WE	SICK r	SICK ρ	SICK MSE	MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
	Doubled Encoder's Dimension vs. Results reported by [6]										
Ours	bi-T-skip	word2vec	0.8503	0.7796	0.2823	74.4 / 82.2	74.8	80.3	91.8	87.0	88.2
Ours	uni-T-skip	word2vec	0.8486	0.7784	0.2857	74.3 / 82.4	72.9	78.0	90.7	85.7	86.4
Ours	C-T-skip	word2vec	**0.8611**	**0.7946**	**0.2634**	**74.5 / 82.2**	75.4	**80.3**	92.2	**87.4**	88.4
Kiros et al.	bi-skip [6]	random	0.8405	0.7696	0.2995	71.2 / 81.2	73.9	77.9	92.5	83.3	89.4
Kiros et al.	uni-skip [6]	random	0.8477	0.7780	0.2872	73.0 / 81.9	75.5	79.3	92.1	86.9	91.4
Kiros et al.	C-skip [6]	random	0.8584	0.7916	0.2687	73.0 / 82.0	**76.5**	80.1	**93.6**	87.1	**92.2**

Furthermore…

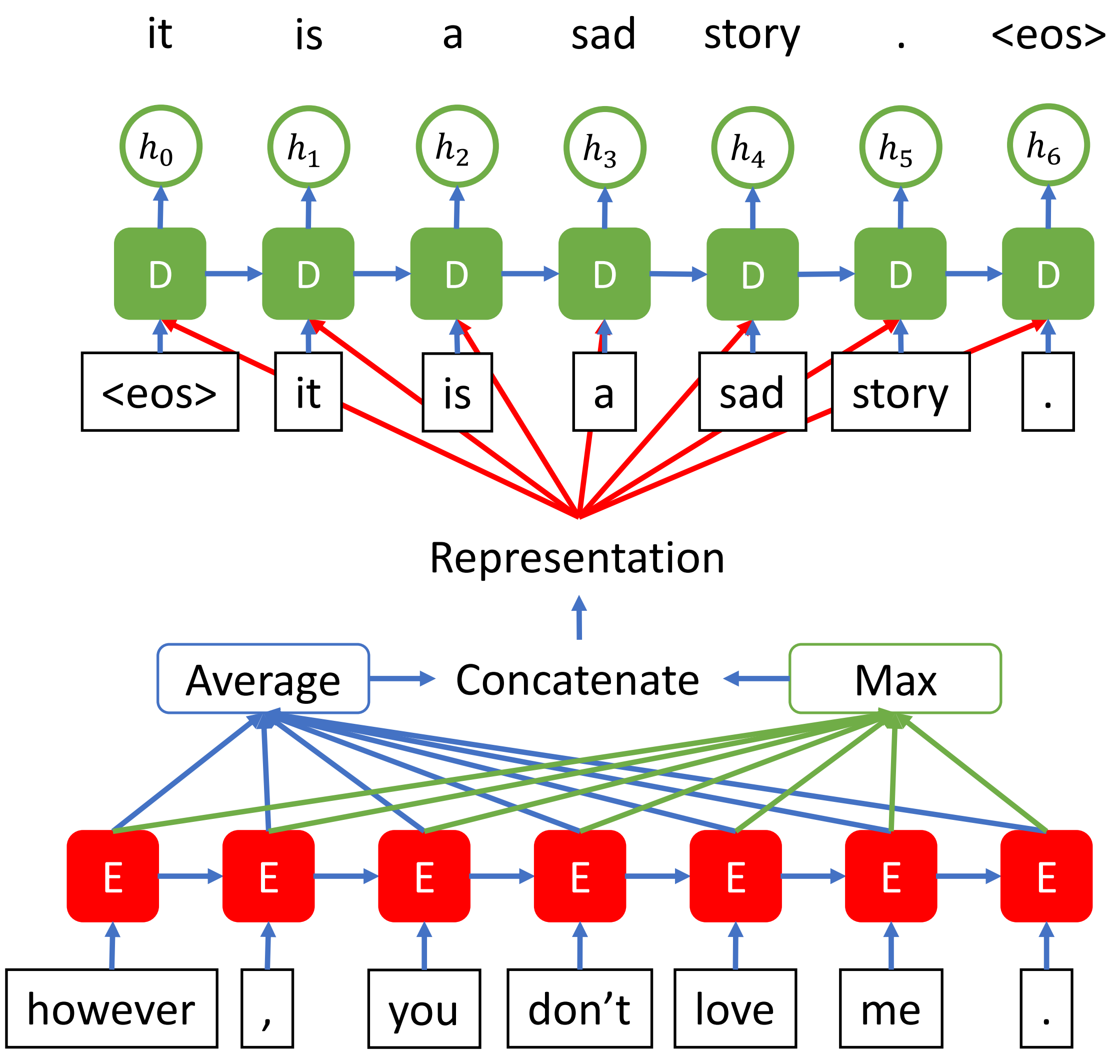
- Double-sized encoder gave us further improvement.

