Pairwise Sentence Model

10-NIPS15-Ryan-Skip-Thought Vectors

PDF, Bib, Review Theono

This paper presented an encoder-decoder model to learn a generic, distributed sentence encoder.

- [**Problem**]: Sentence Representation. Sentence vectors ate extracted and evaluated with linear models on 8 tasks.
- [**Motivation**]:

> In this paper we abstract away from the composition methods themselves and consider an alternative loss function that can be applied with any composition operator. **(step1 purpose: what we want to do?)**
>
> We consider the following question: is there a task and a corresponding loss that will allow us to learn highly generic sentence representations? **(step2 question: The key problem?)**
>
> We give evidence for this by proposing a model for learning high-quality sentence vectors without a particular supervised task in mind. **(step3 plan1: solution we reject)**
>
> Using word vector learning as inspiration, we propose an objective function that abstracts the skip-gram model to the sentence level. That is, instead of using a word to predict its surrounding context, we instead encode a sentence to predict the sentences around it. Thus, any composition operator can be substituted as a sentence encoder and only the objective function becomes modified. **(step4 our work: step by step, more and more deep)**
>
> Figure 1 illustrate the model. We call our model **skip-thoughts** and vectors induced by our model are called **skip-thought vectors**. **(step5 Others: Figure or Name)**

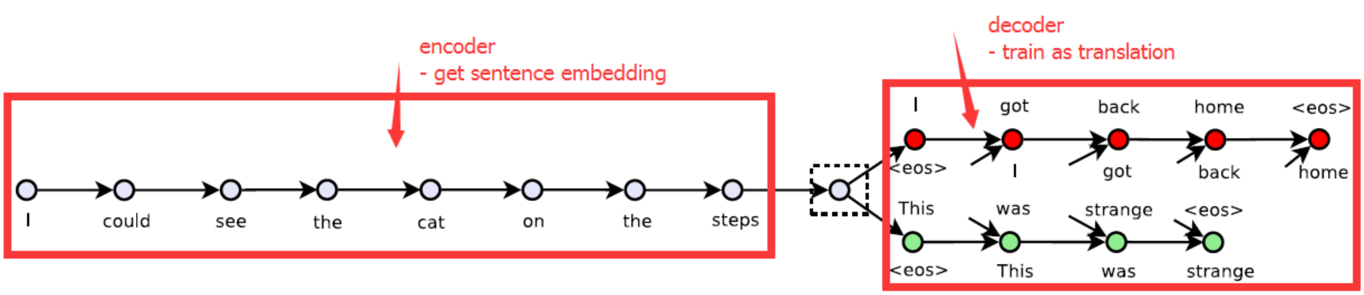

Figure 1: The skip-thoughts model. Given a tuple (s_{i-1}, s_i, s_{i+1}) of contiguous sentences, with s_i the i-th sentence of a book, the sentence s_i is encoded and tries to reconstruct the previous sentence s_{i-1} and next sentence s_{i+1}. In this example, the input is the sentence triplet *I got back home. I could see the cat on the steps. This was strange.* Unattached arrows are connected to the encoder output. Colors indicate which components share parameters. $\langle \text{eos} \rangle$ is the end of sentence token.

9-AAAI16-Mueller-Siamese Recurrent Architectures for Learning Sentence Similarity

PDF, Bib

A new top resluts for Relateness on SICK: 0.8822(pearson)

- [**Model**]
  - replace the top softmax layer with l1 norm similarity function
  - Sentence Representation can capature the following information:
    - negation, not, no
    - topic
    - Entailment classsification
  - I think the model is to enforcement the similarity of the two sentences, which is direct and efficient.
- [**Experiments TODO**]
  - replace the top layer

- learn how to fine-grain the network.
- Read this paper again.
- Read the latest related paper from reference.

