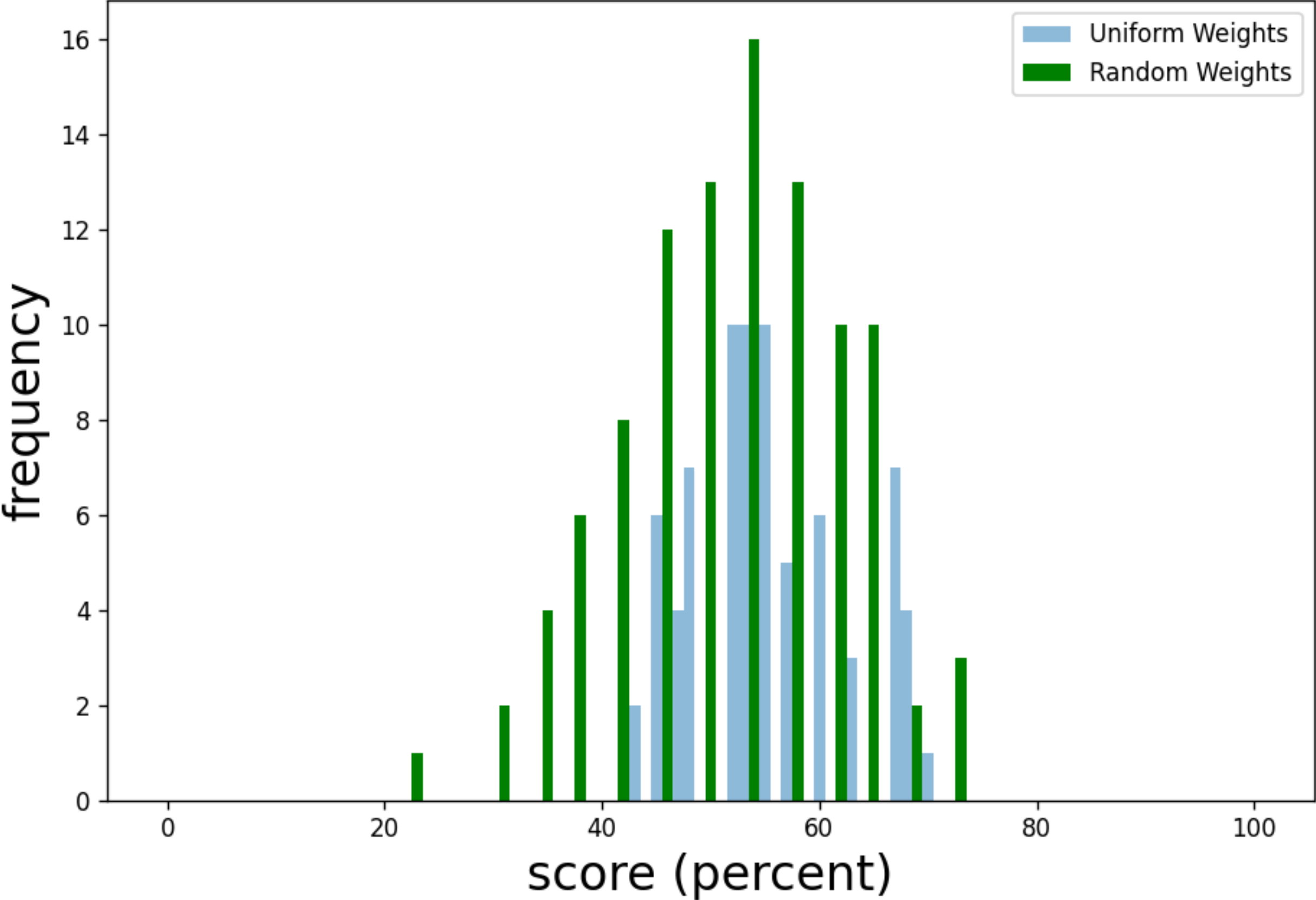


Optimal Sample Weighting

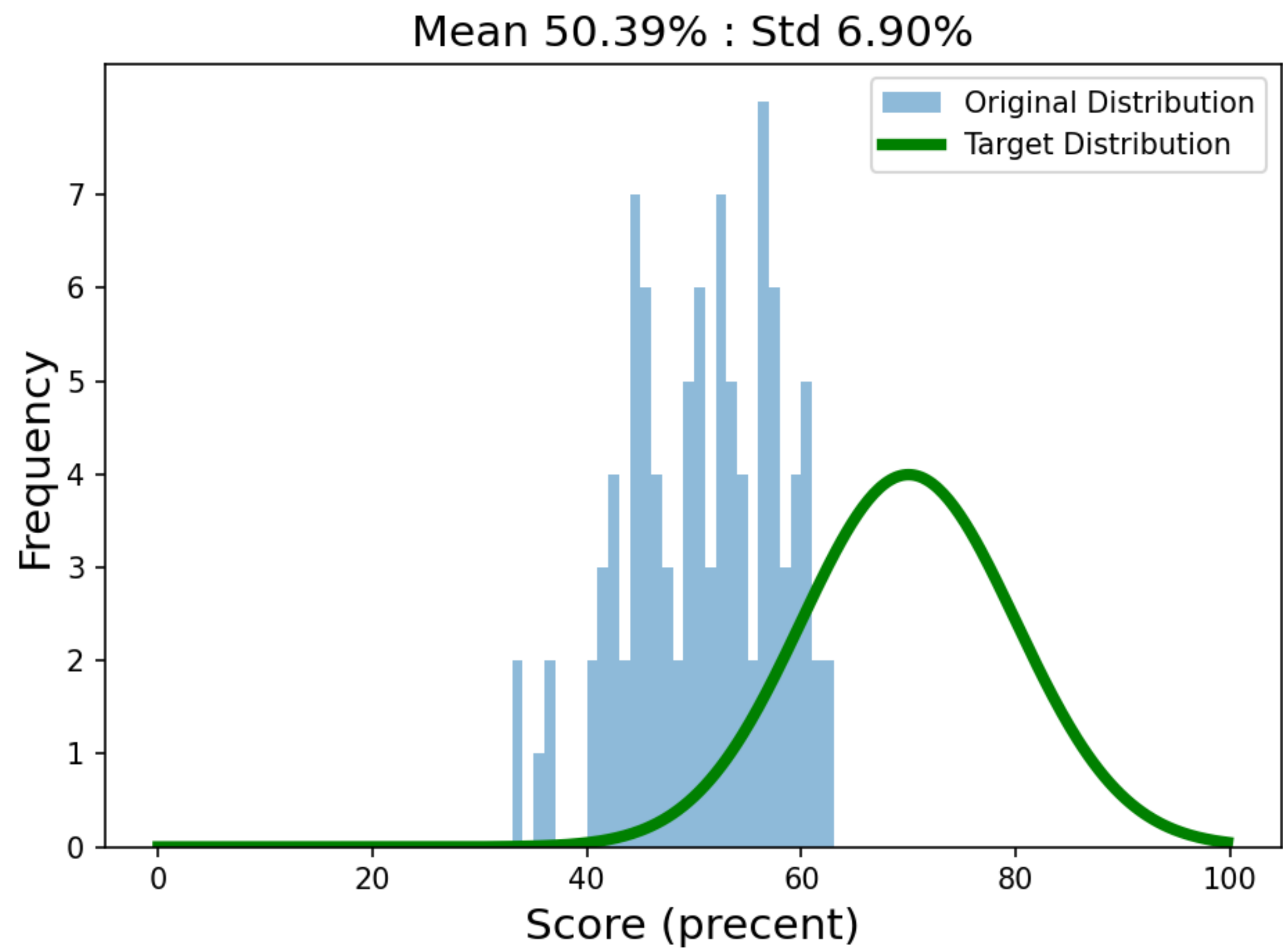
James Chok & Geoff Vasil - June 2023

Student	Q1	Q2	...	Q50
Scrooge	✗	✓		✓
Fezziwig	✓	✓		✓
...				

