PARAMETER ESTIMATION OF EXPONENTIAL HIDDEN MARKOV MODEL AND CONVERGENCE OF ITS PARAMETER ESTIMATOR SEQUENCE

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Abstract: An exponential hidden Markov model (EHMM) is a hidden Markov model which consists of a pair of stochastic processes \{X_t, Y_t\}_{t \in \mathbb{N}}. \{Y_t\}_{t \in \mathbb{N}} is influenced by \{X_t\}_{t \in \mathbb{N}}, which is assumed to form a Markov chain. \{X_t\}_{t \in \mathbb{N}} is not observed. \{Y_t\}_{t \in \mathbb{N}} is an observation process and \text{Y}_t \text{given X}_t has exponential distribution. In this paper, we estimate the parameter of EHMM and study the convergence of the parameter estimator sequence. EHMM is characterized by a parameter \(\phi = (A, \lambda)\) where \(A\) is a transition matrix of \text{X}_t and \(\lambda\) is a vector of parameters of probability density function of \text{Y}_t \text{given X}_t. To determine the parameter estimator, a maximum likelihood method is used. Numerical approximation is used through an Expectation Maximization (EM) algorithm. Under the continuous assumption, the sequence \{\phi^{(k)}\} obtained by the EM algorithm, converges to \(\phi^*\) which is the stationary point of \(\ln L_t(\phi)\) and the sequence \{\ln L_t(\phi^{(k)})\} increasingly converges to \(\ln L_t(\phi^*)\).

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1. Introduction

An exponential hidden Markov model (EHMM) is a continuous hidden Markov model which consists of a pair of stochastic processes \{X_t, Y_t\}_{t \in \mathbb{N}}. \{Y_t\}_{t \in \mathbb{N}} is influenced by \{X_t\}_{t \in \mathbb{N}}, which is assumed to form a Markov chain. \{X_t\}_{t \in \mathbb{N}} is not observed. \{Y_t\}_{t \in \mathbb{N}} is an observation process and \text{Y}_t \text{given X}_t has exponential distribution. In this paper, we estimate the parameter of EHMM and study the convergence of the parameter estimator sequence. EHMM is characterized by a parameter \(\phi = (A, \lambda)\) where \(A\) is a transition matrix of \text{X}_t and \(\lambda\) is a vector of parameters of probability density function of \text{Y}_t \text{given X}_t. To determine the parameter estimator, a maximum likelihood method is used. Numerical approximation is used through an Expectation Maximization (EM) algorithm. Under the continuous assumption, the sequence \{\phi^{(k)}\} obtained by the EM algorithm, converges to \(\phi^*\) which is the stationary point of \(\ln L_t(\phi)\) and the sequence \{\ln L_t(\phi^{(k)})\} increasingly converges to \(\ln L_t(\phi^*)\).
model which consists of a pair of stochastic processes \( \{X_t, Y_t\}_{t \in \mathbb{N}} \). \( \{Y_t\}_{t \in \mathbb{N}} \) is influenced by \( \{X_t\}_{t \in \mathbb{N}} \), which is not observed. \( \{X_t\}_{t \in \mathbb{N}} \) is assumed to form a Markov chain. \( \{Y_t\}_{t \in \mathbb{N}} \) is an observation process which \( Y_t \) given \( X_t \) has exponential distribution. Let \( S_X = \{1, 2, 3, ..., m\} \) be a state space of \( \{X_t\}_{t \in \mathbb{N}} \), \( A = [a_{ij}]_{m \times m} \) be a transition probability matrix with 
\[ a_{ij} = P(X_t = j | X_{t-1} = i) = P(X_2 = j | X_1 = i), \]
where \( a_{ij} \geq 0, 1 \leq i, j \leq m \) and \( \sum_{j=1}^{m} a_{ij} = 1 \) for 
\( i \in S_X \). \( \varphi = [\varphi_i]_{m \times 1} \) is an initial state probability vector with 
\( \varphi_i = P(X_1 = i) \) for \( i = 1, 2, 3, ..., m \), \( \sum_{i=1}^{m} \varphi_i = 1 \) and \( A \varphi = \varphi \). \( \lambda = (\lambda_i)_{m \times 1} \) is a vector that characterizes the probability density function of \( Y_t \) given \( X_t = i \), that is 
\( \gamma_{yi} = f(y) = \frac{1}{\lambda_i} e^{-\frac{1}{\lambda_i} y} \) for \( y > 0 \). So the EHMM can be characterized by a parameter \( \phi = (A, \lambda) \).

The aims of this paper are:

1. To estimate the parameter \( \phi \) for an observation \( \{y_t\} \) which is assumed to be generated by the EHMM.
2. To determine the convergence of parameter estimator sequence.