20-NAACL16-Hua He-PairwiseWord Interaction Modeling with Deep Neural Networks for Semantic Similarity Measurement

PDF, Bib

20-SemEval16-Hua He-Attention-Based Multi-Perspective Convolutional Neural Networks for Textual Similarity Measurement
torch

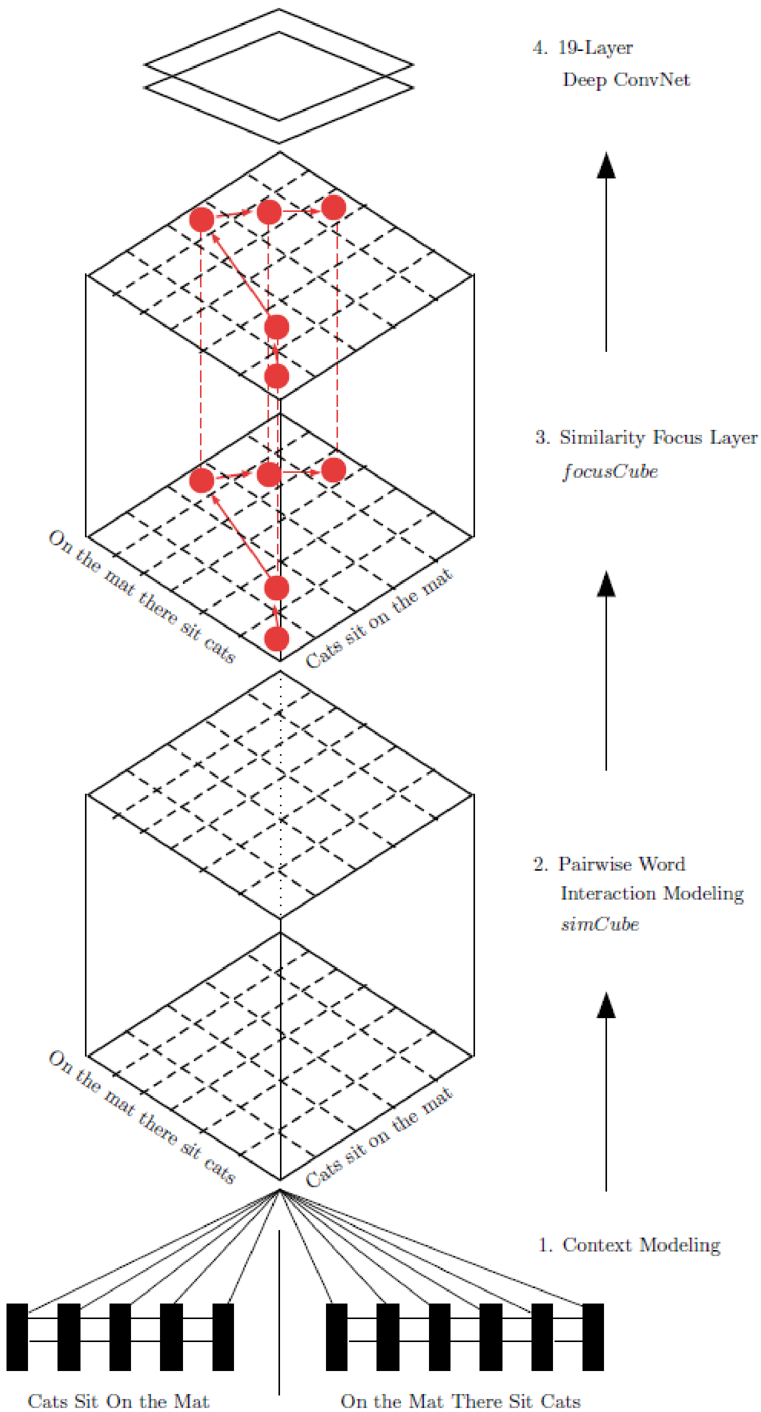

Figure 1: Our end-to-end neural network model, consisting of four major components.

