Supplementary Material

1. Summary of Notation

![Graphical Model Representation](image)

Figure 1. The graphical model representation of the ARHMM-MIL model

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Size</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y_b$</td>
<td>Scalar</td>
<td>The label of bag $b$</td>
</tr>
<tr>
<td>$I_b$</td>
<td>Scalar</td>
<td>$t$th instance label in bag $b$</td>
</tr>
<tr>
<td>$I_b$</td>
<td>$1 \times (T_b - p)$</td>
<td>All the instance labels in bag $b$</td>
</tr>
<tr>
<td>$X_b^t$</td>
<td>$d \times 1$</td>
<td>The $t$th observation in bag $b$</td>
</tr>
<tr>
<td>$X_b$</td>
<td>$d \times T_b$</td>
<td>All the observations in bag $b$</td>
</tr>
<tr>
<td>$X_b^{(t-p):(t-1)}$</td>
<td>$d \times p$</td>
<td>$p$ observations prior to the $t$th observation in bag $b$</td>
</tr>
<tr>
<td>$Z_b^t$</td>
<td>Scalar</td>
<td>Cluster membership of instance $t$ in bag $b$</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Scalar</td>
<td>Parameter of the softmax function</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$K \times 1$</td>
<td>Dirichlet prior parameter for the cluster membership</td>
</tr>
<tr>
<td>$\pi$</td>
<td>$K \times 1$</td>
<td>Probability for initial cluster assignment</td>
</tr>
<tr>
<td>$M$</td>
<td>$K \times K$</td>
<td>Transition matrix, $M_{ij} = P(Z_b^t = j</td>
</tr>
<tr>
<td>$A_{k0}$</td>
<td>$d \times 1$</td>
<td>Intercept term of the $k$th AR cluster</td>
</tr>
<tr>
<td>$A_{kj}$</td>
<td>$d \times d$</td>
<td>Coefficient of the $j$th order of the $k$th AR cluster</td>
</tr>
<tr>
<td>$\Sigma_k$</td>
<td>$d \times d$</td>
<td>Covariance matrix of the $k$th AR cluster</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>$2 \times 1$</td>
<td>Beta prior for each cluster</td>
</tr>
<tr>
<td>$\theta_k$</td>
<td>Scalar</td>
<td>The Bernoulli parameter for the $k$th cluster</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model Parameters</th>
<th>Dimensions</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B$</td>
<td>Number of bags</td>
<td></td>
</tr>
<tr>
<td>$T_b$</td>
<td>Length of time series in bag $b$</td>
<td></td>
</tr>
<tr>
<td>$K$</td>
<td>Number of mixture components</td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>Order of each auto-regressive process</td>
<td></td>
</tr>
<tr>
<td>$d$</td>
<td>Time series dimension</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. A summary of the notation used.
2. E-step Derivation

The complete-data log-likelihood is as follows:

\[
\ell(\Theta) = \sum_{b=1}^{B} \log P(Z_b, I_b, X_b, Y_b | \Theta)
\]

\[
= \sum_{b=1}^{B} \left[ \log P(Y_b | I_b, \omega) + \log P(I_b | Z_b, \theta) + \log P(Z_b | M, \pi) + \log P(X_b | Z_b, A, \Sigma) \right]
\]

\[
= \sum_{b=1}^{B} \left[ \log P(Y_b | I_b, \omega) + \sum_{t=p+1}^{T_b} \log P(I_b^t | Z_b^t, \theta) + \log P(Z_b^{t+1} | \pi) + \sum_{t=p+2}^{T_b} \log P(Z_b^t | Z_b^{t-1}, M) 
+ \sum_{t=p+1}^{T_b} \log P(X_b^t | X_b^{(t-p):(t-1)}, Z_b^t, A, \Sigma) \right]
\]

(1)

In order to form the auxiliary function \(Q(\Theta, \Theta')\), we take the expected value of the complete data log-likelihood under the distribution \(P(Z, I | X, Y, \Theta')\).

