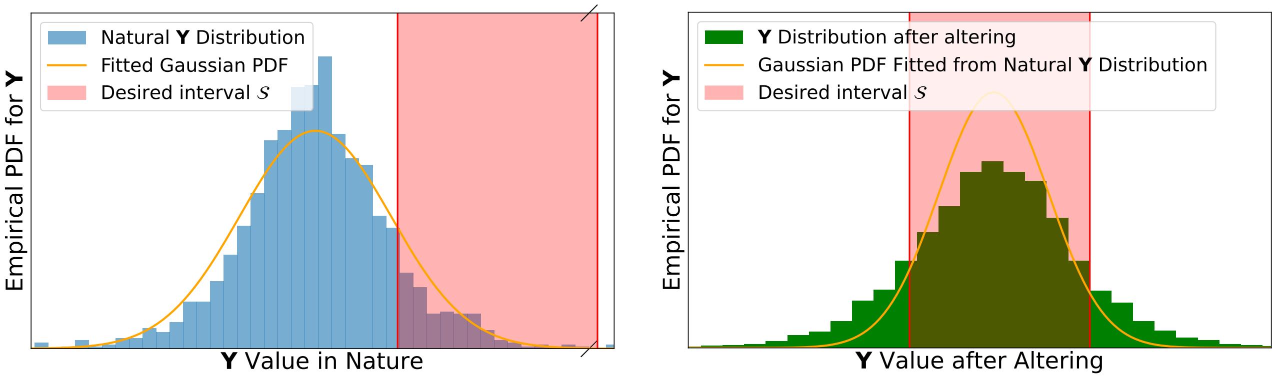

Figure 1: For Dear **Reviewer UMM3**. We modify the noise distribution for variables in Bermuda data to a multivariate t-distribution with 6 degrees of freedom. As shown in the left figure, the target variable Y exhibits a complex heavy-tailed distribution due to being a linear combination of its parents. The yellow line represents a Gaussian distribution fitted using the mean and variance of Y. The right figure shows that applying our proposed method with the fitted Gaussian distribution can still effectively select actions that significantly increase the probability of $Y \in \mathcal{S}$. In both figures, the desired regions and fitted PDF remain identical, while the histogram of Y differs due to structural changes in the graph bringing by alterations, which in turn affect the distribution of Y.

