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Machine Learning
Natural Language Processing
Deep Learning

Keyword Extraction for Expertise Modeling

Problem Statement

Widespread expansion of the scientific community has led to an increased requirement for a reliable peer-review system, to allow unbiased assessment of new scientific works. To allow such comparison, the expertise of reviewers needs to be modeled in a way that both provides reviewers with the ability to edit their expertise and allows comparison between this expertise and a new work, without knowing the identity of its author.

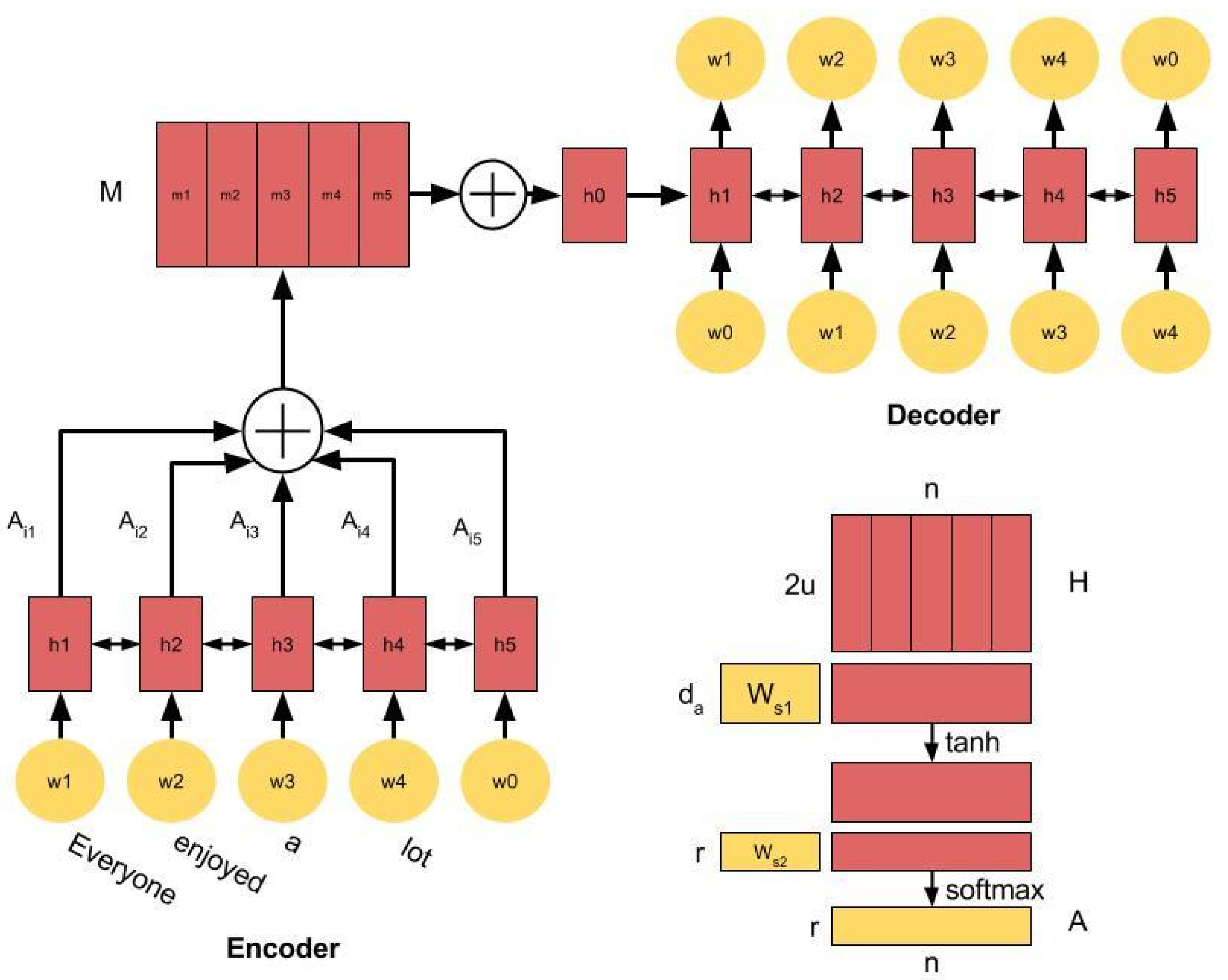
In this poster, I present experiments conducted for extracting keywords to summarize scientific papers, which are then used to compare reviewer publications with new scientific works. A keyword based model provides the following advantages over a model that uses complete text:

- Authors can add or remove keywords from their expertise to consider or ignore a particular topic
- Keywords can be easily converted to real-valued vectors suitable for comparison using simple vector space distance functions

Dataset

- Query papers - Submissions to the uai 2017 conference
- Reviewer archive - Atleast 5 published works of each reviewer in uai 2017 downloaded from dblp
- Ground Truth - Bids placed by reviewers for each submission
- Kp20k dataset [1] used for training seq2seq model for phrase generation

Keyword Extraction



SAKE - The self-attention model [2] provides an attention weight for each input word to a lstm, tuned according to the desired task. For this project, I experimented with two tasks:

- Self attention mechanism trained with an autoencoder on reviewer abstracts
- Self attention mechanism trained with a seq2seq model for abstractive phrase generation

Paper Representation

Final representation for a paper was extracted by averaging the dense representation of keywords extracted using our model. Skip-gram model trained on Google News Dataset was used to extract word embeddings.

$$E_p = \frac{\sum_{n=1}^{N} E_{w_n}}{N}$$

Where E_{wk} represents the embedding of the k^{th} word, N is the total number of words present in paper P and E_P is the resultant embedding of the paper.

