sWMD

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WMD

$$d(w_i, w_j) = \|w_i - w_j\|_2$$

$$d(s_1, s_2)$$

$$\sum_{i,j} \hat{T}_{ij}\, d(w_i, w_j)$$

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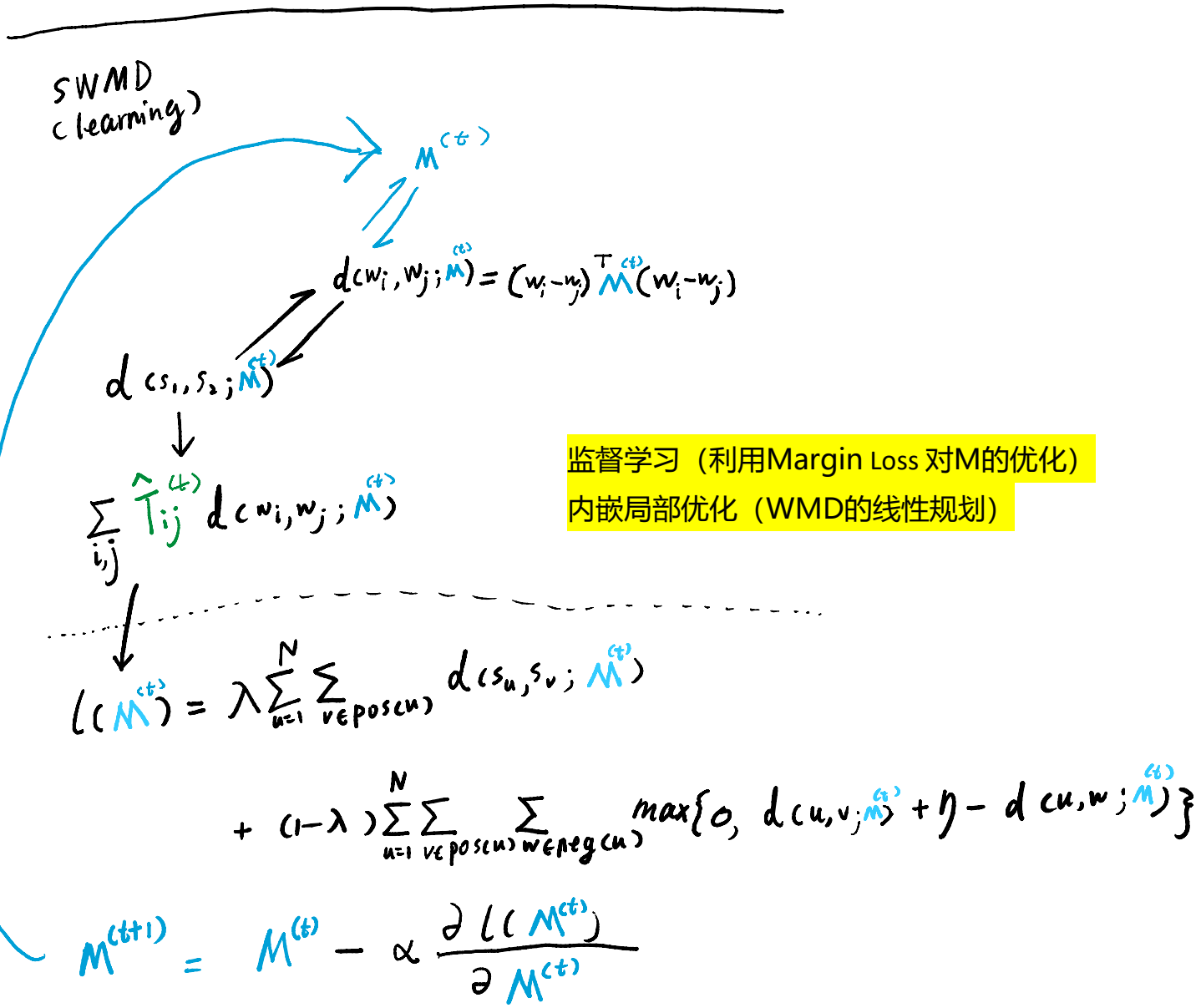
sWMD (forward)

$$M$$

$$d(w_i, w_j; M) = (w_i - w_j)^T M (w_i - w_j)$$

$$d(s_1, s_2; M)$$

$$\sum_{i,j} \hat{T}_{ij}\, d(w_i, w_j; M)$$


SWMD
(learning)
$M^{(t)}$
$d(w_i, w_j; M^{(t)}) = (w_i - w_j)^T M^{(t)} (w_i - w_j)$
$d(s_1, s_2; M^{(t)})$
$\sum_{i,j} \hat{T}_{ij}^{(t)} d(w_i, w_j; M^{(t)})$
监督学习（利用Margin Loss 对M的优化）
内嵌局部优化（WMD的线性规划）
$l(M^{(t)}) = \lambda \sum_{u=1}^{N} \sum_{v \in pos(u)} d(s_u, s_v; M^{(t)})$
$+ (1-\lambda) \sum_{u=1}^{N} \sum_{v \in pos(u)} \sum_{w \in neg(u)} \max\{0, d(u,v;M^{(t)}) + \eta - d(u,w;M^{(t)})\}$
$M^{(t+1)} = M^{(t)} - \alpha \frac{\partial l(M^{(t)})}{\partial M^{(t)}}$