2. Parameter Estimation (see [1])

Let \( T \) be an observation number, \( y = (y_1, y_2, ..., y_T) \) be an observation sequence, and \( x = (i_1, i_2, ..., i_T) \) be a sequence which is not observed. Let \( \epsilon > 0 \) be a number close to 0, and \( \Phi = \{ \phi = (A, \lambda) : A \in [0, 1]^{m^2}, \lambda \in [\epsilon, \frac{1}{\epsilon}]^m \} \) be the EHMM parameter space.

Assume that:

1. \( a_{ij} : \Phi \to \mathbb{R} \) with \( a_{ij} = a_{ij}(\phi) \) is a continuous function in \( \Phi, \forall i, j \in S_X \).
2. \( \lambda_i : \Phi \to \mathbb{R} \) with \( \lambda_i = \lambda_i(\phi) \) is a continuous function in \( \Phi, \forall i \in S_X \).
3. \( \varphi_i : \Phi \to \mathbb{R} \) with \( \varphi_i = \varphi_i(\phi) \) is a continuous function in \( \Phi, \forall i \in S_X \).

Define the likelihood function for the observation process \( Y \) as follows:

\[
L_T(\phi) = f(y_1, y_2, ..., y_T | \phi)
= \sum_{i_1=1}^{m} ... \sum_{i_T=1}^{m} f(Y_T = y_T, X_T = i_T, Y_{T-1} = y_{T-1}, X_{T-1} = i_{T-1}, ...)
\]

\[
= f(Y_1 = y_1, X_1 = i_1 | \phi)
\]  

(1)
\[= \sum_{i_1=1}^{m} \ldots \sum_{i_T=1}^{m} \varphi_{i_1} \gamma_{y_1 i_1} \prod_{t=2}^{T} a_{i_{t-1} i_t} \gamma_{y_t i_t}.\]

Define also:
\[
L^c_T(\phi) = f(y_T, i_T, y_{T-1}, i_{T-1}, \ldots, y_1, i_1|\phi)
= f(y_T|i_T, y_{T-1}, i_{T-1}, \ldots, y_1, i_1, \phi) f(i_T, y_{T-1}, i_{T-1}, \ldots, y_1, i_1|\phi)
= \varphi_{i_1} \gamma_{y_1 i_1} \prod_{t=2}^{T} a_{i_{t-1} i_t} \gamma_{y_t i_t}.\]

From (1) and (2), we have
\[
L_T(\phi) = \sum_{i_1=1}^{m} \ldots \sum_{i_T=1}^{m} \varphi_{i_1} \gamma_{y_1 i_1} \prod_{t=2}^{T} a_{i_{t-1} i_t} \gamma_{y_t i_t}
= \sum_{x} f(y, x|\phi) = \sum_{x} L^c_T(\phi).
\]

Calculating the likelihood function directly is very complicated. So, a Forward-Backward algorithm is used to solve the problem.

### 2.1. Forward-Backward Algorithm

A Forward-backward algorithm is an iterative algorithm which is used to calculate the joint probability of observation process sequence \((y_1, y_2, \ldots, y_T)\). The Forward-Backward algorithm is used to speed up the computing process.

Define the forward probability for \(t = 1, 2, \ldots, T\) and \(i = 1, 2, \ldots, m\) as
\[
\alpha_t(i|\phi) = P(Y_1 = y_1, Y_2 = y_2, \ldots, Y_t = y_t, X_t = i|\phi)
\]
and the backward probability for \(t = T - 1, T - 2, \ldots, 1\) and \(i = 1, 2, \ldots, m\) as
\[
\beta_t(i|\phi) = P(Y_{t+1} = y_{t+1}, \ldots, Y_T = y_T|X_t = i, \phi).
\]

Then, we have
\[
\alpha_1(i|\phi) = \gamma_{y_1 i} \varphi_i,
\]
\[
\alpha_{t+1}(j|\phi) = \left( \sum_{i \in S_X} \alpha_t(i|\phi) a_{ij} \right) \gamma_{y_{t+1} j},
\]
for \(t = 1, 2, \ldots, T - 1\) and
\[
\beta_T(j|\phi) = 1.
\]
\[ \beta_t(j|\phi) = \sum_{i \in S_X} \beta_{t+1}(i|\phi) \gamma_{yt+1} a_{ij}, \]

for \( t = T - 1, T - 2, ..., 1 \) and \( i, j \in S_X \).

**Proposition.** (see [3]) For each \( t = 1, 2, ..., T \):

\[ L_T(\phi) = \sum_{i \in S_X} \alpha_t(i|\phi) \beta_t(i|\phi). \]

The problem is to find \( \phi^* \in \Phi \) which maximizes \( L_T(\phi) \). We modify the problem becomes to find \( \phi^* \in \Phi \) which maximizes \( \ln L_T(\phi) \). The EM algorithm is then used to find them. As a result of EM algorithm, we obtain a sequence \( \{\phi^{(k)}\} \) in \( \Phi \) such that a sequence \( \{\ln L_T(\phi^{(k)})\} \) increases and converges to \( \ln L_T(\phi) \).

