- 1 To All Reviewers We wholeheartedly thank all reviewers for all valuable and insightful feedback, along with taking
- 2 the time to review our submission. We have provided detailed comments to each reviewer below.
- To Reviewer 1 Thanks for the valuable and insightful feedback!
- 4 Regarding the suggestion about more experiments on more datasets, we full wholeheartedly agree that more experiments
- 5 will definitely improve the comprehensiveness of the paper. We are running experiments on these tasks right now and
- 6 include results on these datasets (SST, SNLI, WMT En-De etc.) by the camera ready version as supplementary material.
- 7 Pertaining to Q3, weights are extracted from a trained model (on NLI) on sampled 1K datapoints from the dev set.
- 8 Similar graphs appear with repeated sampling. Regarding deletion being prevalent, our hypothesis is that only tokens
- 9 that are particularly significant will be compositionally (add/subtracted). For most words, the sigmoid function provides
- 10 flexibility of deleting tokens.
- Regarding the value of α , β in equation 1 and equation 2, we set them to 1 in the experiments. The higher value of α , β
- 12 is, the 'harder' the compositional pooling becomes. The hardness of CoDA required is possibly related and analogous
- 3 to hard vs soft attention and can be domain dependent. For most language tasks, we find that not biasing CoDA towards
- being hard is quite sufficient. Not all tokens are important, so CoDA maintains the flexibility of standard attention while
- 15 enabling arithmetic compositionality. We will include more supplementary distribution visualisations on different tasks
- in the revised version.
- 17 Regarding the form of Equation 9 used in the experiments, we used one layer non-linear projection network to compute
- the pairwise affinity. We thank the reviewer for pointing it out and we will mention it clearly in the revision.
- 19 For other comments such as references or typos, we will correct and add them in the revision. We will also be sure to
- 20 include a discussion about sparsemax and softgen.
- To Reviewer 2 Thanks for the insightful and valuable feedback!
- 22 Regarding the evaluation on Tensor2Tensor, IWSLT En-Vi was chosen because of the size and resource limitations.
- 23 Please be assured that the tasks were not cherry-picked and we have not experienced any failure cases on T2T tasks yet.
- 24 We also had success on the arithmetic T2T and subject-verb agreement tasks but did not report due to lack of space.
- 25 We will prepare detailed supplementary material to cater to extra experiments. Moreover, we are currently running
- 26 WMT En-De and WMT En-Ro. This may take sometime due to our limited hardware but will definitely be ready by the
- 27 camera-ready version.
- 28 Regarding the form of CoDA, we use the following version our experiments, i.e. subtract the mean before applying
- 29 the sigmoid or tanh, and they are scaled before applying self-attention. We will make this absolutely clear in the final
- $_{30}$ version. We left several variations open in our technical exposition since certain hyperparameters (e.g., α) could allow
- practitioners to control properties (i.e., hardness) of CoDA. We apologize for any confusion. In the revision, we will
- also include more ablation studies of different alternations of CoDA form, providing better guidance for usage of CoDA
- configurations. We will also include supplementary visualisation as requested.
- 34 Regarding the confusion of using notions and references in the papers, as pointed out in the detailed comments, we
- thank the reviewer for pointing them out. We will correct and clean them in the revision.
- To Reviewer 3 Thanks for the insightful and valuable feedback!
- Our intuition is that tanh saturates at $\{-1,1\}$, which doesn't allow the model the flexibility to *delete* (erase) tokens.
- 38 Sigmoid provides this flexibility to our model. Some early ablation results on retrieval tasks are reported in Table 1. We
- will include more comprehensive ablations in the final version.
- 40 Thanks for the suggestion about adding a visualization of the learned attention weights on examples for interpretability.
- We will definitely include it in the revision. Pertaining aesthetic comments, thanks for pointing them out and we will be
- sure to correct them in the revision.

Method	TrecQA	WikiQA
tanh only	66.78 / 73.49	67.13 / 67.81
CoDA	79.84 / 84.78	68.07 / 68.28

Table 1: Dev set results of tanh only versus CoDA (tanh * sigmoid).