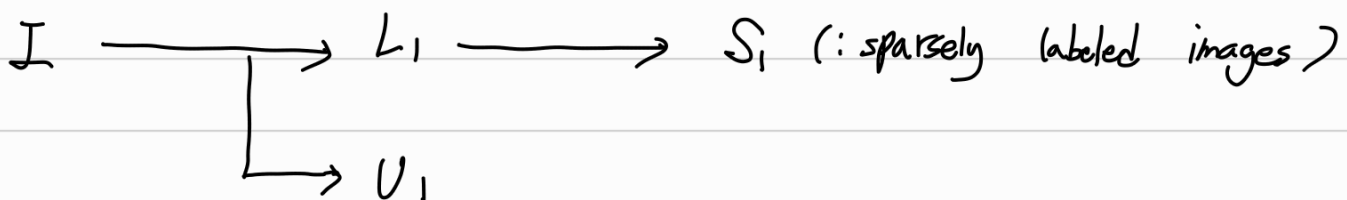


$t=0$ (active sampling ∇)



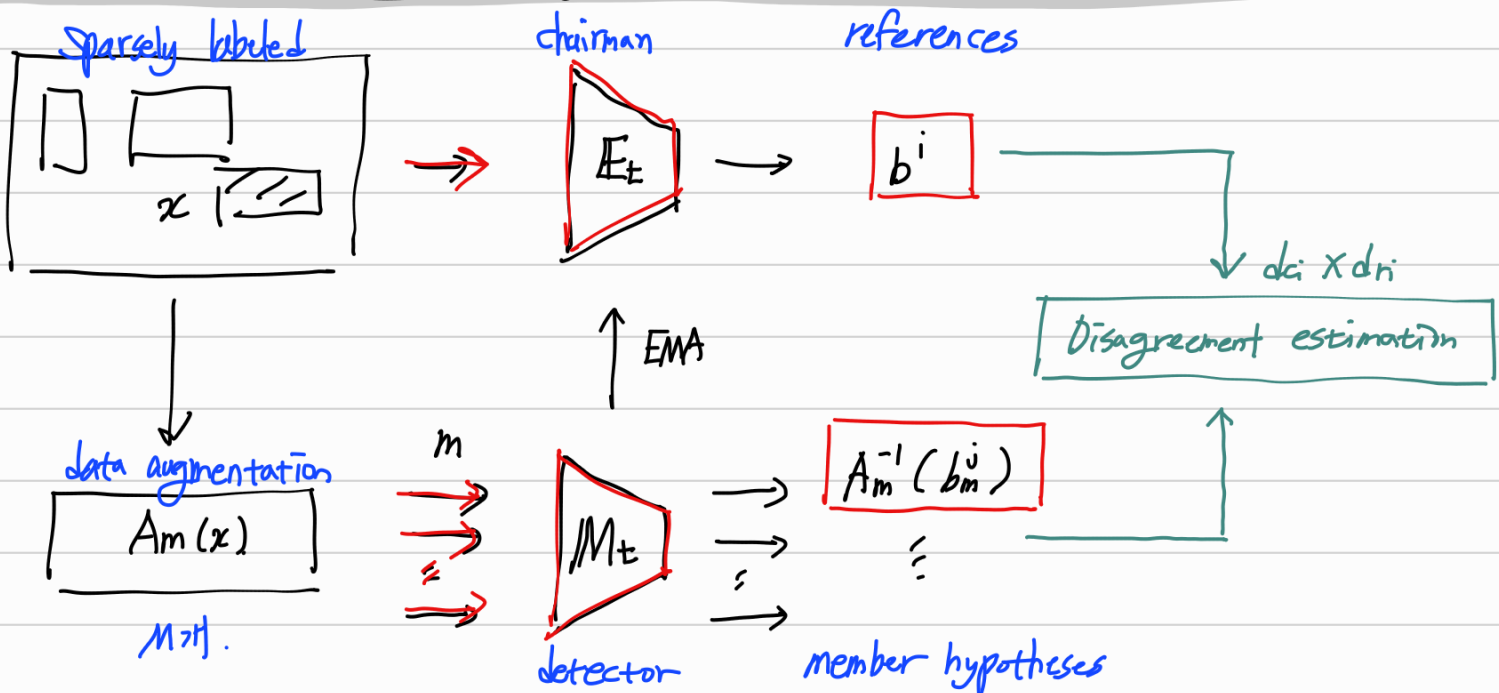
$M(\theta_0)$: generic object detector

$t \geq 1$ (active sampling ∇)