\[
Q(\Theta, \Theta') = E_{P(Z, I | X, Y, \Theta')} \left[ \sum_{b=1}^{B} \sum_{I} \mathbb{I}(I_b = I) \left( Y_b \log P(Y_b = 1 | I_b, \omega) + (1 - Y_b) \log P(Y_b = 0 | I_b, \omega) \right) 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} \mathbb{I}(Z_b^l = j, I_b^l = l) \log P(I_b^l = l | Z_b^l = j, \theta) 
+ \sum_{b=1}^{B} \sum_{j=1}^{K} \log P(Z_b^{p+1} = j | \pi) 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} \sum_{i=1}^{K} \mathbb{I}(Z_b^l = j, Z_b^{l-1} = i) \log P(Z_b^l = j | Z_b^{l-1} = i, M) 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} \log P(X_b^l | X_b^{(l-p):(l-1)}, Z_b^l = j, A, \Sigma) \right]
\]

\[
= \sum_{b=1}^{B} \sum_{I} E_{P(Z, I | X, Y, \Theta')} \left[ \mathbb{I}(I_b = I) \left( Y_b \log P(Y_b = 1 | I_b, \omega) + (1 - Y_b) \log P(Y_b = 0 | I_b, \omega) \right) 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} E_{P(Z, I | X, Y, \Theta')} \left[ \mathbb{I}(Z_b^l = j, I_b^l = l) \log P(I_b^l = l | Z_b^l = j, \theta) \right] 
+ \sum_{b=1}^{B} E_{P(Z, I | X, Y, \Theta')} \left[ \log P(Z_b^{p+1} = j | \pi) \right] 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} \sum_{i=1}^{K} E_{P(Z, I | X, Y, \Theta')} \left[ \mathbb{I}(Z_b^l = j, Z_b^{l-1} = i) \log P(Z_b^l = j | Z_b^{l-1} = i, M) \right] 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} E_{P(Z, I | X, Y, \Theta')} \left[ \mathbb{I}(Z_b^l = j) \log P(X_b^l | X_b^{(l-p):(l-1)}, Z_b^l = j, A, \Sigma) \right] \right]
\]

\[
= \sum_{b=1}^{B} \sum_{I} P(I_b = I | X_b, Y_b, \Theta') \left( Y_b \log P(Y_b = 1 | I_b, \omega) + (1 - Y_b) \log P(Y_b = 0 | I_b, \omega) \right) 
+ \sum_{b=1}^{B} \sum_{l=0}^{T_b} \sum_{j=1}^{K} P(I_b^l = l, Z_b^l = j | X_b, Y_b, \Theta') \log P(I_b^l = l | Z_b^l = j, \theta) \]
In this approach we consider the following steps:

- A first pass in which a **forward message** is computed while traversing the graphical model from left to right; specifically, the forward message is initialized at \( t = p + 1 \) by computing \( \alpha_b^q(t) = P(X_b^{1:t}, S_b^t = q) \) and for \( t = p + 2, \ldots, T_b \) is computed recursively using

\[
\alpha_b^q(t) = P(X_b^{1:t}, S_b^t = q) = \sum_r P(X_b^{1:t-1}, S_b^{t-1} = r)P(S_b^t = q | S_b^{t-1} = r)P(X_b^t | X_b^{1:t-1}, S_b^t = q)
\]

- A second pass in which a **backward message** is computed while traversing the graphical model from right to left; the backward message is initialized at \( t = T_b \) by setting \( \beta_b^q(T_b) = P(Y_b | X_b^{1:T_b}, S_b^{T_b} = q) \) and for \( t = T_b - 1, \ldots, p + 1 \) is computed recursively by

\[
\beta_b^q(t) = P(Y_b, X_b^{t+1:T_b} | X_b^{1:t}, S_b^t = q) = \sum_r P(S_b^{t+1} = r | S_b^t = q)P(X_b^{t+1} | X_b^{1:t}, S_b^{t+1} = r)P(Y_b, X_b^{t+2:T_b} | X_b^{1:t+1}, S_b^{t+1} = r)
\]

Finally, the messages are used to form the pairwise probability for \((S_b^t, S_b^{t-1})\) conditioned on the observed nodes \(X_b^1, \ldots, X_b^T\) and \(Y_b\). The E-step calculation of the proposed model necessitates the probability of the form \( P(S_b^t = q, S_b^{t-1} = r | X_b, Y_b) \) given by

\[
P(S_b^t = q, S_b^{t-1} = r | X_b, Y_b) = \sum_q \sum_r P(S_b^t = q, S_b^{t-1} = r | X_b, Y_b).
\]
We focus on the joint distribution in the numerator of (3) since the denominator can be computed by marginalizing out \( S_b \) and \( S_b^{t-1} \) in the joint distribution. The numerator of (3) can be written in terms of the forward message, the backward message, the state transition probability, and the observation model probability as

\[
P(S_b^t = q, S_b^{t-1} = r, X_b, Y_b) = P(Y_b, X_b^{t+1:T_b} | X_b^{1:t}, S_b^t = q) P(S_b^t = q, S_b^{t-1} = r) P(X_b^{1:t-1}, S_b^t = q) P(X_b^{1:t-1}, S_b^{t-1} = r)
\]

\[
= \beta_b^t(t) P(S_b^t = q | S_b^{t-1} = r) P(X_b^t | X_b^{t-1}, S_b^t = q) P(S_b^t = q) (t - 1)
\]

This approach provides the framework for computing the E-step probability terms after expanding the node \( S \) to \((N_b^t, Z_b^t)\) as follows.