- **[Model]**

- [**Bi-LSTMs**] for context modeling of input sentences
- [**Pairwise word interaction**] encourage direct comparisons between word contexts across sentences
- [**Similarity focus layer**] help identify important pairwise word interactions
- [**19-layer ConvNet**] converts the similarity measurement problem into similarity measurement

- [**Experiment**]

Model	train	trial	test(r)	settings
termfreq TF-IDF #w	0.479906	0.456354	0.478802	`freq_mode='tf'`
termfreq BM25 #w	0.476338	0.458441	0.474453	(defaults)
ECNU run1			0.8414	STS2014 winner
Kiros et al. (2015)			0.8655	skip-thoughts
Mueller et al. (2016)			0.8822	MaLSTM; state-of-art
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from https://github.com/brmson/dataset-sts/tree/master/data/sts/sick2014

Model	Pearson's r	Spearman's p	MSE
Socher et al. (2014) DTRNN	0.7863	0.7305	0.3983
Socher et al. (2014) SDTRNN	0.7886	0.7280	0.3859
Lai and Hockenmaier (2014)	0.7993	0.7538	0.3692
Jimenez et al. (2014)	0.8070	0.7489	0.3550
Bjerva et al. (2014)	0.8268	0.7721	0.3224
Zhao et al. (2014)	0.8414	-	-
LSTM	0.8477	0.7921	0.2949
Bi-LSTM	0.8522	0.7952	0.2850
2-layer LSTM	0.8411	0.7849	0.2980
2-layer Bi-LSTM	0.8488	0.7926	0.2893
Tai et al. (2015) Const. LSTM	0.8491	0.7873	0.2852
Tai et al. (2015) Dep. LSTM	0.8676	0.8083	0.2532
He et al. (2015)	0.8686	0.8047	0.2606
He et al. (2016)	0.8784	0.8199	0.2329

- [**Remark**]
  - from STS work to NAACL
  - old question, old model, new combination and high performance
  - **Since combine difference features will imporove the system performance, how to apply this strategy into Neural Networks**

11-EMNLP15-Hua He-Multi-Perspective Sentence Similarity Modeling with Convolutional Neural Networks

PDF, Bib

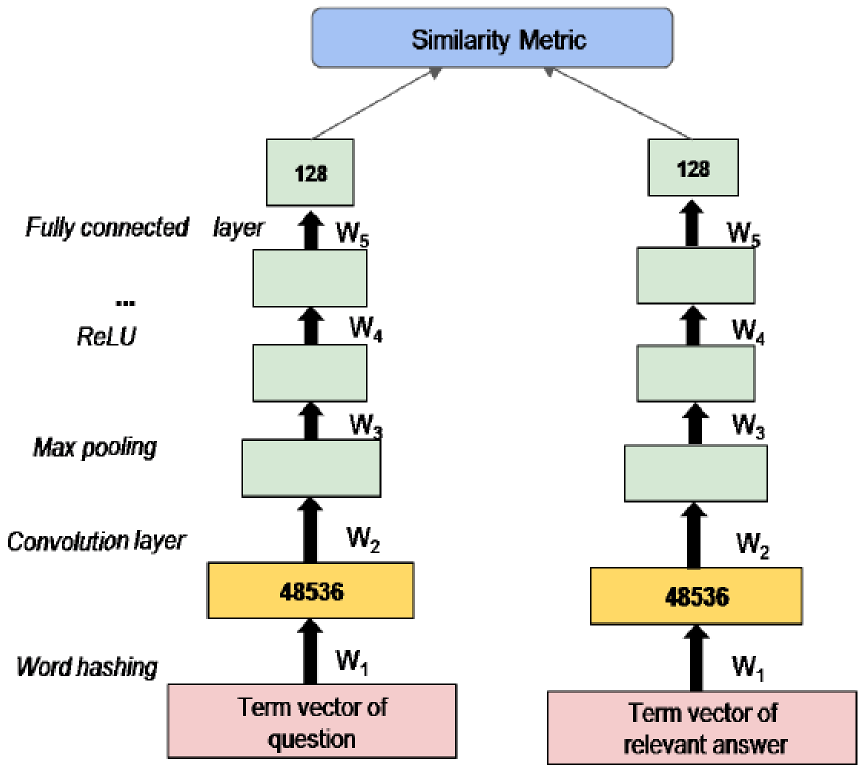
Multi-Perspective: 1). Multiple granularities 2). Window size 3). Multiple types of pooling 4). Similarity Measurement: Multiple

distance functions

- [**Remarks**]:
  - This model tries to explore multi-perspective method on CNNs, so how to combine the local component I think is the key problem in the experiment, and the author proposed **building block** as a set of groups, which make the whole process clear and efficient.
- [**Experiments TODO**]
  - treat each **Perspective** as **Component** implemented in CNNs.
  - analysis different combination's efficient
  - add the thought of **Semantic Similarity** into the **Model**.