$M(\theta_t)$ updated w labeled images $L_t \cup S_t$
or all images $L_t \cup S_t \cup U_t$

S_t : sparsely labeled images



chairman : $\mathbb{E}(\theta')$ of $M(\theta)$: generate box references.
 EMA detector

$$\theta'_{tr} = \alpha \theta'_{tr-1} + (1-\alpha) \cdot \theta_{tr}$$

(tr : training step within one cycle)

①

- Disagreement on classification.

1. Given chairman's $n_{tr}^{k,i}$ box candidates : $\{b^i\}$ >

member boxes $\{b_m^j\}$ are assigned to each reference box in $\{b^i\}$

using detector - defined assignment strategy > such as max-IoU assigner.

2. Given matched pair of boxes $\{b^i, b_m^j\}$ >
 classification disagreement $\xrightarrow{\text{CE}}$

: CE b/w one-hot chairman prediction g^i &
 posterior predictive member distribution g^j

$$d_c^{ij} = -\mathbb{E}_{g^i} [\log g^j]$$

3. Disagreement about box b^i is aggregated among M committee members.

$$d_c^i = \frac{1}{M} \cdot \sum_m \left(\frac{1}{k_{mi}} \sum_j d_c^{ij} \right)$$

(k_{mi} : # of positively matched member predictions in m -th stochastic view.)

(2)

- Disagreement on localization

1. $\{b^i, b_m^j\}$: matched pair of boxes.

2. $\{A_m^{-1}(b_m^j)\}$: inverse transformations on those boxes.

fed into localization branch of chairman model \mathbb{H}^{reg} .

3. Disagreement over the location of b^i is measured based on chairman re-calibrated boxes.

$$d_r^i = \frac{1}{4} \cdot \sum_k \hat{\sigma}_k \left(\{ \mathbb{H}^{reg}(A_m^{-1}(b_m^j)) \} \right)$$

localization task \Rightarrow fully regression task based on coordinates.

- Our scoring function for box-level detection task

$$d^i = d_c^i \times d_r^i$$

- Supervised loss for labeled images

· fully labeled images $\{x_e^i\}$ from L_{\pm} : $N_e \gg 1$

$$L_e = \frac{1}{N_e} \sum_i \underbrace{d_{cls}(x_e^i, y_e^i)}_{\text{classification loss}} + \underbrace{d_{loc}(x_e^i, t_e^i)}_{\text{localization loss function}}$$

Annotations:
- x_e^i : fully labeled image
- y_e^i : gt class label
- t_e^i : corresponding box location

- Pseudo - active synergy for sparse images

$$G(y_s, \hat{y}_{sc})$$

sparse gt label

pseudo label

$$= y_s \cup \{ \hat{y}_{sc}^i \mid \text{IOU}(\hat{b}_{sc}^i, b_s^i) \leq \lambda_g, \forall b_s^i \in b_s \}$$

corresponding box

jaccard overlap

$$G(t_s, \hat{t}_{sr}) \propto |f_{\text{act}}|.$$

∴ supervision quality for sparse images.

$$\mathcal{L}_s = \frac{1}{N_s} \cdot \sum_i^{N_s} \mathcal{L}_{cls}(A(x_s^i), G(y_s^i, \hat{y}_{sc}^i)) + \mathcal{L}_{loc}(A(x_s^i), G(t_s^i, \hat{t}_{sr}^i))$$

sparsely labeled image