

## Conformal GAN Model Pseudocode

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**Algorithm 1** Conformal GAN Training

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- 1: **Input:** Training data  $\{\mathbf{x}_i, y_i\}_{i=1}^n$ , number of epochs  $E$ , batch size  $B$ , learning rates  $\eta_D, \eta_G$ , regularization parameters  $\lambda, \mu$
- 2: Initialize generator  $G$  and discriminator  $D$  with appropriate architectures
- 3: **for** epoch = 1 to  $E$  **do**
- 4:   **for** batch = 1 to  $\frac{n}{B}$  **do**
- 5:     **Train Discriminator:**
- 6:     Sample real batch  $\{\mathbf{x}_r, y_r\}$  from training data
- 7:     Generate fake batch  $\{\mathbf{x}_f, y_f\}$  using  $G$
- 8:     Compute discriminator loss:

$$L_D = L_{\text{real}} + L_{\text{fake}} - \lambda \cdot L_{\text{reg}}$$

- 9:     Update discriminator parameters using gradient descent with learning rate  $\eta_D$
- 10:    **Train Generator:**
- 11:    Compute generator loss:

$$L_G = L_{\text{gen}} + \mu \cdot L_{\text{conform}}$$

- 12:    Update generator parameters using gradient descent with learning rate  $\eta_G$
  - 13:   **end for**
  - 14: **end for**
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**Algorithm 2** Discriminator and Generator Loss Computations

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1: **Discriminator Losses:**

2: Real loss:

$$L_{\text{real}} = -E_{\mathbf{x}_r, y_r} [\log D(\mathbf{x}_r, y_r)]$$

3: Fake loss:

$$L_{\text{fake}} = -E_{\mathbf{x}_f, y_f} [\log(1 - D(\mathbf{x}_f, y_f))]$$

4: Conformity Regularization Loss:

$$L_{\text{reg}} = \frac{1}{B} \sum_{i=1}^B |\text{conf}(\mathbf{x}_{r,i}, y_{r,i}) - \text{conf}(\mathbf{x}_{f,i}, y_{f,i})|$$

5: **Generator Loss:**

6: Generator adversarial loss:

$$L_{\text{gen}} = -E_{\mathbf{x}_f, y_f} [\log D(\mathbf{x}_f, y_f)]$$

7: Conformity loss:

$$L_{\text{conform}} = \frac{1}{B} \sum_{i=1}^B |\text{conf}(\mathbf{x}_{f,i}, y_{f,i}) - \text{target\_conf}|^2$$

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**Algorithm 3** Conformity Score Functions

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1: **Inductive Conformal Prediction (ICP):**

2: Compute conformity scores for a batch  $\{\mathbf{x}_b, y_b\}$ :

$$\text{conf}(\mathbf{x}_b, y_b) = \|\mathbf{x}_b - \bar{\mathbf{x}}_b\|_2$$

where  $\bar{\mathbf{x}}_b$  is the mean of  $\mathbf{x}_b$ .

3: **Mondrian Conformal Prediction:**

4: Compute conformity scores for each class:

$$\text{conf}_c(\mathbf{x}_b) = \|\mathbf{x}_b - \bar{\mathbf{x}}_{b,c}\|_2$$

where  $\bar{\mathbf{x}}_{b,c}$  is the mean of  $\mathbf{x}_b$  for class  $c$ .

5: **Cross-Conformal Prediction:**

6: Compute conformity scores using cross-validation:

7: **For each fold  $i$  in  $k$ -fold cross-validation:**

8:   Define training and calibration sets based on fold  $i$

9:   Compute mean of training set:  $\bar{\mathbf{x}}_i$

10:   Compute conformity scores for calibration set:

$$\text{conf}_i(\mathbf{x}_b) = \|\mathbf{x}_b - \bar{\mathbf{x}}_i\|_2$$

11: **Venn-Abers Predictors:**

12: Fit an Isotonic Regression model to the data:

$$\hat{y} = \text{IsotonicRegression}(\mathbf{x}_b, y_b)$$

13: Compute conformity scores:

$$\text{conf}(\mathbf{x}_b, y_b) = \hat{y}$$

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**Algorithm 4** Conformal Prediction Interval Computation

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1: **Input:** Synthetic data  $\mathbf{X}_s$ , significance level  $\alpha$

2: Compute non-conformity scores for synthetic data:

$$\text{scores} = \text{compute\_conformity\_scores}(\mathbf{X}_s)$$

3: Compute the  $(1 - \alpha)$ -quantile of the scores:

$$q = \text{quantile}(\text{scores}, 1 - \alpha)$$

4: Define prediction intervals for each synthetic sample:

$$\text{interval}_i = [\mathbf{x}_{s,i} - q, \mathbf{x}_{s,i} + q]$$

5: **Output:** List of prediction intervals

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