2.2. Message passing for the chain based on \((N_b^t, Z_b^t)\)

In this section, we provide more detailed intermediate steps for the forward/backward message passing based on \((N_b^t, Z_b^t)\).

Recall that we use a simplified graphical model to represent the structure with a single bag as in Fig. 3. We use the \( q \) and \( r \) to compactly denote \( q = (q_N, q_Z) \) and \( r = (r_N, r_Z) \) for \( t = p + 1, \ldots, T_b \).

\[
\begin{aligned}
\text{Figure 3. A graphical model representing a bag in Fig. 1 with the instance label } I \text{ replaced by a counting variable } N. \\
\end{aligned}
\]

2.2.1. Forward Message

We assume the first \( p \) observations \( X_1, \ldots, X_p \) follow a joint distribution \( P(X_b^{1:p}) \) that is independent of any proposed model parameters. The forward message starts with \( t = p + 1 \), so it is clear that \( N_b^{p+1} = I_b^{p+1} \). Hence, the forward message at \( t = p + 1 \) is initialized by

\[
\alpha_b^{q_N,q_Z}(p + 1) = P(X_b^{1:p+1} | N_b^{p+1} = q_N, Z_b^{p+1} = q_Z)
\]

\[
= P(X_b^{p+1} | N_b^{p+1} = q_N, Z_b^{p+1} = q_Z) P(X_b^{1:p})
\]

\[
= P(X_b^{p+1} | X_b^{1:p}, Z_b^{p+1} = q_Z) P(N_b^{p+1} = q_N | Z_b^{p+1} = q_Z) P(Z_b^{p+1} = q_Z) P(X_b^{1:p})
\]

\[
= P(X_b^{p+1} | X_b^{1:p}, Z_b^{p+1} = q_Z) P(I_b^{p+1} = q_N | Z_b^{p+1} = q_Z) P(Z_b^{p+1} = q_Z) P(X_b^{1:p})
\]

\[
= A_b^{q_Z}(p + 1)(\theta_{q_Z})^{q_N(1 - \theta_{q_Z})^{(1 - q_N)}} P(X_b^{1:p})
\]

(5)

for \( q_N \in \{0, 1\} \) and \( q_Z \in \{1, \ldots, K\} \), where \( A_b^{q_Z}(p + 1) = P(X_b^{p+1} | X_b^{1:p}, Z_b^{p+1} = q_Z) \), \( \pi_{q_Z} = P(Z_b^{p+1} = q_Z) \) and \( \theta_{q_Z} = P(I_b^{p+1} = 1 | Z_b^{p+1} = q_Z) \). Then, the forward message is recursively computed for \( t = p + 2, \ldots, T_b \) using

\[
\alpha_b^{q_N,q_Z}(t) = P(X_b^{1:t} | N_b^t = q_N, Z_b^t = q_Z)
\]

\[
= P(X_b^{1:t} | X_b^{1:t-1}, Z_b^t = q_Z) P(N_b^t = q_N, Z_b^t = q_Z, X_b^{1:t-1})
\]

\[
= P(X_b^{1:t} | X_b^{1:t-1}, Z_b^t = q_Z) \sum_{r_N} \sum_{r_Z} P(N_b^t = q_N, Z_b^t = q_Z, N_b^{t-1} = r_N, Z_b^{t-1} = r_Z, X_b^{1:t-1})
\]

\[
\cdot P(Z_b^t = q_Z | N_b^{t-1} = r_N, Z_b^{t-1} = r_Z) P(X_b^{1:t-1}, N_b^{t-1} = r_N, Z_b^{t-1} = r_Z)
\]

\[
= P(X_b^{1:t} | X_b^{1:t-1}, Z_b^t = q_Z) \sum_{r_N} \sum_{r_Z} P(N_b^t = q_N, Z_b^t = q_Z, N_b^{t-1} = r_N)
\]
for all \( q_z \in \{1, \ldots, K\} \), where \( P(Y_b|N^{T_b}) = q_N \) is computed using the positive bag probability (29). Then, the backward message is recursively computed for \( t = T_b - 1, \ldots, p + 1 \) using

\[
\beta^{q_N, q_z}_b(t) = P(Y_b|X^{t+1:T_b}_b, Z^{T_b}_b = q_N, N^{T_b}_b = q_N) = P(Y_b|N^{T_b}_b = q_N)
\]

where \( M_{q_z, q_x} = P(Z^t_b = q_z|Z^{t-1}_b = r_z), A^{q_z}_b(t) = P(X^t_b|X^{t-1}_b, Z^t_b = q_z) \) and \( \theta_{q_z} = P(I^t_b = 1|Z^t_b = q_z) \).

