① Burn-In [Train the object detector using available labeled data]

model → θ supervised loss → $\mathcal{L}_{sup}$ Supervised data $D_s = \{x_i^s, y_i^s\}_{i=1}^{N_s}$

The supervised loss of object detection consist of four losses –

① RPN classification Loss $\mathcal{L}_{cls}^{rpn}$
② RPN regression loss $\mathcal{L}_{reg}^{rpn}$
③ ROI classification Loss $\mathcal{L}_{cls}^{roi}$
④ ROI regression Loss $\mathcal{L}_{reg}^{roi}$

$$\mathcal{L}_{sup} = \sum_i \mathcal{L}_{cls}^{rpn}(x_i^s, y_i^s) + \mathcal{L}_{reg}^{rpn}(x_i^s, y_i^s) + \mathcal{L}_{cls}^{roi}(x_i^s, y_i^s) + \mathcal{L}_{reg}^{roi}(x_i^s, y_i^s) \quad \text{—(1)}$$

② Teacher-student mutual Learning

1Student Learning with pseudo-Learning

After obtaining pseudo labels, from teacher, only learnable weights of student model is updated via (back-propagation)

$$\theta_s \leftarrow \theta_s + \gamma \frac{\partial(\mathcal{L}_{sup} + \lambda_u \mathcal{L}_{unsup})}{\partial \theta_s}$$

$$\mathcal{L}_{unsup} = \sum_i \mathcal{L}_{cls}^{rpn}(x_i^u, \hat{y}_i^u) + \mathcal{L}_{cls}^{roi}(x_i^u, \hat{y}_i^u) \quad \text{—(2)}$$

Teacher refinement via Exponential Moving Average (EMA)

$$\theta_t \leftarrow \alpha \theta_t + (1-\alpha)\theta_s \quad \text{—(3)}$$

Teacher model is improved

$$\theta_t^i = \hat{\theta} - \gamma \sum_{K=1}^{i-1} (1-\alpha^{-K+(i-1)}) \frac{\partial(\mathcal{L}_{sup} + \lambda_u \mathcal{L}_{unsup})}{\partial \theta_s^K} \quad \text{— (4)}$$

$\hat{\theta}$ = model weight after burn-in stage
θ_t^i = Teacher model weight in i^{th} iteration
θ_s^k = Student model weight in k^{th} iteration
γ = Learning rate
α = EMA coefficient