	Model	WE	SICK r	SICK ρ	SICK MSE	MSRP (Acc/F1)	MR	CR	SUBJ	MPQA	TREC
			Relationship of sentence pair				Classification on single sentence				
	Doubled Encoder's Dimension vs. Results reported by [6]										
Ours	bi-T-skip	word2vec	0.8503	0.7796	0.2823	74.4 / 82.2	74.8	80.3	91.8	87.0	88.2
Ours	uni-T-skip	word2vec	0.8486	0.7784	0.2857	74.3 / 82.4	72.9	78.0	90.7	85.7	86.4
Ours	C-T-skip	word2vec	**0.8611**	**0.7946**	**0.2634**	**74.5 / 82.2**	75.4	**80.3**	92.2	**87.4**	88.4
Kiros et al.	bi-skip [6]	random	0.8405	0.7696	0.2995	71.2 / 81.2	73.9	77.9	92.5	83.3	89.4
Kiros et al.	uni-skip [6]	random	0.8477	0.7780	0.2872	73.0 / 81.9	75.5	79.3	92.1	86.9	91.4
Kiros et al.	C-skip [6]	random	0.8584	0.7916	0.2687	73.0 / 82.0	**76.5**	80.1	**93.6**	87.1	**92.2**

Trimming and Improving Skip-thought Vectors

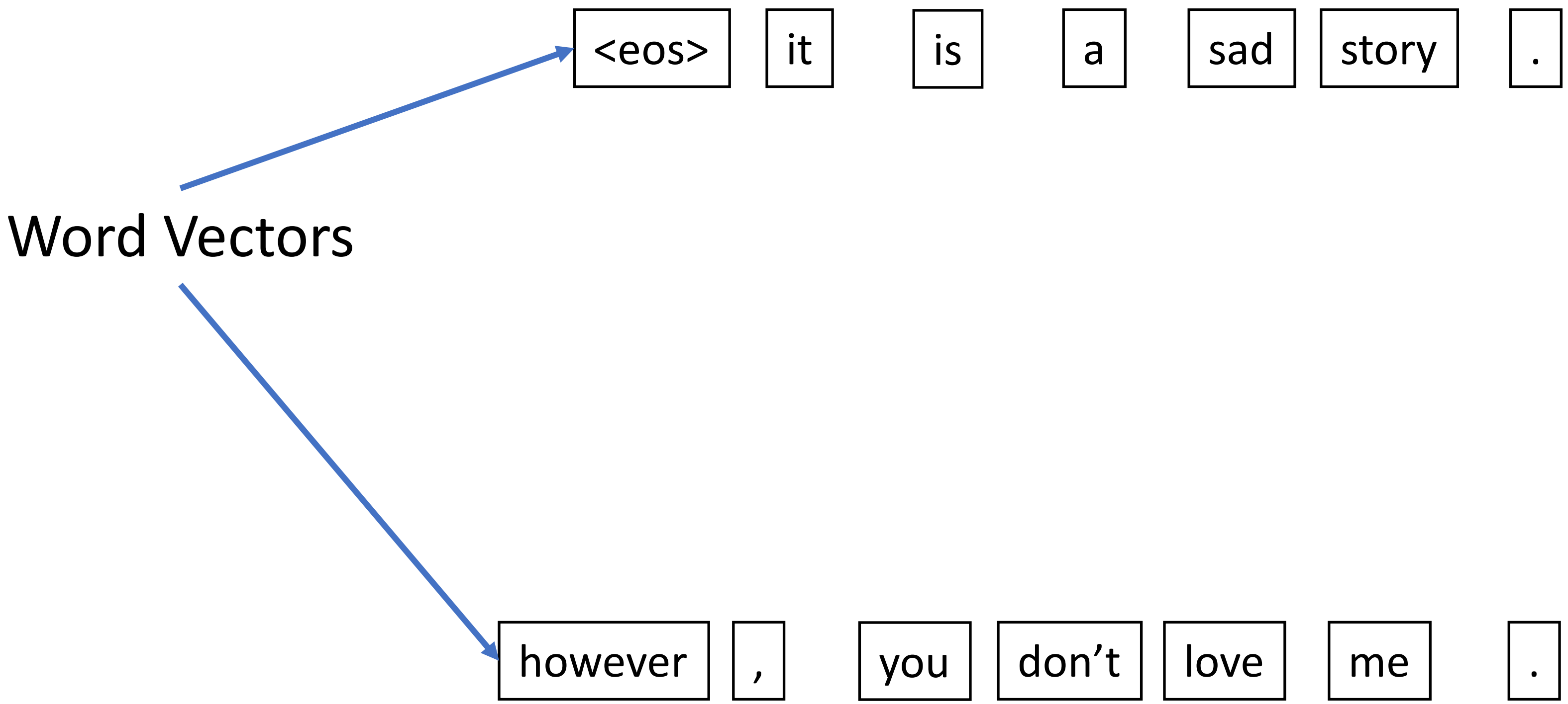
- Skip-thought
- Our hypotheses to improve skip-thought
- **Comparison between our trimmed skip-thought model and the skip-thought model**
  - Number of Parameters
  - Training Time
- Conclusion