### 2.2.2. Backward Message

The backward message is initialized at \( t = T_b \) with

\[
\beta^{q_N, q_z}_b(T_b) = \sum_{r_N} \sum_{r_z} P(Y_b|X^{T_b+1:T_b}_b, Z^{T_b}_b = q_N, N^{T_b}_b = q_N) = P(Y_b|N^{T_b}_b = q_N)
\]

We expand (4) by changing \( S^t_b \) to the pair \((N^t_b, Z^t_b)\) where we can compute the pairwise state probability \( P(N^t_b = q_N, Z^t_b = q_z, N^{t-1}_b = r_N, Z^{t-1}_b = r_z, X^{t-1}_b, Y_b) \) using

\[
\begin{align*}
\beta^{q_N, q_z}_b(t) = & \sum_{r_N} \sum_{r_z} P(Y_b, X^{t+1:T_b}_b|X^{t-1}_b, N^t_b = q_N, Z^t_b = q_z)P(N^{t+1}_b = q_N, Z^{t+1}_b = r_z, N^{t-1}_b = r_N, Z^{t-1}_b = r_z) \\
= & \sum_{r_N} \sum_{r_z} P(N^{t+1}_b = r_N|Z^{t+1}_b = r_z, N^t_b = q_N)P(Z^{t+1}_b = r_z|Z^t_b = q_z) \\
& \cdot P(X^{t+1}_b|X^{t-1}_b, Z^{t+1}_b = r_z)P(Y_b, X^{T_b+1:T_b}_b|X^{t+1}_b, Z^{t+1}_b = r_z, N^{t+1}_b = r_N, Z^{t+1}_b = r_z) \\
= & \sum_{r_N} \sum_{r_z} P(N^{t+1}_b = r_N|Z^{t+1}_b = r_z, N^t_b = q_N)P(Z^{t+1}_b = r_z|Z^t_b = q_z) \\
& \cdot \sum_{r_N} \sum_{r_z} P(X^{t+1}_b|X^{t-1}_b, Z^{t+1}_b = r_z)P(Y_b, X^{T_b+1:T_b}_b|X^{t+1}_b, Z^{t+1}_b = r_z, N^{t+1}_b = r_N, Z^{t+1}_b = r_z) \\
= & \sum_{r_N} \sum_{r_z} M_{q_z, q_x} A^{q_z}_b(t) + 1 \sum_{r_N} (1 - \theta_{q_z}) \beta^{q_N, q_z}_b(t+1)
\end{align*}
\]

(8)

where \( M_{q_z, q_x} = P(Z^t_b = q_z|Z^{t-1}_b = r_z), A^{q_z}_b(t) = P(X^t_b|X^{t-1}_b, Z^t_b = q_z) \) and \( \theta_{q_z} = P(I^t_b = 1|Z^t_b = q_z) \).
3. M-Step Derivation

In this section, we derive the equations for the M-step for all the parameters of the ARHMM-MIL model. Under the maximum-a-posteriori (MAP) framework, the objective function for the M-step is

\[
Q(\Theta, \Theta') + \log P(\Theta)
\]

\[
= \sum_{b=1}^{B} \sum_{i} \sum_{l=0}^{T_b} P(I_b = l | X_b, Y_b, \Theta') \left( Y_b \log P(Y_b = 1 | I_b, \omega) + (1 - Y_b) \log P(Y_b = 0 | I_b, \omega) \right)
\]

\[
+ \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{l=p+1}^{T_b} \sum_{t=0}^{1} P(I_b^j = l, Z_b^j = j | X_b, Y_b, \Theta') \log P(I_b^j = l | Z_b^j = j, \theta) + \log P(\theta_j | \zeta)
\]

\[
+ \sum_{j=1}^{K} \sum_{b=1}^{B} P(Z_b^{p+1} = j | X_b, Y_b, \Theta') \log P(Z_b^{p+1} = j | \pi) + \log P(\pi_j | \beta)
\]

\[
+ \sum_{j=1}^{K} \sum_{l=0}^{B} \sum_{t=p+2}^{T_b} P(Z_b^l = j, Z_b^{l-1} = i | X_b, Y_b, \Theta') \log P(Z_b^l = j | Z_b^{l-1} = i, \beta) + \log P(M_{ij} | \beta)
\]

\[
+ \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{l=p+1}^{T_b} P(Z_b^l = j | X_b, Y_b, \Theta') \log P(X_b^l | X_b^{(l-p):(l-1)}, Z_b^j = j, \mathcal{A}, \Sigma)
\]