19-ACL16-IIIT-Together We Stand: Siamese Networks for Similar Question Retrieval

PDF, Bib



> Figure 2: Architecture of SCQA. The network consists of repeating convolution, max pooling and ReLU layers and a fully connected layer. Also the weights W1 to W5 are shared between the sub-networks.

- [**Problem**]: Similar Question Retrieval, "lexico-syntactic gap"
- [**Model**]: **Siamese Convolutional Neural Network for cQA (SCQA) learns th similarity metric for question-question pairs by leveraging the question-answer pairs available in cQA forum archives.** The idea is to project similar question pairs nearer to each other and dissimilar question pairs farther away from each other in the semantic space.(**Similar to TRANs in Reconmmendation System**).

  However, questions pairs is not availabble, so this paper leverages existing question-anwer pairs. Input is word hashing, which is character level representation of documents that takes care of out-of-vocabulary(OOV)words and with minor spelling errors.

  The SCQA is used to get question-question pair score, in addition, BM25 metrics was added into with weight \alpha to improve the retrive performance.
- [**Experiments**]
  - Quantitative Analysis: Sevaral model compares.
  - Qualitative Analysis: Compare with each two model to analysis the effect of the model
- [**Remark**]
  - The idea and model is simple, but the result is good and Qualitative Analysis is very meticulous

2-ACL16-IBM-Addressing Limited Data for Textual Entailment Across Domains

PDF, !Bib

- [**Problem-Paper**] exploit unlabled data to improve F-score for TE task.
- [**Problem-Experiment**] find all sentences in a corpus that entail a given hypothsis.
  Domain: Newswire (RTE-5,6,7) & Clinical (self construct)
- [**Model**] Tradition Features + self-training/activate learning
- [**Conclusion**] The author analysis the possible explanation for the improvement: Class Distribution. down-sampling and up-sampling is not useful. Activate learning will sampling positive examples, thus it can match the performance with fewer examples.
- [**Remark**] Experiment is beautiful and convising, Information Retrival Method.

This paper illustrates that how self-training will influence the classification and why active learning will reduce the examples to only 6 percent.
The author experiments on two domains -- newswire and clinical. First, the author creates an entailment dataset for clinical domain with human annoted. Second, he builds a highly competitive supervised system, called ENT. Last, he explore two strategies - self-training and active learning to address the lack of labled data. Experiment is done in detail and convincing.

6-NAACL16-Sultan-Bayesian Supervised Domain Adaptation for Short Text Similarity

PDF, Bib

- [**Problem**] Domain Adaptation for Short Text Similarity
- [**Model**] A two-level hierachical Bayesian model -- Each w_d depends not on its domain-specific observations (first level) but also on information derived from the global, shared parameter $w*$ (second level). And the hierarchical structure (1) jointly learns global, task-level and domain-level feature weights, (2) retaining the distinction between in-domain and out-of-domain annotations.
- [**Features**]
  - monolingual word aligner
  - cosine similarity from 400-dimensional embedding(Baroni et.al, 2014)
- [**Experiment**]
  - a). Short Text Similarity(STS), 10 domains
  - b). Short Answer Scoring(SAS), Dataset: Mohler et al., 2011
  - c). Answer Sentence Ranking(ASR), Dataset: Wang et al., 2007, TREC8-13
- [**Remarks**]
  - Although this is traditional feature method, and the results is not inspiring, the author construt **amount of Analysis** to show the advantage of the system and answer why it does not perform well(**because of the data, smile**).