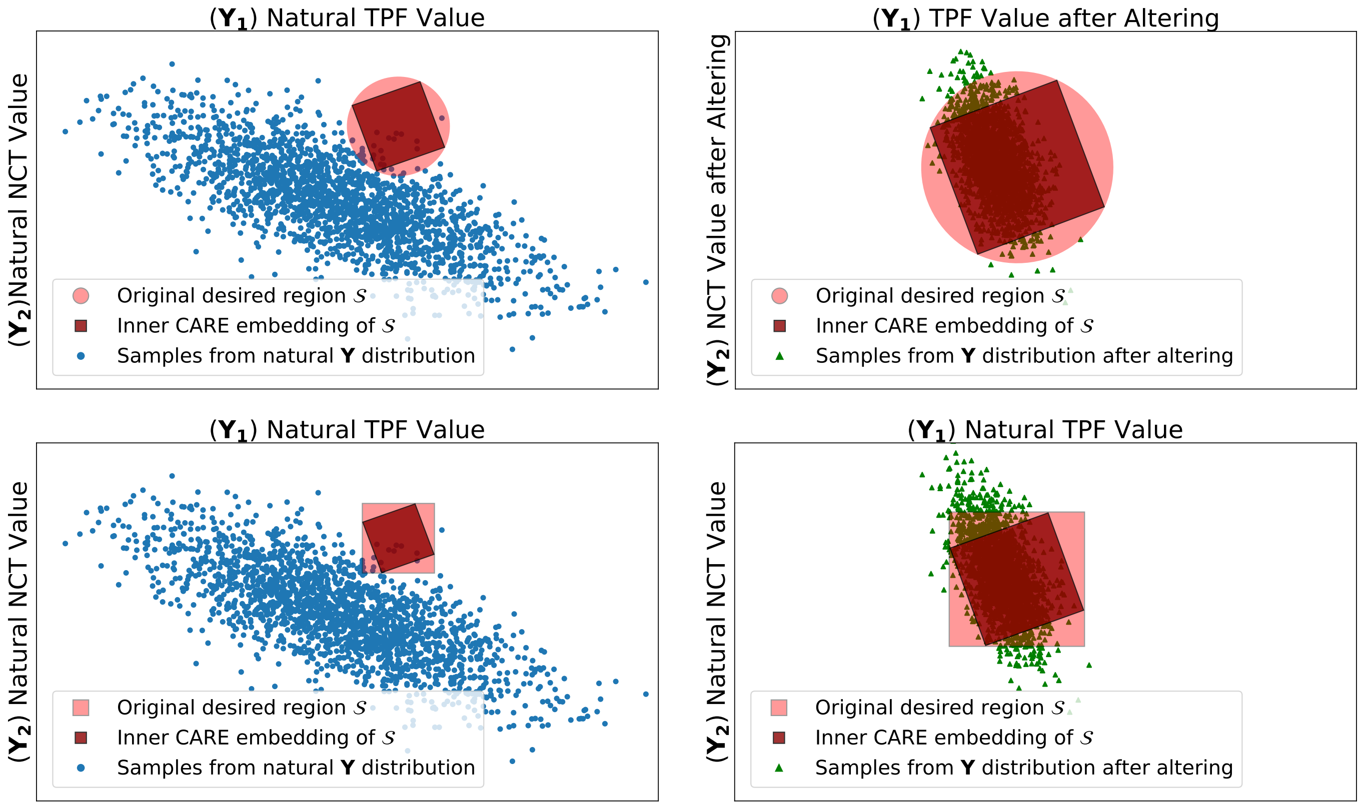

Figure 2: For Dear **Reviewer XTv5**. We conduct experiments where Y_1 and Y_2 are dependent after alterations. As shown in the figures above, two desired regions are considered: in the first row, the desired region is a circle; in the second row, the desired region is a rectangle (but not canonical, constraining $a_1 \leq Y_1 \leq b_1$ and $a_2 \leq Y_2 \leq b_2$ instead). The inner CARE embeddings are shaded in dark red, and optimizations are performed based on these embeddings. This demonstrates that our generalization approach is effective in solving the AUF problem with these irregular/non-canonical regions. The regions on the left are identical to those on the right.

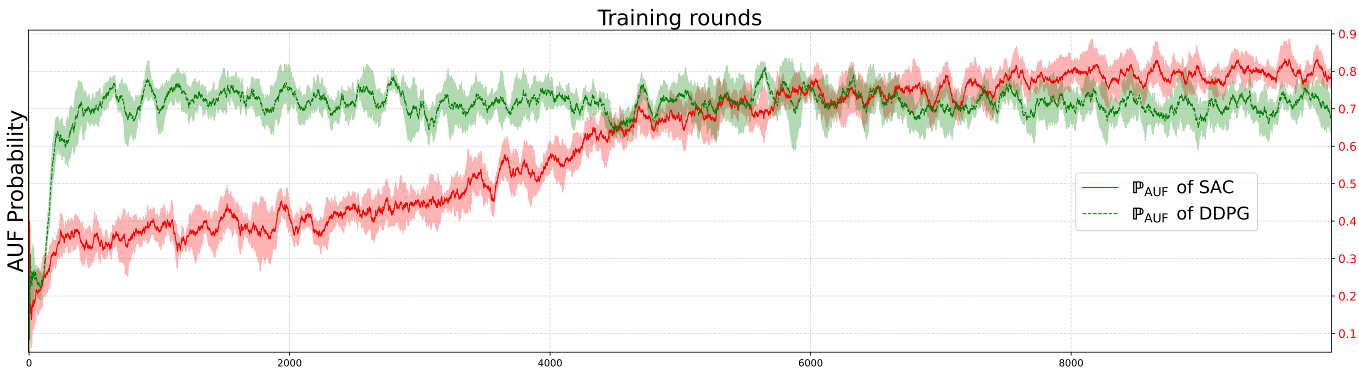

Figure 3: For Dear **Reviewer YMZh**. We conduct a simple experiment for validation in a designated environment based on the Bermuda data, where DDPG and SAC (implemented using *stable_baseline3*) are trained with 5 random seeds. As shown in the figure, when interactions are allowed, both algorithms converge to an effective policy after sufficient training, achieving a relatively high AUF probability.