(9)

In general, each equation in the M-step involves a maximum likelihood estimation problem. We simply take the derivative of the objective function (9) with respect to each parameter, set the derivative to zero and solve. We can efficiently estimate the parameter if its closed-form solution exists; otherwise, we apply gradient ascent.

3.1. Update the initial prior \( \pi \) of the hidden states \( Z \)

In order to update \( \pi_j \), we collect the terms in (9) that involve \( \pi_j \) and also add a Lagrangian multiplier \( \eta \) for the constraint \( \sum_{j=1}^{K} \pi_j = 1 \). The resulting function is:

\[
L(\pi_j) = \sum_{j=1}^{K} \left( \sum_{b=1}^{B} P(Z_b^{p+1} = j | X_b, Y_b, \Theta') \log \pi_j + (\beta_j - 1) \log \pi_j \right) + \eta(\sum_{j=1}^{K} \pi_j - 1)
\]

(10)

Taking derivative of \( L(\pi_j) \) with respect to \( \pi_j \) and setting to 0 we get

\[
\sum_{b=1}^{B} \frac{P(Z_b^{p+1} = j | X_b, Y_b, \Theta') \pi_j + \beta_j - 1}{\pi_j} + \eta = 0.
\]

(11)

Setting the derivative to 0 and solving for \( \pi_j \) results in:

\[
\pi_j = \frac{-\sum_{b=1}^{B} P(Z_b^{p+1} = j | X_b, Y_b, \Theta') \pi_j + \beta_j - 1}{\eta}
\]

(12)

Set \( \frac{\partial L(\pi_j)}{\partial \eta} = \sum_{j=1}^{K} \pi_j - 1 = 0 \) we get \( \sum_{j=1}^{K} \pi_j = 1 \). If we sum up (12) over \( j = 1, \ldots, K \), we get:

\[
\sum_{j=1}^{K} \pi_j = \sum_{j=1}^{K} \frac{-\sum_{b=1}^{B} P(Z_b^{p+1} = j | X_b, Y_b, \Theta') \pi_j + \beta_j - 1}{\eta}
\]

[659]
\[
\eta = -\sum_{j=1}^{K} \sum_{b=1}^{B} P(Z_{b}^{p+1} = j|X_b, Y_b, \Theta') + \beta_j - 1 \tag{13}
\]

Substitute (13) into (12), we get:
\[
\pi_j = \frac{\sum_{b=1}^{B} P(Z_{b}^{p+1} = j|X_b, Y_b, \Theta') + \beta_j - 1}{\sum_{j'=1}^{K} \sum_{b=1}^{B} P(Z_{b}^{p+1} = j'|X_b, Y_b, \Theta') + \beta_{j'} - 1} \tag{14}
\]

### 3.2. Update the transition matrix \( M \) of the hidden states

Since the rows in the hidden state transition matrix sum to 1, we need to include the constraints that \( \sum_{j=1}^{K} M_{ij} = 1 \) for \( i = 1, \ldots, K \). Similar to (10), the Lagrangian of \( M_{ij} \) can be formulated by collecting all terms involving \( M_{ij} \) in (9) and introducing Lagrangian multipliers \( \eta_i \) for \( i = 1, \ldots, K \):
\[
L(M_{ij}) = \sum_{i=1}^{K} \sum_{b=1}^{B} \sum_{t=p+2}^{T_b} P(Z_{b}^{t} = j, Z_{b}^{t-1} = i|X_b, Y_b, \Theta') \log M_{ij} + (\beta_j - 1) \log M_{ij} + \sum_{i=1}^{K} \eta_i (\sum_{j=1}^{K} M_{ij} - 1) \tag{15}
\]

Taking the derivative of \( L(M_{ij}) \) with respect to \( M_{ij} \) and setting it equal to 0 we obtain:
\[
\frac{\partial L(M_{ij})}{\partial \eta_i} = \sum_{j=1}^{K} M_{ij} = 0 \quad \text{we get} \quad \sum_{j=1}^{K} M_{ij} = 1. \]