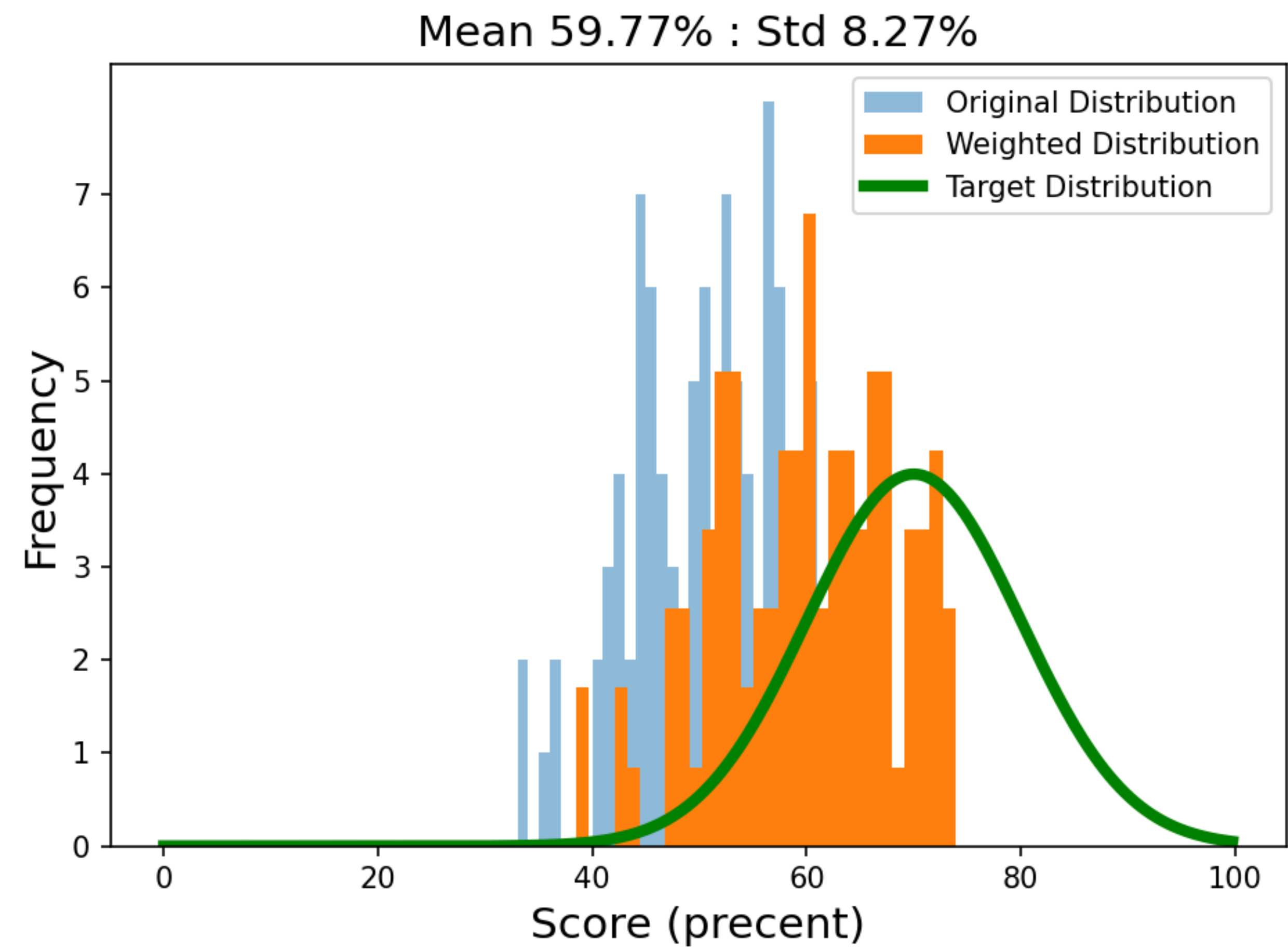


Scrooge's Mark = $\sum_i w_i \cdot (\text{ith question is correct})$

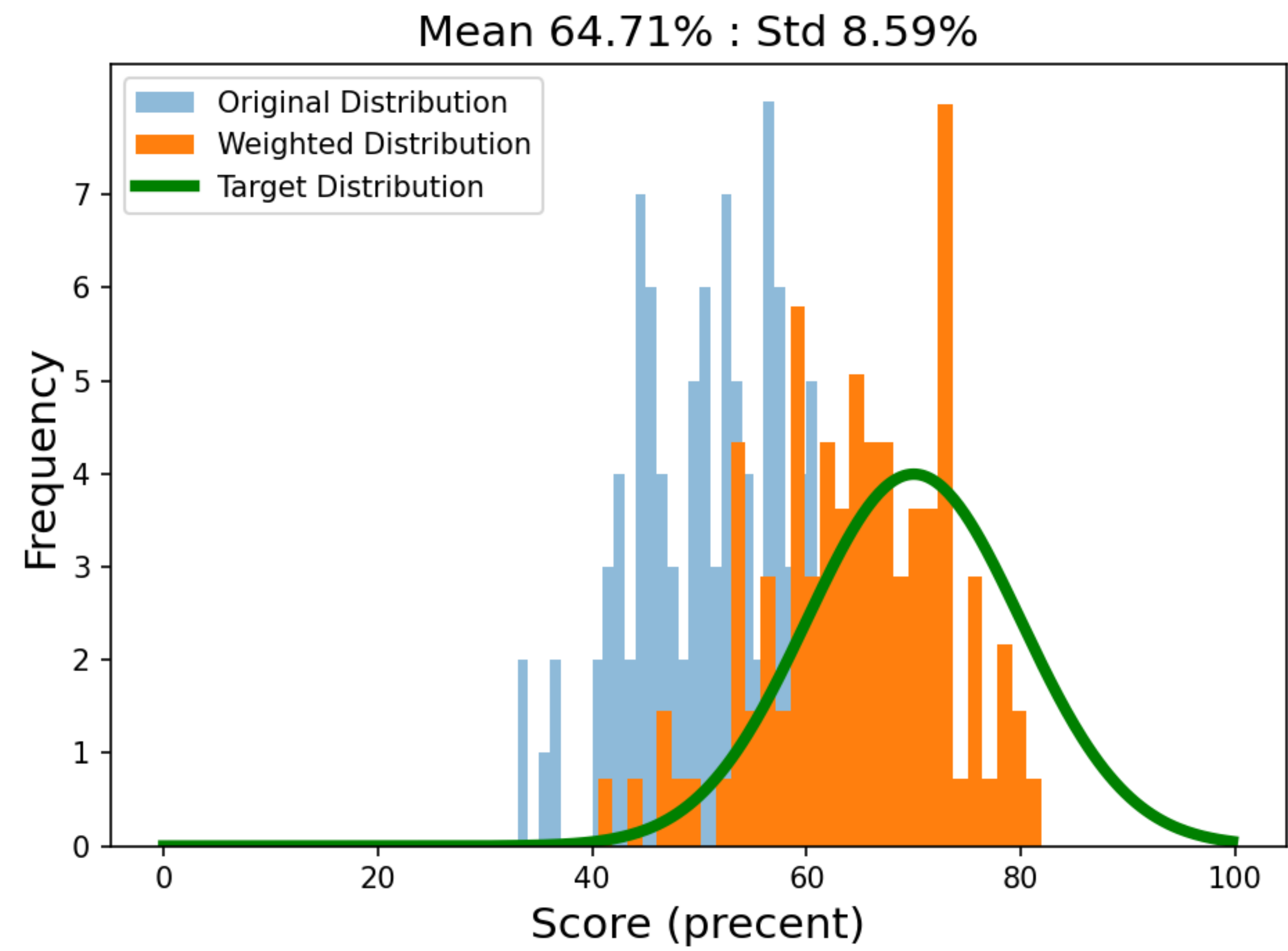
Iteration 0



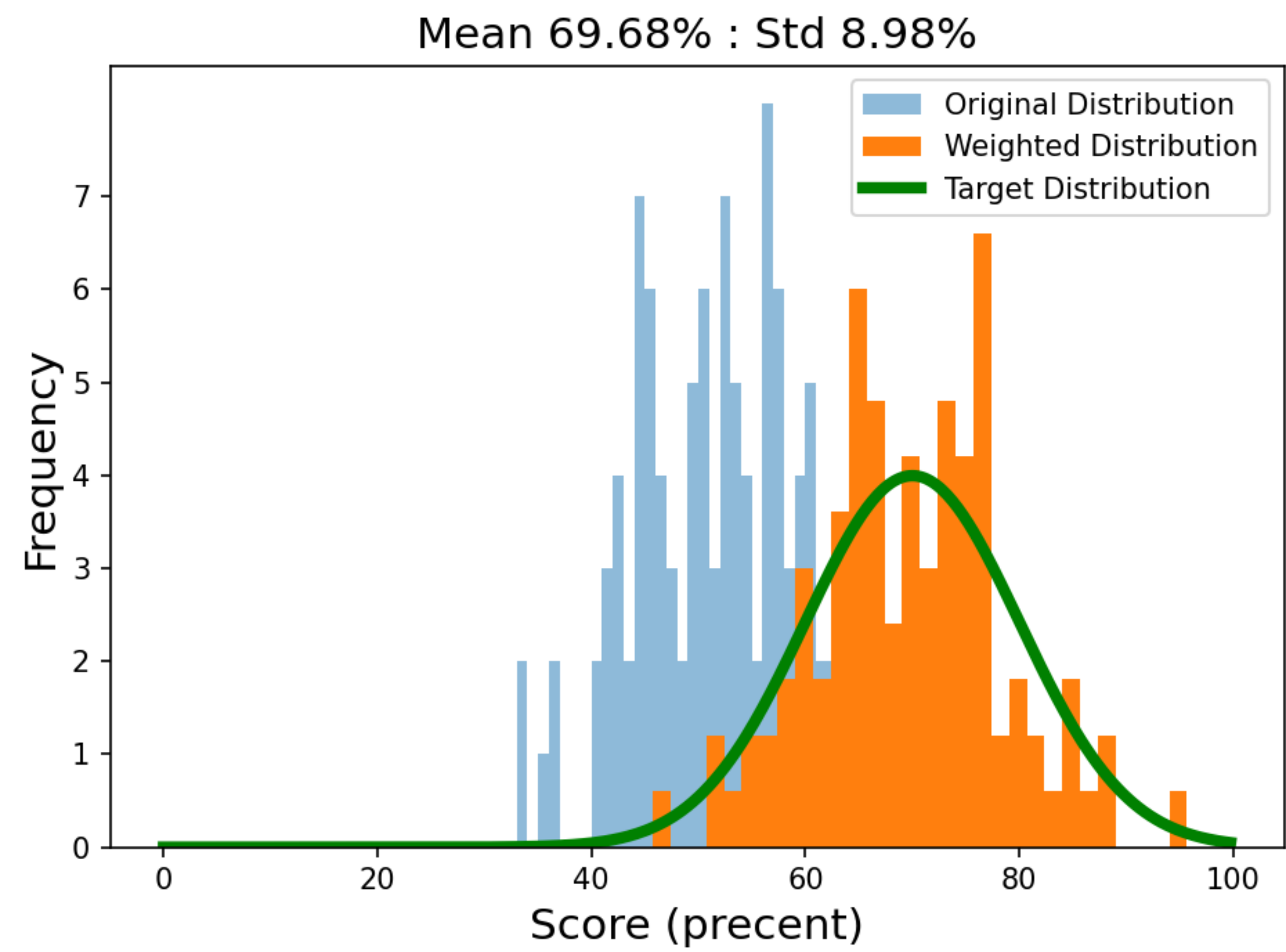