Our Trimmed Skip-thought

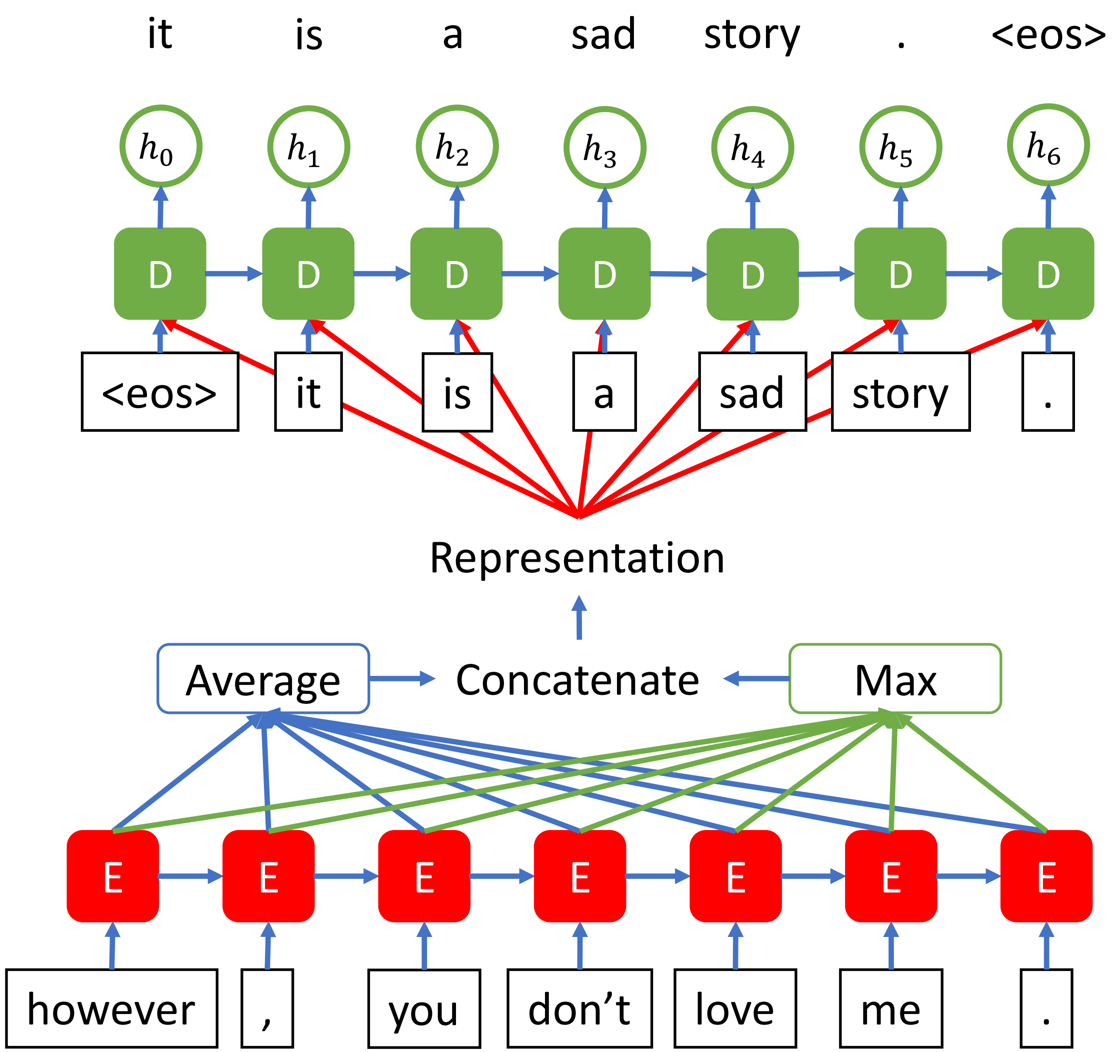


Our Trimmed Skip-thought

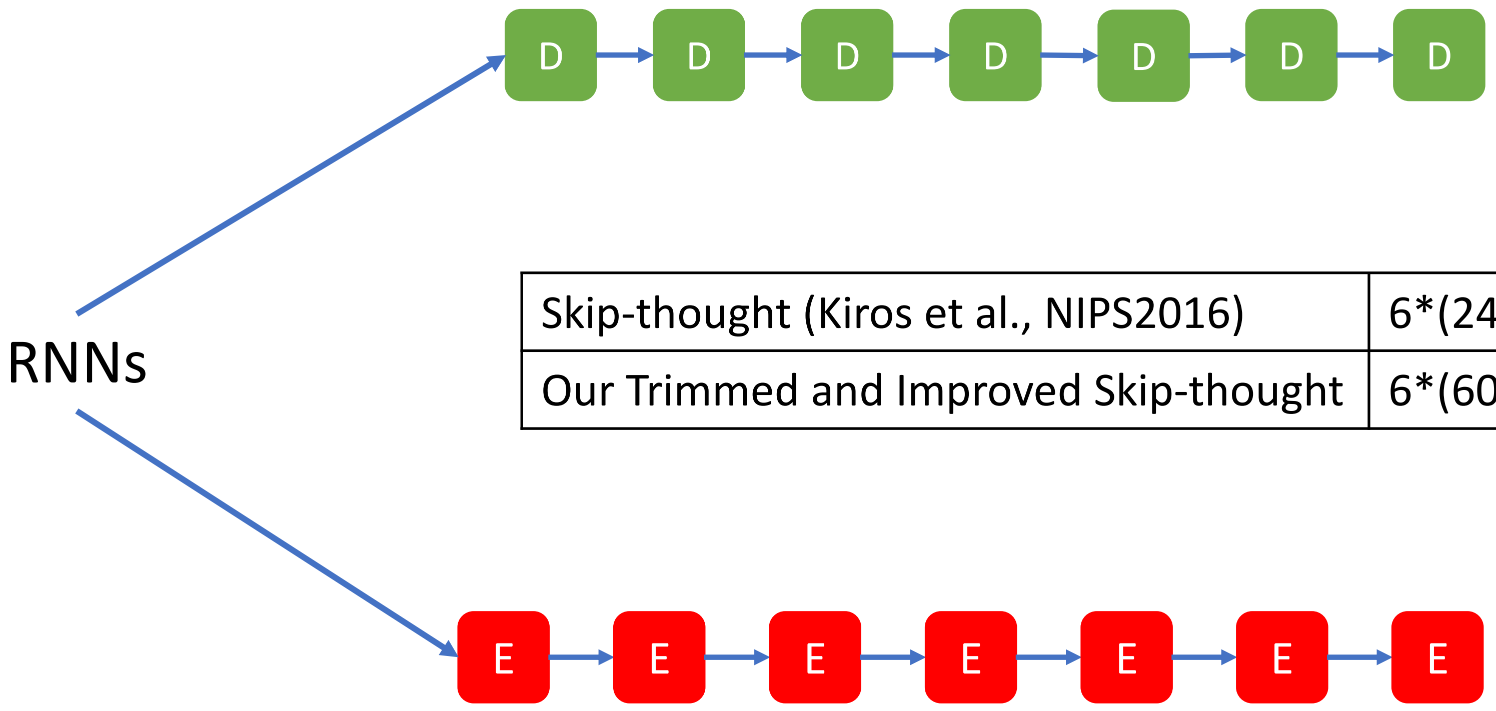
Skip-thought (Kiros et al., NIPS2016)	620*20000
Our Trimmed and Improved Skip-thought	300*20000



