Algorithm 1: Self-paced contrastive learning in pretraining stage.

Input: Unlabeled dataset $\mathcal{U}$ and their respective meta-label set D_{meta}; Encoder of the segmentation network $E(\cdot)$; Temperature τ; Learning pace γ scheduler ;

Output: Pre-trained model parameters $\{\boldsymbol{\theta}\}$ for $E(\cdot)$;

Initialize network parameters $\boldsymbol{\theta}$;

Initialize hyper-parameters: learning pace: $\gamma \leftarrow \gamma_0 = $ Scheduler (0) ;

for epoch $= 1, \ldots, n_{\text{epochs}}$ **do**

- **for** n $= 1, \ldots, n_{\text{iter}}$ **do**
  - Sample unlabeled training batch $\{\mathcal{U}_n\}$;
  - For all $\mathbf{x}_u \in \mathcal{U}_n$, do random transformation and get $\mathbf{x}_u^T$;
  - Compute z using non-linear project $g(\cdot)$ for the features $E(\mathbf{x}_u)$;
  - Compute the sample-wise contrastive loss using Eq. (2):
  - $\ell_{ij} = -\log \frac{\exp\left(z_i^\intercal z_j/\tau\right)}{\sum_{a\in\mathcal{A}(i)} \exp\left(z_i^\intercal z_a/\tau\right)}$;
  - Compute self-paced importance weight ω_{ij} using Eq. (6):
  - $w_{ij}^* = \underset{w_{ij}\in[0,1]}{\arg\min}\ w_{ij}\,\ell_{ij} + R_\gamma(w_{ij})$;
  - Compute self-paced contrastive loss using Eq. (3):
  - $\mathcal{L}_{\text{SP-con}}^k = \frac{1}{2N}\sum_{i=1}^{2N} \frac{1}{|\mathcal{P}^k(i)|} \sum_{j\in\mathcal{P}^k(i)} w_{ij}\,\ell_{ij} + R_\gamma(w_{ij})$;
  - According to Eq. (14), do a batch gradient descent step on the model's parameters $\boldsymbol{\theta}$;
  - Update the model's parameters $\boldsymbol{\theta}$;
- Adjust the SGD learning rate;
- Update learning pace according to the scheduler: $\gamma \leftarrow$ Scheduler (epoch)

return $\{\boldsymbol{\theta}\}$;