If we sum up (16) over \( j = 1, \ldots, K \), we get:
\[
\sum_{j=1}^{K} M_{ij} = \frac{\sum_{b=1}^{B} \sum_{t=p+2}^{T_b} P(Z_{b}^{t} = j, Z_{b}^{t-1} = i|X_b, Y_b, \Theta') + \beta_j - 1}{\eta_i} \tag{16}
\]

Set \( \frac{\partial L(M_{ij})}{\partial \eta_i} = \sum_{j=1}^{K} M_{ij} = 0 \) we get \( \sum_{j=1}^{K} M_{ij} = 1 \). If we sum up (16) over \( j = 1, \ldots, K \), we get:
\[
\sum_{j=1}^{K} M_{ij} = \sum_{j=1}^{K} \frac{\sum_{b=1}^{B} \sum_{t=p+2}^{T_b} P(Z_{b}^{t} = j, Z_{b}^{t-1} = i|X_b, Y_b, \Theta') + \beta_j - 1}{\eta_i} \tag{17}
\]

Substitute (17) into (16), we get the update equation for \( M_{ij} \):
\[
M_{ij} = \frac{\sum_{b=1}^{B} \sum_{t=p+2}^{T_b} P(Z_{b}^{t} = j, Z_{b}^{t-1} = i|X_b, Y_b, \Theta') + \beta_j - 1}{\sum_{j'=1}^{K} \sum_{b=1}^{B} \sum_{t=p+2}^{T_b} P(Z_{b}^{t} = j', Z_{b}^{t-1} = i|X_b, Y_b, \Theta') + \beta_{j'} - 1} \tag{18}
\]
3.3. Update the covariance matrix $\Sigma_j$ for each AR process

In order to simplify the notation, we denote that $\xi_{btj} = P(Z'_b = j | X_b, Y_b, \Theta)$ is a $K \times K$ matrix for $t = p + 1, \ldots, T_b$. The objective for estimating $\Sigma_j$ can be written as:

$$L(\Sigma_j) = \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} (X_b^t - A_j \mu_{btj} - \sum_{k=1}^{p} A_{jk} X_b^{t-k})' \Sigma_j^{-1} (X_b^t - A_j \mu_{btj} - \sum_{k=1}^{p} A_{jk} X_b^{t-k}) - \frac{1}{2} \log |\Sigma_j| \right]$$

(19)

For convenience, denote $\mu_{btj} = X_b^t - (A_j \mu_{btj} + \sum_{k=1}^{p} A_{jk} X_b^{t-k})$.

$$L(\Sigma_j) = \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} \mu_{btj}' \Sigma_j^{-1} \mu_{btj} - \frac{1}{2} \log |\Sigma_j| \right]$$

$$= \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} Tr(\mu_{btj}' \Sigma_j^{-1} \mu_{btj}) - \frac{1}{2} \log |\Sigma_j| \right]$$

$$= \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} Tr(\mu_{btj} \mu_{btj}' \Sigma_j^{-1}) - \frac{1}{2} \log |\Sigma_j| \right]$$

Using the fact that $|\Sigma_j^{-1}|^{-1} = |\Sigma_j|$, we have:

$$L(\Sigma_j) = \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} Tr(\mu_{btj} \mu_{btj}' \Sigma_j^{-1}) + \frac{1}{2} \log |\Sigma_j|^{-1} \right]$$

(20)

Now, instead of differentiating $L(\Sigma_j)$ with respect to $\Sigma_j$, we differentiate with respect to $\Sigma_j^{-1}$. Setting the derivative to 0 and solving, we get:

$$\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} \mu_{btj} \mu_{btj}' + \frac{1}{2} |\Sigma_j^{-1}| \Sigma_j \right] = 0$$

$$\Rightarrow \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2} \mu_{btj} \mu_{btj}' + \frac{1}{2} \Sigma_j \right] = 0$$

$$\Rightarrow \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ \mu_{btj} \mu_{btj}' - \Sigma_j \right] = 0$$

$$\Rightarrow \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \mu_{btj} \mu_{btj}' = \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \sum_{l=0}^{p} \sum_{j=1}^{K} \xi_{btj} \Sigma_{j,l}$$

$$\Rightarrow \Sigma_j = \frac{\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \mu_{btj} \mu_{btj}'}{\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj}}$$

(20)

3.4. Update the AR coefficients $A_{j0}$ and $A_{jk}$

In (21) below, we collect the terms in (9) that are related to the AR coefficients. Recall that $A_{j0}$ is a $d \times 1$ vector and $A_{jk}$ are matrices of size $d \times d$.

