We thank the reviewers for their valuable and encouraging feedback.

**Reviewer #1:**

Thank you for the supportive comments!

It is straightforward to adapt the AutoAugment policy model into our framework, by simply parameterizing the augmentation model $g_\phi(\boldsymbol{x}|\boldsymbol{x}^*, y)$ in Eq.(9) as the policy used in AutoAugment. If the policy contains discrete components to be learned (i.e., $\boldsymbol{\phi}$ has discrete factors), we can use policy gradient for optimizing $\boldsymbol{\phi}$.

The present work has primarily focused on the generality of the proposed framework. We thus tested in both text and image domains, with data augmentation and weighting. We are excited to apply the approach in more problem settings and manipulation schemes, and compare with other work including AutoAugment in the future.

We will polish the writing as pointed out. Thank you for the suggestion!

**Reviewer #2:**

* *Novelty:*

The core novelty of the approach is the generality of the formulation, in which different manipulation schemes boil down to different parameterization of the data reward function. The generality enables us to study augmentation and weighting in text and image domains, which differs from previous work that typically applies to a single type of manipulation and often in a single domain.

The resulting augmentation/manipulation algorithms also differ from previous RL-based methods, as explained in Line.151–156. In particular, learning manipulation in our algorithms is carried out by learning the *reward* function, which is a new perspective compared to previous work that learns a *policy* [e.g., 4]. The (intrinsic) reward learning procedure we adopted enables efficient iterative optimization of the model and the manipulation. We will summarize the novelty clearer in the revised version.

* *Simultaneous weighting and augmentation*

The primary focus of the present work is to develop the general framework that supports a variety of manipulation schemes. We have studied the effectiveness of the approach in richer settings than previous work, including weighting and augmentation on text and/or images. As pointed out by the reviewer, our approach can also naturally enable simultaneous weighting and augmentation (by parameterizing the data reward function accordingly). We apply the simultaneous manipulation on the imbalanced SST-2 task (Table 3), where we only augment the rare class, and induce weights for both the real and augmented data. In 50:1000 and 100:1000 settings, we achieve $81.62 \pm 2.26$ and $82.39 \pm 2.04$ accuracy, respectively, which improve over the weighting-only results by around 1–1.5 accuracy points (Table 3). We will provide more complete results in the revised version.

* *Augmentation over CIFAR data*

We tested data augmentation in the text domain which is less well-studied than image augmentation. Our approach can support augmenting images by parameterizing the augmentation model $g_\phi(\boldsymbol{x}|\boldsymbol{x}^*, y)$ (Eq.9) as an image augmentation model. We leave the study in future work.

**Reviewer #3:**

* *Data weighting in low data regime*

Data weighting helps low-data tasks by emphasizing important data points so that the small datasets are used in a more effective way. The results in Table 2 verify the effectiveness. Besides, comparing data weighting and augmentation in the low-data regime shows different effectiveness of the two manipulation schemes (Table 1, augmentation v.s. weighting), which highlights the need of a general approach that enables different manipulation through simple variation (in the data reward function). We agree that the noisy-label task, similar to the class-imbalance setting which we have studied, is another great application for data weighting. We expect to study this setting in the future.

* *Class-imbalance data*

We have followed the experiment setup in Ren et al. [26] which also studied on a two-class imbalanced (MNIST) data. Our approach has shown consistent improvement over Ren et al. [26] in both text and image imbalance settings. Also note that the low-data tasks in Table 1 (SST-2 and TREC) are multi-class settings. Applying the approach in more contexts including naturally imbalanced datasets is an exacting direction to investigate in future work.