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**Algorithm 1:** Hybrid Prior Posterior Update with Distribution Shift Adapter

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**Input:** Support set embeddings  $Z_s$ , support labels  $Y_s$ ; Base priors  $\mathcal{B} = \{(\mu_b, \sigma_b^2)\}$ ;  
 Distribution Shift Adapter  $f_{\text{adapt}}$  (optional); Precision scalar  $\lambda$ ; Hybrid mixing factor  
 $\lambda_{\text{mix}}$ ; Temperature  $T$ .

**Output:** Posterior mean  $\mu_{\text{post}}^c$  and variance  $\sigma_{\text{post}}^{c2}$  for each class  $c$ ; Query predictions.

**for** each class  $c$  in the support set or novel classes **do**

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 $Z_s^c \leftarrow \{z_i \in Z_s \mid y_i = c\};$ 
 $N_c \leftarrow |Z_s^c|;$ 
// -- Step 1: Compute Self Prior --
 $\mu_{\text{self}} \leftarrow \text{mean}(Z_s^c);$ 
if  $N_c > 1$  then
|  $\sigma_{\text{self}}^2 \leftarrow \text{variance}(Z_s^c)$ 
else
|  $\sigma_{\text{self}}^2 \leftarrow \epsilon \cdot \mathbf{1}$ 
end
// -- Step 2: Compute Base-driven Prior if available --
if  $\mathcal{B} \neq \emptyset$  then
| for each base class  $(\mu_b, \sigma_b^2) \in \mathcal{B}$  do
| |  $s_b \leftarrow \text{cosine\_similarity}(\mu_{\text{self}}, \mu_b)$ 
| end
|  $w_b \leftarrow \text{softmax}(\beta \cdot s_b)$  // Similarity weights
|  $\mu_{\text{base}} \leftarrow \sum_b w_b \mu_b;$ 
|  $\sigma_{\text{base}}^2 \leftarrow \sum_b w_b \sigma_b^2;$ 
end
else
| |  $\mu_{\text{base}} \leftarrow \mathbf{0}, \sigma_{\text{base}}^2 \leftarrow \mathbf{1}$ 
end
// -- Step 3: Hybrid Prior --
 $\mu_{\text{hybrid}} \leftarrow (1 - \lambda_{\text{mix}}) \cdot \mu_{\text{self}} + \lambda_{\text{mix}} \cdot \mu_{\text{base}};$ 
 $\sigma_{\text{hybrid}}^2 \leftarrow (1 - \lambda_{\text{mix}}) \cdot \sigma_{\text{self}}^2 + \lambda_{\text{mix}} \cdot \sigma_{\text{base}}^2;$ 
// -- Step 4: Optional Adapter Adjustment --
if  $f_{\text{adapt}}$  is not None then
|  $\Sigma_{\text{hybrid}} \leftarrow \text{diag}(\sigma_{\text{hybrid}}^2);$ 
|  $(\mu_{\text{prior}}, \Sigma_{\text{prior}}) \leftarrow f_{\text{adapt}}(\mu_{\text{hybrid}}, \Sigma_{\text{hybrid}});$ 
|  $\sigma_{\text{prior}}^2 \leftarrow \text{diag}(\Sigma_{\text{prior}});$ 
end
else
| |  $\mu_{\text{prior}} \leftarrow \mu_{\text{hybrid}};$ 
| |  $\sigma_{\text{prior}}^2 \leftarrow \sigma_{\text{hybrid}}^2$ 
end
// -- Step 5: Posterior Update --
 $\text{prec}_{\text{prior}} \leftarrow 1/(\sigma_{\text{prior}}^2 + \epsilon);$ 
 $\text{prec}_{\text{likelihood}} \leftarrow \lambda;$ 
 $\text{prec}_{\text{post}} \leftarrow \text{prec}_{\text{prior}} + N_c \cdot \text{prec}_{\text{likelihood}};$ 
 $\mu_{\text{post}}^c \leftarrow (\text{prec}_{\text{prior}} \cdot \mu_{\text{prior}} + \text{prec}_{\text{likelihood}} \cdot N_c \cdot \mu_{\text{self}}) / \text{prec}_{\text{post}};$ 
 $\sigma_{\text{post}}^{c2} \leftarrow 1 / \text{prec}_{\text{post}};$ 
end
for each query embedding  $z_q$  do
|  $\hat{z}_q \leftarrow z_q / \|z_q\|;$ 
| for each class  $c$  do
| |  $\hat{\mu}_c \leftarrow \langle \hat{z}_q, \hat{z}_q \rangle / \|z_q\|^2$ 
| end
| end

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