$$L(A_{j0}, A_{j1}, \ldots, A_{jp}) =$$
Efficient Multi-Instance Learning for Activity Recognition from Time Series Data With ARHMM

\[
\sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2}(X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s})' \Sigma_j^{-1}(X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s}) \right] = 0 \tag{21}
\]

Setting the derivative of (21) with respect to \( A_{j0} \) to 0 and solving, we obtain the following:

\[
\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ -\frac{1}{2}(\Sigma_j^{-1} + \Sigma_j^{-1}') (X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s})(-1) \right] = 0
\]

\[
\Rightarrow \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left[ \frac{1}{2}(\Sigma_j^{-1} + \Sigma_j^{-1}') (X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s}) \right] = 0
\]

\[
\Rightarrow \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} (\Sigma_j^{-1})(X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s}) = 0 \tag{22}
\]

Analogously, setting the derivative of (21) with respect to \( A_{jk} \) to 0, we will get the following:

\[
\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} (\Sigma_j^{-1})(X_b^t - A_{j0} - \sum_{s=1}^{p} A_{js} X_b^{t-s})(X_b^{t-k})' = 0 \tag{23}
\]

Reorganizing (22) and (23) will lead to a fully determined system, which is equivalent to the generalized Yule-Walker equations for solving the AR coefficients. The update rule for the set of AR parameters are listed below.

\[
\begin{align*}
\left\{ \begin{array}{l}
\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} \left( A_{j0} + \sum_{s=1}^{p} A_{js} (X_b^{t-s}) \right) = 0 \\
\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \xi_{btj} (X_b^t) = 0
\end{array} \right.
\]

3.5. Update the Bernoulli instance positive probability parameter \( \theta_j \)

The parameter \( \theta_j \) controls the probability of an instance being positive, and we denote \( Z_b^t = j|X_b, Y_b, \Theta' \). Collecting the terms in (9) related to \( \theta_j \), we obtain:

\[
\ell(\theta_j) = \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \sum_{l=0}^{1} \delta^{l}_{btj} \left[ l \log \theta_j + (1-l) \log(1-\theta_j) \right] + (\zeta_1 - 1) \log \theta_j + (\zeta_2 - 1) \log(1-\theta_j)
\]

\[
= \sum_{j=1}^{K} \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \left[ \delta^{l}_{btj} \log \theta_j + \delta^{0}_{btj} \log(1-\theta_j) \right] + (\zeta_1 - 1) \log \theta_j + (\zeta_2 - 1) \log(1-\theta_j)
\]

\[
= \sum_{j=1}^{K} \left[ \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{l}_{btj} + \zeta_1 - 1 \right) \log \theta_j + \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{0}_{btj} + \zeta_2 - 1 \right) \log(1-\theta_j) \right] \tag{24}
\]

Setting the derivative of \( \ell(\theta_j) \) with respect to \( \theta_j \) to 0, we will obtain the following equation

\[
\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{1}_{btj} + \zeta_1 - 1 = \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{0}_{btj} + \zeta_2 - 1
\]

\[
\Rightarrow \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{1}_{btj} + \zeta_1 - 1 \right)(1-\theta_j) - \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{0}_{btj} + \zeta_2 - 1 \right) \theta_j = 0
\]

\[
\Rightarrow \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{1}_{btj} + \zeta_1 - 1 + \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{0}_{btj} + \zeta_2 - 1 \right) \theta_j = \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^{1}_{btj} + \zeta_1 - 1
\]
\[ \theta_j = \frac{\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^1_{btj} + \xi_1 - 1}{\left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^1_{btj} + \xi_1 - 1 \right) + \left( \sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^0_{btj} + \xi_2 - 1 \right)} \]  

(25)

Denote \( \phi_j \) as shown in (26),

\[ \phi_j = \frac{\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^1_{btj} + \xi_1 - 1}{\sum_{b=1}^{B} \sum_{t=p+1}^{T_b} \delta^0_{btj} + \xi_2 - 1} \]  

(26)

Then the update rules for \( \theta_j \) are shown below.

\[ \theta_j = \frac{\phi_j}{1 + \phi_j} \]  

(27)