Iteration 1

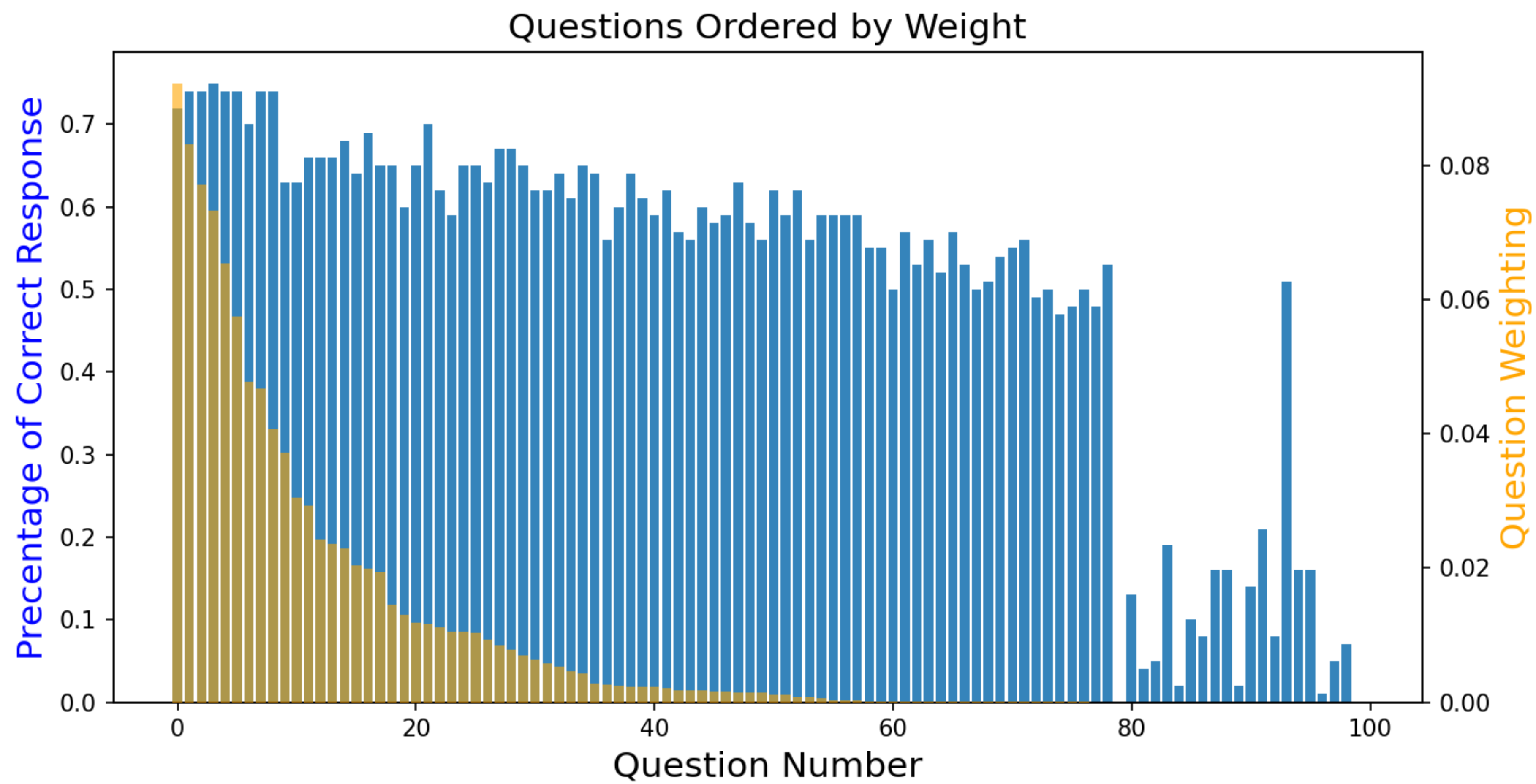


Iteration 5



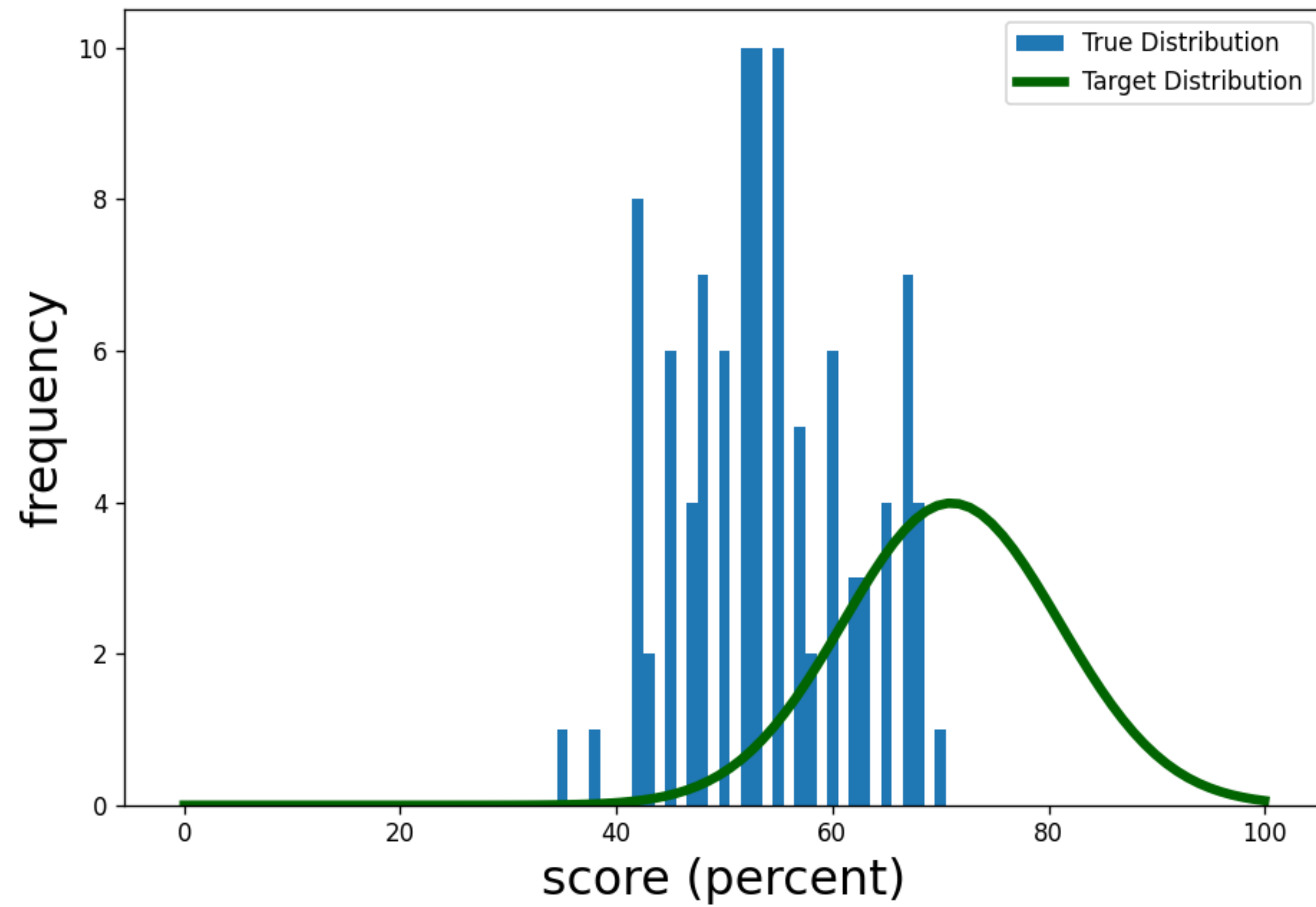
Iteration 20





$$\min_w f(w)$$

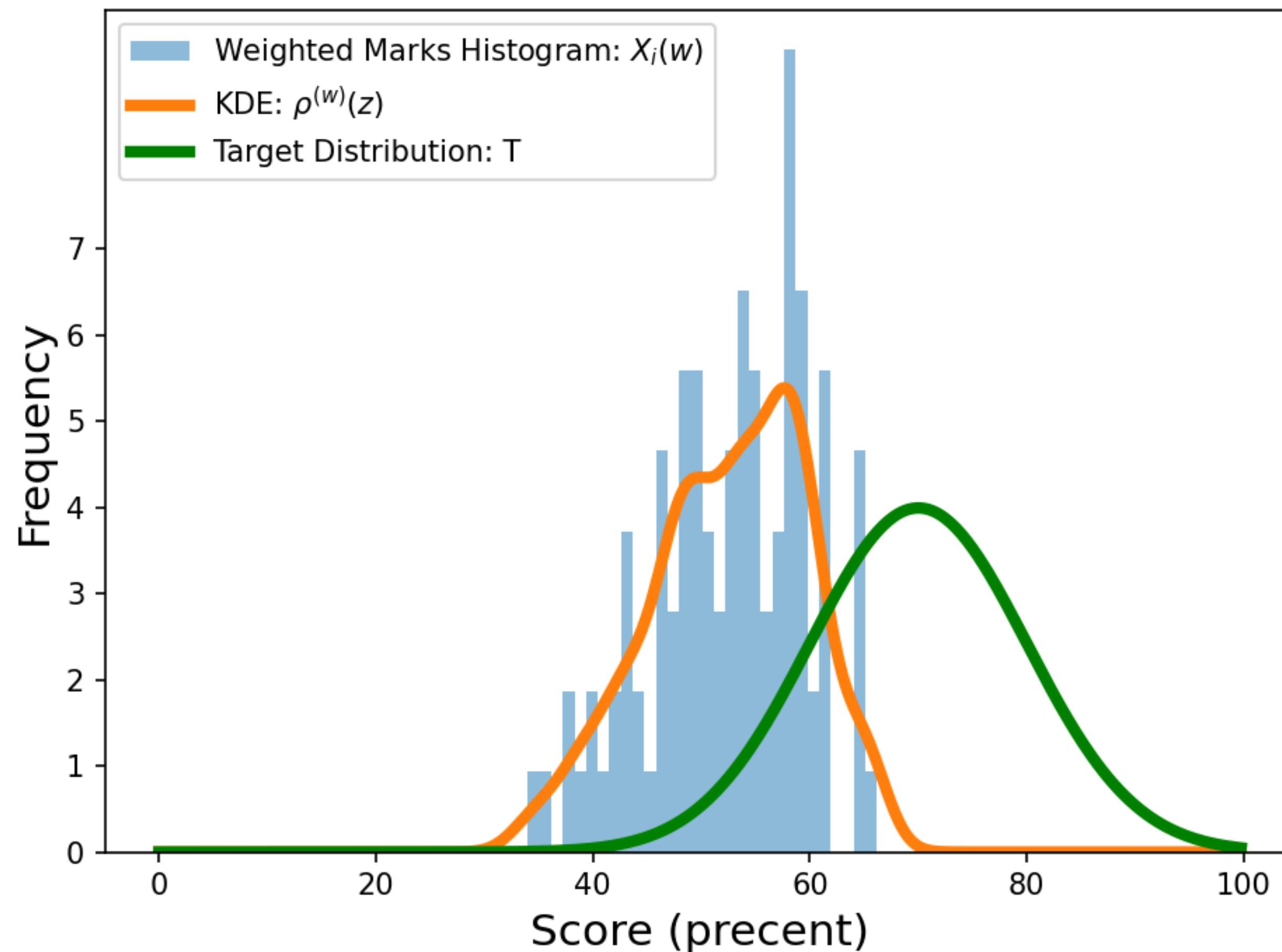
$$w_i \geq 0, \quad \sum_i w_i = 1$$



$X_i(w)$ - Weighted mark of student i

Discrete Distribution of $X_i(w) \approx$ Continuous Distribution: $\rho^{(w)}(z)$

$$\text{KDE: } \rho^{(w)}(z) = \frac{1}{N} \sum_{i=1}^N \mu(z - X_i(w)) \quad \mu \text{ is a Gaussian Kernel}$$



$$\text{KL}(\rho^{(w)}, T) = \int \rho^{(w)}(z) \log \left(\frac{\rho^{(w)}(z)}{T(z)} \right) dz$$

$$\min_w \text{KL}(\rho^{(w)}, T)$$

$$w_i \geq 0, \quad \sum_i w_i = 1$$

Gradient Descent

$$w^{t+1} = w^t - \eta_t \nabla_w f$$

$$w_i \geq 0, \quad \sum_i w_i = 1$$

Our Proposal

$$w^{t+1} = w^t - \eta_t w^t (\nabla_w f - w^t \cdot \nabla_w f)$$

$$w_i \geq 0, \quad \sum_i w_i = 1$$

Convex optimization over a probability simplex
– James Chok and Geoffrey M. Vasil

<https://arxiv.org/abs/2305.09046>