We thank the reviewers for their valuable feedback. $\mathbf{R}m.n$ below refers to our response to comment n from reviewer m.

R1.1 Intuition behind Rumi-GANs: As the title emphasizes, the motivation is to leverage *negative* class samples to improve a GAN's capability of generating samples coming from the *positive* class. The proposed approach is particularly useful when one is required to generate under-represented class samples (cf. Section 5). We showed that presenting the GAN with information of the data manifold that it must avoid boosts its generation performance on the desired manifold. We will add a few sentences in the Introduction of the final paper to further emphasize this point.

R1.2 TAC-GAN and CCGAN: A comparison with TAC-GAN is provided in Table 1 below and will be included in the final paper. While Rumi-GANs emphasize the generative aspect, complementary learning frameworks such as CCGAN (Xu *et al.*, arXiv, 2019) deal with *discriminative learning*. A comparative assessment will be included in the final paper.

R1.3 Tabulation of FID and sensitivity to α^+: The converged FID scores for the experiments reported will be included in a table (Table 1 below) in the final paper. The fraction of the generated positive class samples increases with α^+. Fig. 2(a) below shows FID scores evaluated with respect to the negative and positive classes versus α^+.

R1.4 Typo errors in the caption of Figure 1: We have rectified the typographical error.

R1.5 Novelty: The Rumi framework is based on a new mathematical formulation aimed at leveraging negative samples for boosting the generative capability for a desired target class. It is a *light-weight adaptation* and is applicable to any existing GAN. Unlike discriminative learning approaches, the emphasis here is on the generative aspect (cf. **R1.2**).

R2.1 Motivation and setting not clear: Our objective is to obtain a better generator and thereby improve the performance of GANs by leveraging undesirable samples to boost the generative capability for the desired class. The objective function is appropriately formulated. We also demonstrated a concrete application to generating samples belonging to under-represented classes in unbalanced datasets (cf. Section 5). Also refer to **R1.1** and **R1.5** above.

R2.2 On splitting of data: The designation of what constitutes a positive class or a negative class is a *design specification*. Considering MNIST, we presented results highlighting the merit of the Rumi formulation for two illustrative specifications of the positive and negative classes. In an unbalanced data application, the under-represented class that is required to be modeled is the positive one and everything else is labelled negative (cf. Section 5).

R2.3 Regularization of the generator loss: Regularization functionals enforcing the integral and non-negativity constraints are expressly needed in the Rumi framework. They apply to LSGAN as well (cf. Line 112 in the main document and Section 1 of the supplementary). While the constraints may not be needed from an implementation perspective, from a theoretical standpoint, they are necessary mathematical safeguards and have to be enforced explicitly.

R3.1 Related works: We'll discuss the suggested related methods in the Introduction section of the final paper.

R3.2 Error in β^+: We've fixed the bug in the main document. The supplementary (L32-L33) has the correct expression.

R3.3 ACGAN on MNIST: The ACGAN is indeed trained on the full dataset regardless of the positive/negative split. However, we found that the ACGAN performance varies based on the split. Performing additional runs and averaging the scores obtained was found to reduce that difference only marginally (cf. Table 1 below, ACGAN on MNIST).

R3.4 High-resolution Images: We resorted to experiments on low-resolution images due to Covid-19-related closure of the compute facility at our university. We now have results on CelebA 128×128 images as well (cf. Fig. 1 below).

R3.5 Domain-shift applications: This is an interesting proposition. We deployed the Rumi-GAN formulation for the experiment suggested by the reviewer (CelebA as the positive class and CIFAR-10 as the negative one). The FID curves shown in Fig. 2(b) below indicate an improvement over the baseline demonstrating the strength of the formulation.

R3.6 Averaging the results over classes: Done. See Table 1 below (rows CelebA and CIFAR-10).

R4.1 Benefit for real-world applications: The Rumi formulation is promising for domain-shift applications (cf. **R3.5**) and for handling data imbalance in medical image classification problems (similar to the one illustrated in Section 5).

Figure 1: Rumi-LSGAN results on high-resolution (128×128) CelebA images for *Bald* class and *Female* class.

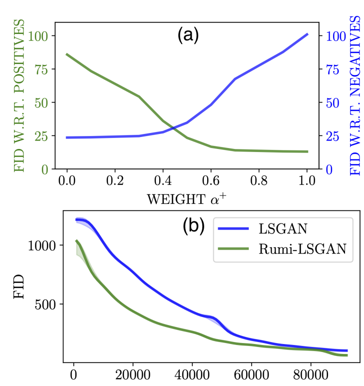

Figure 2: (a) FID versus α^+, and (b) FID improvement in a domain-shift application with the Rumi formulation.

		LSGAN	ACGAN	TAC-GAN	**Rumi-LSGAN**
Balanced	MNIST (Even)	29.92	26.75	23.48	**22.68**
	MNIST (Overlap)	34.63	32.75	31.25	**31.17**
Unbalanced	MNIST (Digit 5)	148.55	127.91	121.3	**118.93**
	CelebA (Averaged)	326.25	243.95	213.6	**169.34**
	CIFAR-10 (Averaged)	231.02	455.06	275.43	**217.15**

Table 1: FID scores upon convergence for various GANs on both balanced and unbalanced datasets. Rumi-LSGAN has better FID scores.