Our Trimmed Skip-thought

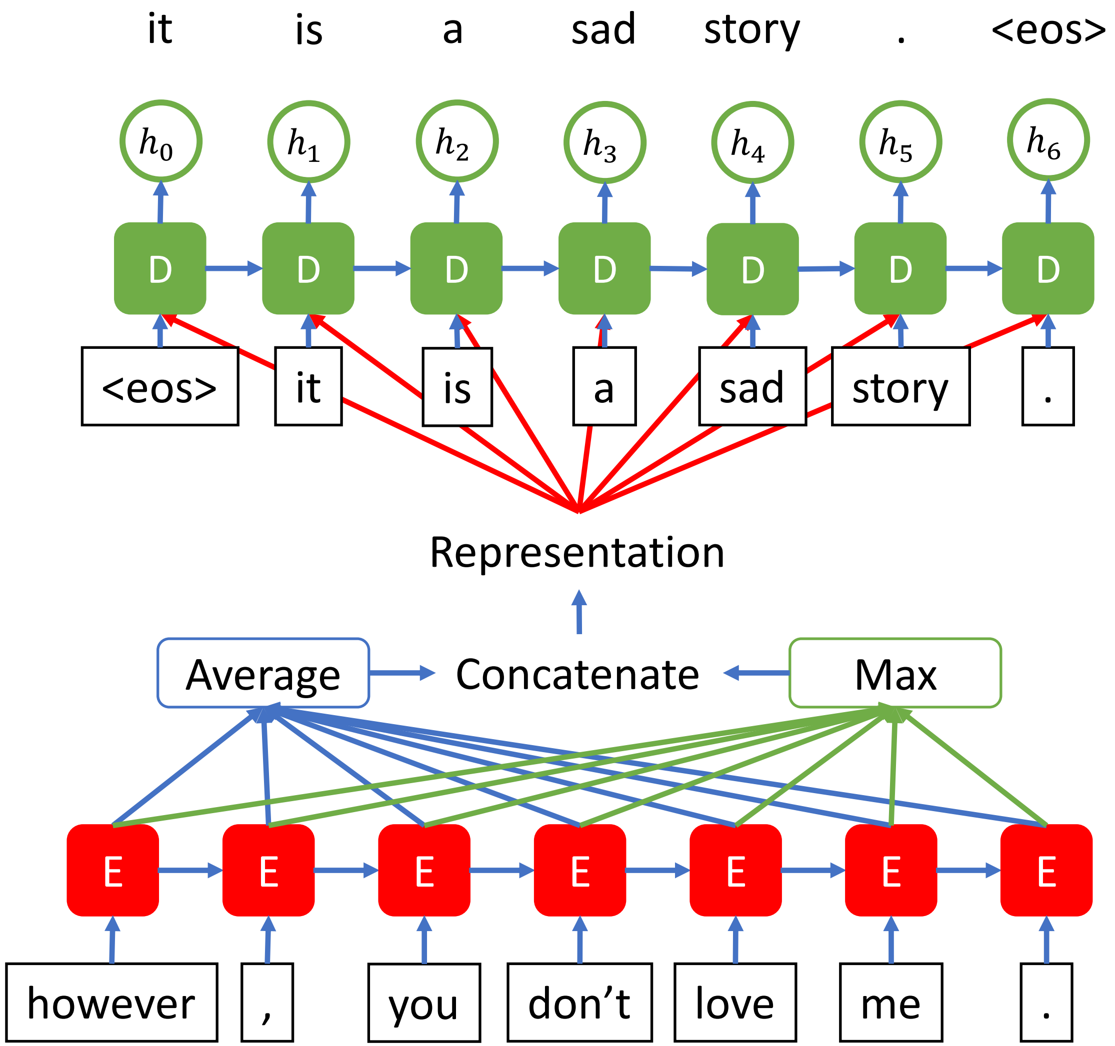


Our Trimmed Skip-thought

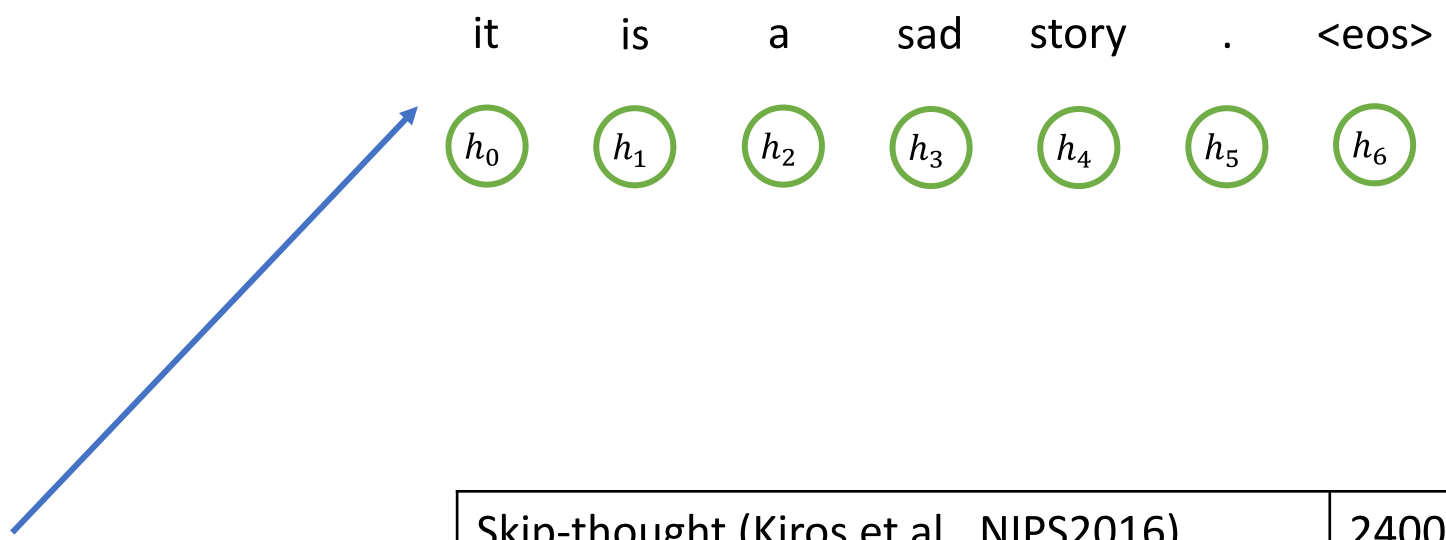


Skip-thought (Kiros et al., NIPS2016)	6*(2400*2400)*2
Our Trimmed and Improved Skip-thought	6*(600*600)*2

Our Trimmed Skip-thought



Our Trimmed Skip-thought



Linear Prediction

Skip-thought (Kiros et al., NIPS2016)	2400*20000
Our Trimmed and Improved Skip-thought	600*20000

