

tasks. Experimental results on the Stanford Sentiment Treebank show that AdaMC significantly improves the baselines with fewer parameters. We further compare the distribution similarities of composition functions for phrase pairs, and the results verify the effectiveness of AdaMC on modeling and leveraging the semantic categories of words and phrases in the process of composition. There are several interesting directions for further research studies. For instance, we can evaluate our method in other NLP tasks. Moreover, external information (such as part-of-speech tags) can be used as features to select the composition functions. In addition, we can mix different types of composition functions (such as the linear combination approach in RNN and the tensor based approach in RNTN) to achieve more flexible choices in the adaptive composition methods.

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