In terms of **motivation** and **technical implementation**, we systematically compare our two modules, ANA and IC in our paper, with COSTA [3].

- We think that our anchor-neighbor alignment (ANA) has the **similar motivation** with [3]. Paper [3] extensively investigates the biases introduced by graph augmentation, with a particular emphasis on the impact of edge perturbations, which significantly affect the message aggregation in GNNs. [3] proposes feature augmentation to mitigate the bias issue. In lines 331 to 345 of our paper, we also mention that unreasonable augmentation can be detrimental to performance. We propose ANA to bring the central anchor closer to neighbors, allowing nodes to more effectively gather information from their neighbors, thereby alleviating potential negative impact of graph augmentation (**refer to the bottom for newly added experiments**).
- In terms of **technical implementation**, both our isotropic constraints (IC) and feature augmentation employ projection techniques. Specifically, IC maps representations to various directions, aiming for the same distribution along these directions. [3] utilizes projection to obtain augmented versions of original features (representations).

In our revision, we cite and compare the paper [3].

| | **COSTA** | |
|---|---|---|
| | **Motivation** | **Technical Implementation** |
| **Anchor-Neighborhood Alignment (ANA)** | Partially Consistent:<br>Alleviating potential negative impact of (unreasonable) graph augmentation | Different |
| **Isotropic Constraints (IC)** | Different | Partially Consistent:<br>• Employing projection techniques<br>• The goals of utilizing projection techniques differ |

[3] COSTA: Covariance-Preserving Feature Augmentation for Graph Contrastive Learning.

**Table 7: Performance with ANA-IC under strong augmentation ($p_e = 0.9, p_f = 0.9$). $K = 0$ denotes no ANA.**

| $K$ | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| Computers | 79.81 | 87.17 | 87.71 | 87.92 | 87.97 | 88.10 |
| Pubmed | 75.7 | 78.8 | 79.2 | 80.3 | 80.2 | 80.3 |
| Citeseer | 67.3 | 70.3 | 70.7 | 70.4 | 70.2 | 69.8 |

*E.1.4 Robustness and Resilience toward Strong Augmentation.* As mentioned earlier, when $K = 0$ in Eq. (3), the anchor-neighborhood alignment degenerates into strict alignment between various augmented views of the same instance. Here, we conduct experiments to illustrate the anchor-neighborhood alignment is more robust to strong augmentations than the strict alignment. Specifically, both edge removal ratio $p_e$ and feature masking ratio $p_f$ are set to 0.9 and various values of $K$ are validated. The experimental results are summarized in Table 7 where the performance under $K > 0$ are consistently better than those under $K = 0$ with considerable margin, which demonstrates that the proposed anchor-neighborhood alignment strategy has greater robustness and resilience in the face of strong augmentation. ANA can still capture valuable information from structural context for self-supervised learning, even with unreasonable data augmentation. The great robustness can make our approach more stable in real-world scenario applications.