

CoRe Optimizer

```
CLASS core_optimizer.CoRe(params, lr=1e-3, step_sizes=(1e-6, 1e-2), etas=(0.7375, 1.2),
betas=(0.7375, 0.8125, 250.0, 0.99), eps=1e-8, weight_decay=0.1, score_history=0,
frozen=0.0, *, maximize=False, foreach=None)
```

Implements the Continual Resilient (CoRe) optimizer.

input : θ (params), $f(\theta)$ (objective), s_{\min}, s_{\max} (step sizes),
 η_-, η_+ (etas), $\beta_1^a, \beta_1^b, \beta_1^c, \beta_2$ (betas), ϵ (eps),
 d (weight decay), t_{hist} (score history), p_{frozen} (frozen)
initialize : $s_0 \leftarrow lr$, $g_0 \leftarrow 0$, $h_0 \leftarrow 0$, $S_0 \leftarrow 0$

for $t = 1$ **to** ... **do**
 $G_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})$
if maximize
 $G_t \leftarrow -G_t$
 $\beta_{1,t} \leftarrow \beta_1^b + (\beta_1^a - \beta_1^b) \exp\{-[(t-1)/\beta_1^c]^2\}$
 $g_t \leftarrow \beta_{1,t} g_{t-1} + (1 - \beta_{1,t}) G_t$
if $\beta_2 \geq 0$
 $h_t \leftarrow \beta_2 h_{t-1} + (1 - \beta_2) G_t^2$
 $P_t \leftarrow 1$
if $t_{\text{hist}} > 0 \wedge t > t_{\text{hist}} \wedge S_{t-1}$ top- p_{frozen} in \mathbf{S}_{t-1}
 $P_t \leftarrow 0$
if $g_{t-1} g_t P_t > 0$
 $s_t \leftarrow \min(\eta_+ s_{t-1}, s_{\max})$
else if $g_{t-1} g_t P_t < 0$
 $s_t \leftarrow \max(\eta_- s_{t-1}, s_{\min})$
else
 $s_t \leftarrow s_{t-1}$
if $\beta_2 \geq 0$
 $u_t \leftarrow g_t / (1 - \beta_{1,t}^t) / \{[h_t / (1 - \beta_2^t)]^{0.5} + \epsilon\}$
else
 $u_t \leftarrow \text{sgn}(g_t)$
if $t_{\text{hist}} > 0$
if $t \leq t_{\text{hist}}$
 $S_t \leftarrow S_{t-1} + t_{\text{hist}}^{-1} g_t u_t P_t s_t$
else
 $S_t \leftarrow (1 - t_{\text{hist}}^{-1}) S_{\xi}^{\tau-1} + t_{\text{hist}}^{-1} g_t u_t P_t s_t$
 $\theta_t \leftarrow (1 - d |u_t| P_t s_t) \theta_{t-1} - u_t P_t s_t$

return θ_t

For further details regarding the algorithm we refer to the papers [Lifelong Machine Learning Potentials](#) and [CoRe optimizer: an all-in-one solution for machine learning](#).

Parameters:

- **params** (*iterable*): iterable of parameters to optimize or dicts defining parameter groups
- **lr** (*float, optional*): learning rate to set initial step size (default: 1e-3)
- **step_sizes** (*Tuple[float, float], optional*): pair of minimal and maximal allowed step sizes (recommendation: maximal step size of 1e-3 for mini-batch learning, 1.0 for batch learning, and 1e-2 for intermediate cases) (default: (1e-6, 1e-2))
- **etas** (*Tuple[float, float], optional*): pair of etaminus and etaplus that are multiplicative increase and decrease factors (default: (0.7375, 1.2))
- **betas** (*Tuple[float, float, float, float], optional*): coefficients beta1a, beta1b, beta1c, and beta2 used for computing running averages of gradient and its square (default: (0.7375, 0.8125, 250.0, 0.99))
- **eps** (*float, optional*): term added to the denominator to improve numerical stability (default: 1e-8)
- **weight_decay** (*float or List[float], optional*): weight decay for all parameters or list of weight decays for parameter groups (default: 0.1)
- **score_history** (*int, optional*): number of optimization steps to build the score history before applying plasticity factors (default: 0)
- **frozen** (*float or List[float], optional*): fraction of all parameters frozen by the plasticity factors or list of fractions for parameter groups (applies if score_history > 0) (default: 0.0)
- **maximize** (*bool, optional*): maximize the objective with respect to the params, instead of minimizing (default: False)
- **foreach** (*bool, optional*): whether foreach implementation of optimizer is used. If unspecified by the user (so foreach is None), we will try to use foreach over the for-loop implementation on CUDA, since it is usually significantly more performant. Note that the foreach implementation uses $\sim \text{sizeof}(\text{params})$ more peak memory than the for-loop version due to the intermediates being a tensorlist vs just one tensor. If memory is prohibitive, batch fewer parameters through the optimizer at a time or switch this flag to False (default: None)