Number of Parameters

Model	RNNs	Word Vectors	Linear Prediction
uni-T-skip (ours)	4.32M	6M	12M
bi-T-skip (ours)	3.24M		
uni-T-skip-double (ours)	10.80M		
bi-T-skip-double (ours)	6.48M		
uni-skip (Kiros et al., NIPS2015)	69.12M	12.4M	48M
bi-skip (Kiros et al., NIPS2015)	51.84M		

\`\`RNNs'' refers to recurrent networks in the encoder and the decoder.
\`\`Word Embedding'' refers to all word vectors in unsupervised training.
\`\`Linear Prediction'' refers to the linear prediction layer in the decoder.

Training Time

Model		Training Time
Skip-thought	(Kiros et al., NIPS2015)	2 weeks

Training Time

Model		Training Time
Skip-thought	(Kiros et al., NIPS2015)	2 weeks
Skip-thought	(our implementation)	4 days

Training Time

Model		Training Time
Skip-thought	(Kiros et al., NIPS2015)	2 weeks
Skip-thought	(our implementation)	4 days
Our Trimmed and Improved Skip-thought		1 day

Trimming and Improving Skip-thought Vectors

- Skip-thought
- Our hypotheses to improve skip-thought
- Comparison between our trimmed skip-thought model and the skip-thought model
- **Conclusion**

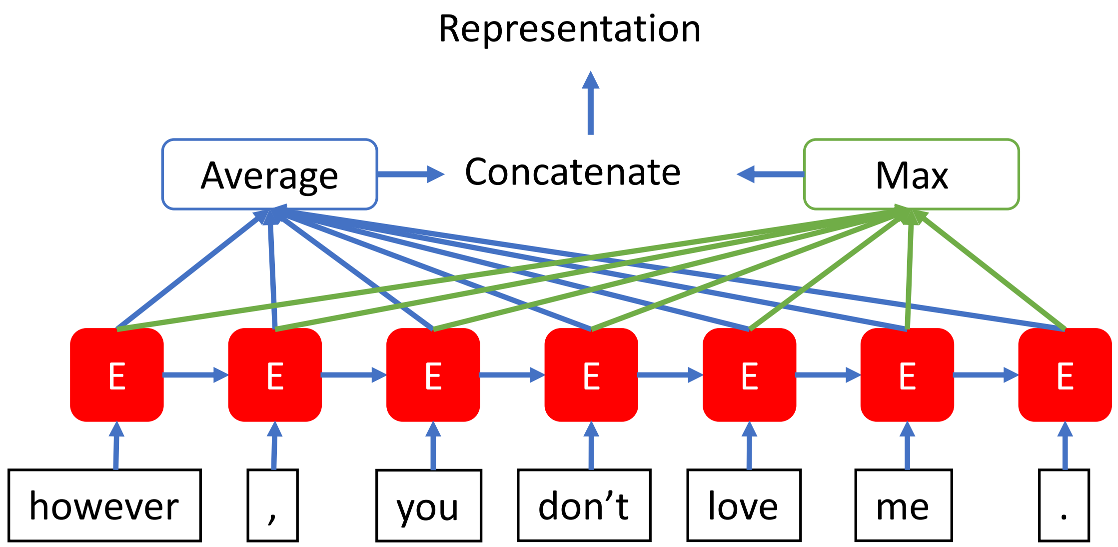
Conclusion: We improved skip-thought model

- by **dropping one decoder**

$$\boldsymbol{Sentence_i} \xrightarrow{\text{encode}} \boldsymbol{Representation_i} \xrightarrow{\text{decode}} \boldsymbol{Sentence_{i+1}}$$