[2] R. Meng, S. Zhao, S. Han, D. He, P. Brusilovsky, and Y. Chi, "Deep keyphrase generation," CoRR, vol. abs/1704.06879, 2017.. [Online].-http://arxiv.org/abs/1704.06879

[2] Z. Lin, M. Feng, C. N. dos Santos, M. Yu, B. Xiang, B. Zhou, and Y. Bengio, "A structured self-attentive sentence embedding," CoRR, vol. abs/1703.03130, 2017. [Online]-http://arxiv.org/abs/1703.03130

Evaluation Criteria

All models evaluated using thresholded recall score

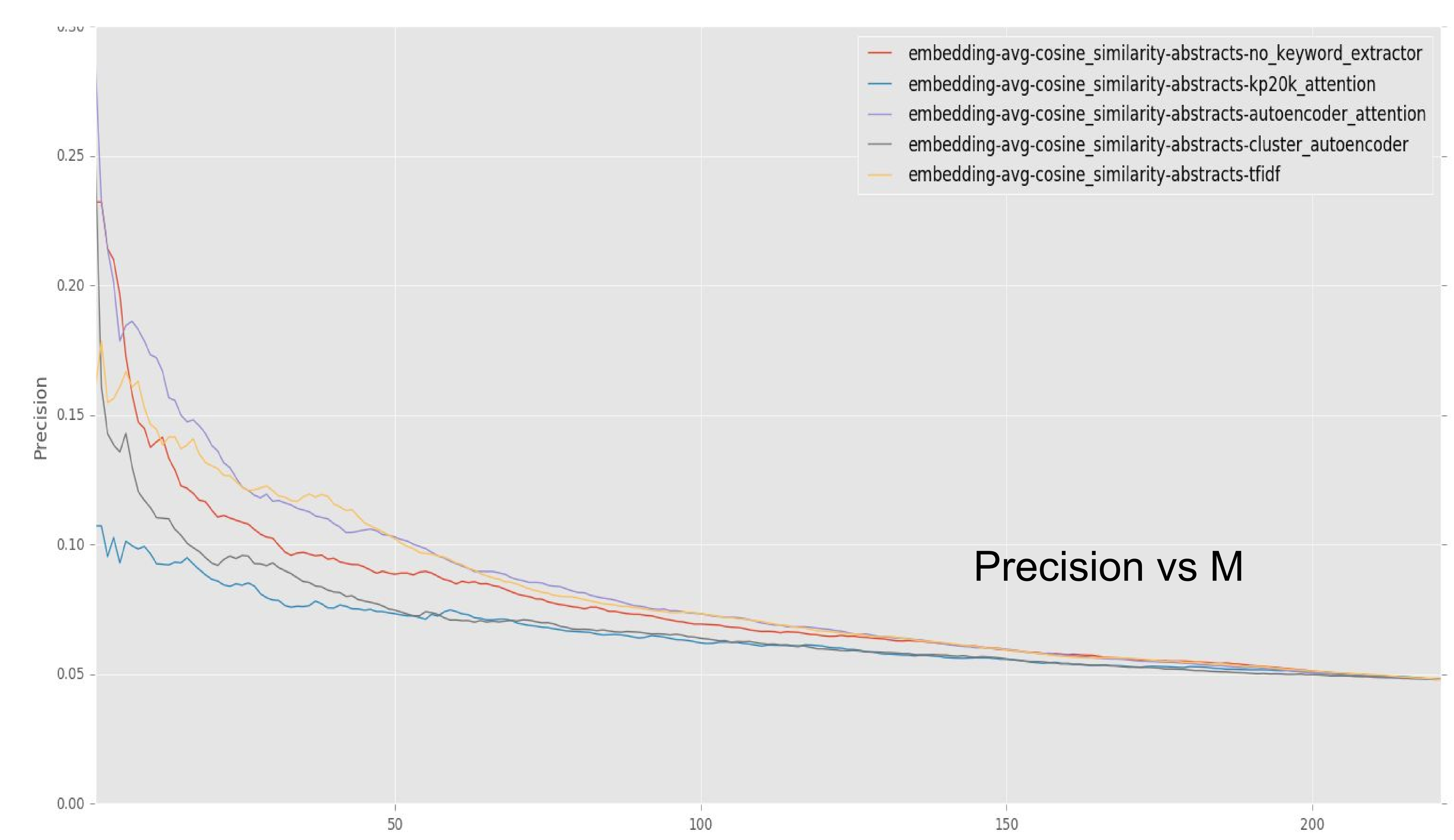
$$Recall@M = \frac{|V \cap T|}{|V|}$$

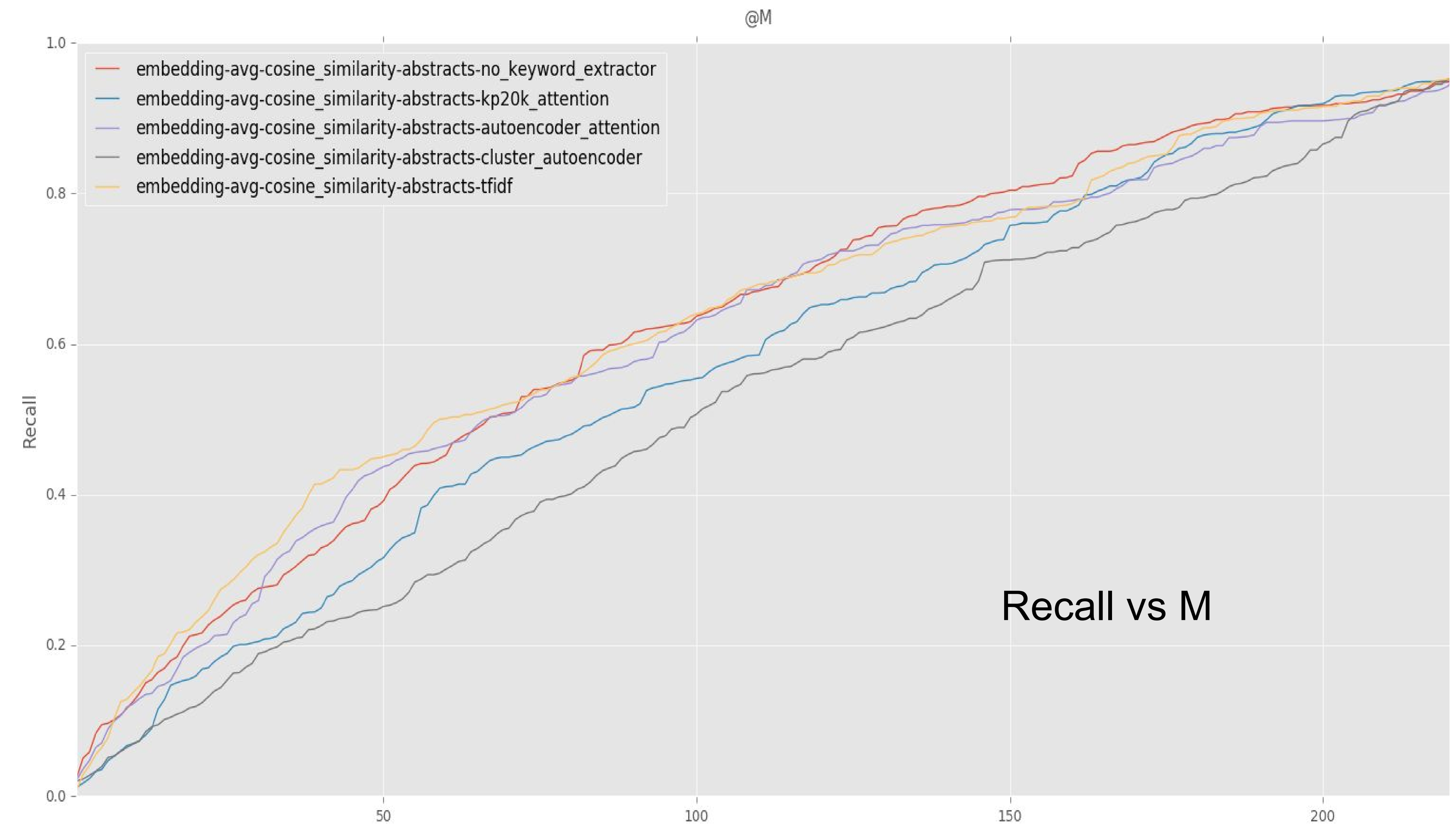
Where V is the set of relevant reviewers and T is the top M reviewers retrieved by the experimental model.

Experiments

1. Tfidf value based keywords
2. SAKE - self attention based keywords extractor trained on re-generating input with an autoencoder
3. SAKE - self attention based keywords extractor trained on abstractive keyphrase generation using seq2seq model
4. Words closest to cluster centers of clustered word representations (extracted from SAKE) as keywords

Results and Conclusion





- Keywords extracted from tfidf scores have better recall@M than complete text.
- Keywords extracted from Self attention based autoencoder have worse recall@M than tfidf values but better than complete text. It has better precision@M values than both tfidf and complete text.