

1 We thank all reviewers for their constructive comments. Clarity and presentation inputs will be used in the final version.
 2 All reviewers confident [scores 4,4,4,3] and concur that OVIS is a novel control variate for the score function estimator
 3 for importance weighted bounds and that, unlike existing IW score-based estimators (VIMCO, Reinforce) and unlike
 4 the basic pathwise IWAE, it allows for more efficient inference network learning because its SNR increases with K .
 5 Reviewers found that OVIS improves the learning of reparameterization-free DGMs [R1,R3,R4] and the experiments
 6 were sufficient to convince the reviewers [R2, R3, R4]. Except for the section on OVIS_{\sim} [R1], all the reviewers have
 7 found the paper to be well-written and clear. We address your concerns below.

8 **Reweight Wake Sleep [R1]** We use the RWS algorithm with wake- ϕ updates, which have been found to be more
 9 effective than sleep- ϕ updates.

10 **Biased induced by the use of the IWR bound [R1]** The scheduling scheme for the experiment 6.3 was indeed
 11 crucial for the Sigmoid Belief Network, but not for Gaussian VAE, which performed well using a fixed value $\alpha = 0.7$.

12 **Ablation Study [R2]** Studying Reinforce and VIMCO acts as an ablation study for OVIS.

13 **Implementation for OVIS_{\sim} [R1]** Numerical instabilities can be avoided by clipping the normalized weights. The
 14 full code will be released upon publication. Eq. (17) relies on Eq. (3). This will be explicitly stated in the main text.

15 **Complexity of OVIS_{MC} and motivations for OVIS_{\sim} [R1]** OVIS_{MC} has complexity $\mathcal{O}(K + S)$ because the S
 16 samples for estimating the K baselines can be reused. OVIS_{\sim} has a complexity $\mathcal{O}(K)$. Estimating ϕ using OVIS_{MC}
 17 requires a budget of $K' = K + S$ particles. The ratio S/K is a trade-off between the tightness of the bound \mathcal{L}_K and the
 18 variance of the control variate estimate. The manuscript focuses on studying the sole effect of the control variate given
 19 the bound \mathcal{L}_K . For the other estimators, this is a sub-optimal use of the budget K' because $\mathcal{L}_{K'} \geq \mathcal{L}_K$. OVIS_{\sim} both
 20 validates our asymptotic results and bypasses the burden of requiring auxiliary samples. By contrast with the previous
 21 experiments, we trained the Gaussian VAE using the budget K' optimally (i.e. relying on $\mathcal{L}_{K'}$ whenever no auxiliary
 22 samples are used). We observed that OVIS_{\sim} outperforms OVIS_{MC} despite the generative model is evaluated using
 23 $\mathcal{L}_{K'}$ in all cases (figure 1). This experiment will be detailed in the Appendix.

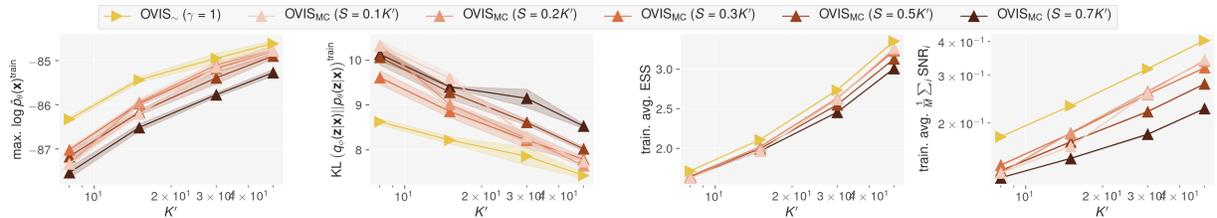


Figure 1: Training the Gaussian VAE model with a fixed and optimally used particle budget $K' = K + S$ and $\alpha = 0.7$.

24 **Extended comparison with reparameterization-based IWAE estimators [R1, R4]** Although we focus on
 25 reparameterization-free methods, we concur that advanced reparameterization-based IWAE estimators (STL and
 26 DReG) should be added to the experiments. Comparing OVIS with the pathwise estimator also requires studying the
 27 use of the IWVR bound ($\alpha > 0$) for both estimators. We updated the experiment and 6.3 accordingly (figure 2).

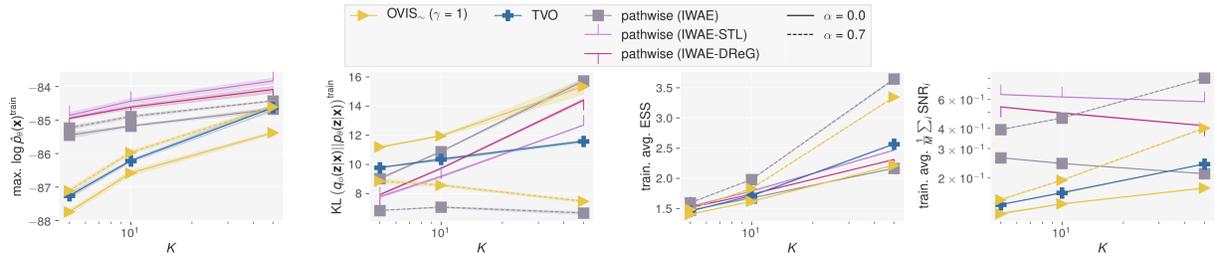


Figure 2: Training the Gaussian VAE (3 seeds) using OVIS_{\sim} with $\alpha \in \{0, 0.7\}$ and using multiple baseline estimators.