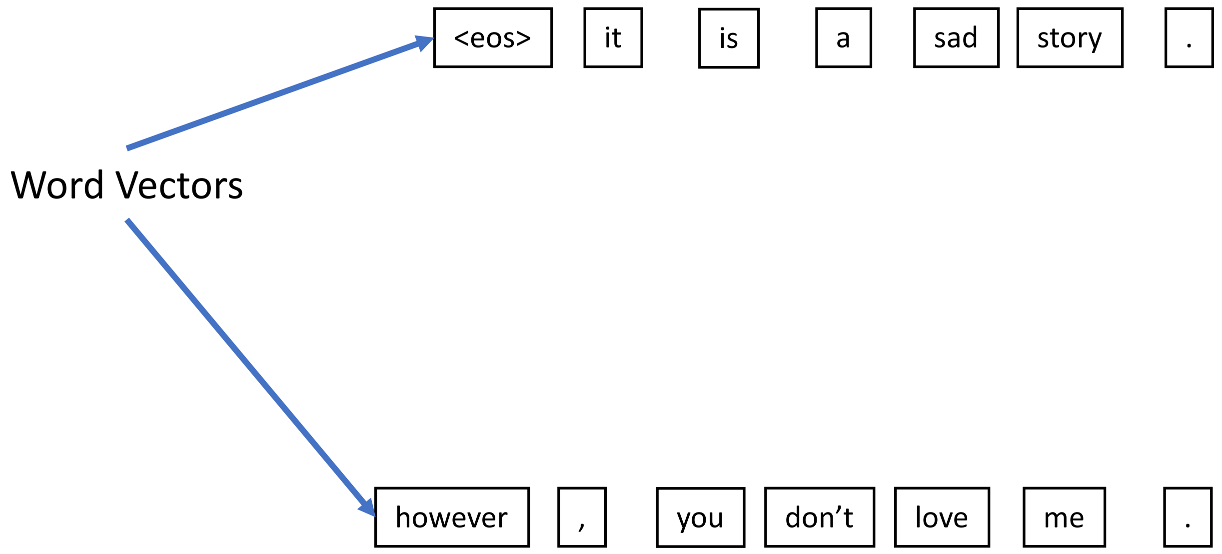
Conclusion: We improved skip-thought model

- by applying the **average+max connection** between the encoder and the decoder



Conclusion: We improved skip-thought model

- by **initializing** the model with **pretrained word vectors** instead of random values



Conclusion: We improved skip-thought model

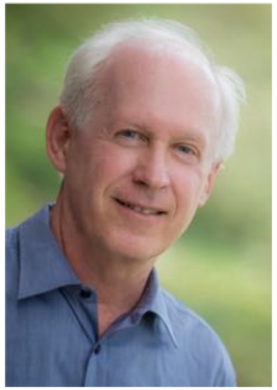
- by **accelerating** the training procedure, because we cut out 80% parameters in the skip-thought model.

Model		Training Time
Skip-thought	(Kiros et al., NIPS2015)	2 weeks
Skip-thought	(our implementation)	4 days
Our Trimmed and Improved Skip-thought		1 day

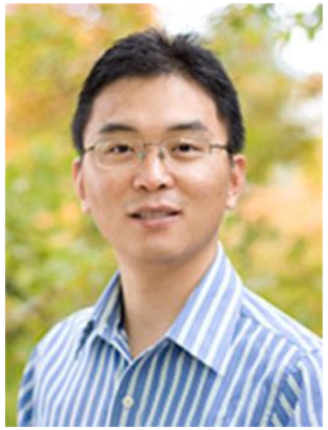
Committee & Collaborators

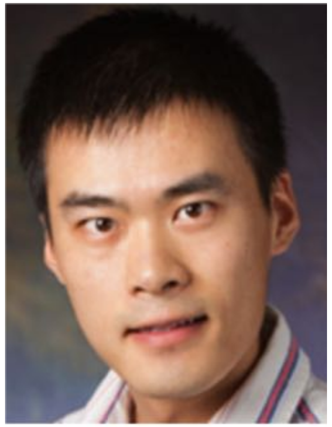
- Committee members
  - Virginia R. de Sa, CogSci
  - Benjamin K. Bergen, CogSci
  - Jeffrey L. Elman, CogSci
  - Julian J. McAuley, CSE






- Collaborators
  - Hailin Jin, Chen Fang, Zhaowen Wang
  - Researchers at Adobe research lab





Acknowledgements

- Many thanks to Adobe Research Lab for GPUs support, also to NVIDIA for DGX-1 trial.

Acknowledgements

- Many thanks to cohort, and Marta.

Q & A