### 3.6. Update bag positive probability parameter \( \omega \)

Collecting the terms in (9) that involve the parameter \( \omega \), we get:

\[ \ell(\omega) = \sum_{b=1}^{B} \sum_{I} \mathbb{E}_{Z, I, X, Y} \left[ I(\mathbf{I}_b = I) \left( Y_b \log P(Y_b = 1|\mathbf{I}_b) + (1 - Y_b) \log P(Y_b = 0|\mathbf{I}_b) \right) \right] \]

\[ = \sum_{b=1}^{B} \sum_{I} P(\mathbf{I}_b = I|X_{1:T_b}, Y_b) \left( Y_b \log P(Y_b = 1|\mathbf{I}_b) + (1 - Y_b) \log P(Y_b = 0|\mathbf{I}_b) \right) \]  

(28)

As we showed in our Dynamic Programming approach, we can transform our model into an equivalent model by introducing count variables \( N^1_b, \ldots, N^T_b \) to represent the counts of positive instances in bag \( b \). Recall that \( I^0_b \in \{0, 1\} \). Consequently, the positive bag probability \( P(Y_b = 1|\mathbf{I}_b) \) can be equivalently computed using the total number of positive instances in the bag \( N^T_b = \sum_{I=1}^{T_b} I^1_b \) as follows:

\[ P(Y_b = 1|N^T_b) = \sum_{I=p+1}^{T_b} \frac{I^1_b \exp(\omega I^1_b)}{\sum_{I=p+1}^{T_b} \exp(\omega I^1_b)} = \frac{N^T_b \exp(\omega)}{N^T_b \exp(\omega) + T_b - p - N^T_b} \]  

(29)

In the denominator above, the term \( T_b - p - N^T_b \) corresponds to the number of negative instances in the bag (since the instance labels are predicted starting on \( t = p + 1 \)). Using this representation and using \( C \) to represent the total number of positive instances in bag \( b \), we can similarly rewrite (28) as:

\[ \ell(\omega) = \sum_{b=1}^{B} \sum_{C=0}^{T_b-p} P(N^T_b = C|X^{1:T_b}, Y_b) \left[ Y_b \log P(Y_b = 1|N^T_b = C) + (1 - Y_b) \log P(Y_b = 0|N^T_b = C) \right] \]

\[ = \sum_{b=1}^{B} \sum_{C=0}^{T_b-p} P(N^T_b = C|X^{1:T_b}, Y_b) \left[ Y_b \log \left( \frac{C \exp(\omega)}{C \exp(\omega) + T_b - p - C} \right) + (1 - Y_b) \log \left( \frac{T_b - p - C}{C \exp(\omega) + T_b - p - C} \right) \right] \]

\[ = \sum_{b=1}^{B} \sum_{C=0}^{T_b-p} P(N^T_b = C|X^{1:T_b}, Y_b) \left[ Y_b \log(C \exp(\omega)) - Y_b \log(C \exp(\omega) + T_b - p - C) + (1 - Y_b) \log(T_b - p - C) \right. \]

\[ - (1 - Y_b) \log(C \exp(\omega) + T_b - p - C) \]
The second-order gradient of the (30) with respect to $\omega$

$$
= \sum_{b=1}^{B} \sum_{T_b > 0} P(N_b^{T_b} = C|X_b^{1:T_b}, Y_b) \left[ Y_b \log(C \exp(\omega)) - Y_b \log(C \exp(\omega) + T_b - p - C) + \log(T_b - p - C) - Y_b \log(T_b - p - C) \right]
$$

Combining Equation 31 and 32, the update rule for $\omega$ with a Newton step is $\omega_{new} = \omega_{old} - \frac{l'(\omega_{old})}{l''(\omega_{old})}$. For the efficiency of M-step update, we choose to update the $\omega$ with only one gradient step per E-M iteration.
4. Experiment Results

4.1. Running Time Illustration

We demonstrate the running time comparison with/without the dynamic programming speedup with an illustrative example. The exhaustive enumeration in the E-step has a runtime complexity of \( O(B(2^K)^T) \), where \( K \) is the number of clusters and \( T \) is the bag length. In contrast, the dynamic programming approach we proposed runs in polynomial time \( O(BK^2T^2) \). On Fig. 4 on the left, to keep the running time of exhaustive enumeration under 24 hours, we varied the bag length from 4 to 10 with a total of 20 bags.

![Running Time Per Iteration With Different Bag Lengths](image)

*Figure 4. Left: The running time comparison between the exhaustive approach and dynamic programming. The black error bars denote the 95% confidence interval.*

The experiment at each bag length is repeated 10 times, and the average running time per E-M iteration is reported. We make the scale on the y-axis to grow exponentially on Fig. 4, so it is clear to see that the dynamic programming approach we proposed has made the exact inference by running in quadratic time; by contrast, the exhaustive enumeration is running in exponential time.