It is known that

\[ f(x|y, \phi) = \frac{f(y, x|\phi)}{f(y|\phi)} = \frac{L_T^c(\phi)}{L_T(\phi)}, \]

then

\[ \ln f(x|y, \phi) = \ln \left( \frac{L_T^c(\phi)}{L_T(\phi)} \right) = \ln L_T^c(\phi) - \ln L_T(\phi), \]

\[ \ln L_T(\phi) = \ln L_T^c(\phi) - \ln f(x|y, \phi). \]

From above, for each \( \hat{\phi} \in \Phi \),

\[ E_{\hat{\phi}}(\ln L_T(\phi)|y) = E_{\hat{\phi}}(\ln L_T^c(\phi)|y) - E_{\hat{\phi}}(\ln f(x|y, \phi)|y) \quad (3) \]

and

\[ E_{\hat{\phi}}(\ln L_T(\phi)|y) = \sum_x \ln L_T(\phi) f(x|y, \phi) = \sum_x \ln f(y|\hat{\phi}) \frac{f(x, y|\hat{\phi})}{f(y|\hat{\phi})} \]

\[ = \frac{f(y|\hat{\phi})}{f(y|\hat{\phi})} \sum_x f(x, y|\hat{\phi}) = \ln \frac{f(y|\hat{\phi})}{f(y|\hat{\phi})} f(y|\hat{\phi}) \]

\[ = \ln f(y|\phi) = \ln L_T(\phi). \quad (4) \]

Define

\[ Q(\phi|\hat{\phi}) = E_{\hat{\phi}}(\ln L_T^c(\phi)|y) \]

and

\[ H(\phi|\hat{\phi}) = E_{\hat{\phi}}(\ln f(x|y, \phi)|y). \]

From (3) and (4),

\[ \ln L_T(\phi) = Q(\phi|\hat{\phi}) - H(\phi|\hat{\phi}). \quad (5) \]
**Theorem 2.1.** (see [2]) Let $\epsilon > 0$ be a number close to 0, and $\Phi = \{ \phi = (A, \lambda) : A \in [0, 1]^m, \lambda \in [\epsilon, \frac{1}{\epsilon}]^m \}$ be the EHMM parameter space. Then:

1. $\Phi$ is a bounded subset in $\mathbb{R}^m$.

2. $\ln L_T(\phi)$ is a continuous function in $\Phi$ and differentiable in the interior of $\Phi$.

3. $\Phi_{\phi(0)} = \{ \phi \in \Phi : \ln L_T(\phi) \geq \ln L_T(\phi(0)) \}$ is compact for each $\ln L_T(\phi(0)) > -\infty$.

4. $Q(\phi|\hat{\phi})$ is continuous in $\phi$.

**Proof.**

1. $a_{ij} \in [0, 1]$ for each $i, j$ since $a_{ij} = P(X_t = j|X_{t-1} = i)$ and $\lambda_i \in [\epsilon, \frac{1}{\epsilon}]$. Therefore $\Phi \subseteq [0, 1]^m \times [\epsilon, \frac{1}{\epsilon}]^m$ which is a bounded subset in $\mathbb{R}^m$.

2. Since $L_T(\phi)$ is obtained from an addition and multiplication of continuous and differentiable function in interior $\Phi$, then $L_T(\phi)$ is continuous.

3. Set $\phi(0) \in \Phi$. It will be proven that $\Phi_{\phi(0)}$ is compact. It is enough to prove that $\Phi_{\phi(0)}$ is closed and bounded in $\Phi$. Since $\Phi_{\phi(0)} \subset \Phi$ and $\Phi$ is bounded then $\Phi_{\phi(0)}$ is bounded. $\Phi_{\phi(0)}$ is closed $\iff \Phi_{\phi(0)} = \overline{\Phi_{\phi(0)}}$. Since $\Phi_{\phi(0)} \subset \overline{\Phi_{\phi(0)}}$, it is enough to prove $\overline{\Phi_{\phi(0)}} \subset \Phi_{\phi(0)}$. Let $\phi^* \in \overline{\Phi_{\phi(0)}}$ then $\phi^*$ is a limit point of $\Phi_{\phi(0)}$. Thus, there is a sequence $\{\phi(k)\}$ in $\Phi_{\phi(0)}$ with $\ln L_T(\phi(k)) > \ln L_T(\phi(0))$ and $\lim_{k \to \infty} \phi(k) = \phi^*$. If $\phi^* \notin \Phi_{\phi(0)}$ then $\ln L_T(\phi^*) < \ln L_T(\phi(0))$. Let $\epsilon = L_T(\phi(0)) - L_T(\phi^*) > 0$, since $\lim_{k \to \infty} \phi(k) = \phi^*$ and $\ln L_T(\phi)$ is continuous in $\Phi$, then $\lim_{k \to \infty} L_T(\phi(k)) = L_T(\phi^*)$. For each $\epsilon > 0$, there is $k^*$ such that for each $k \geq k^*$ then $L_T(\phi(k)) - \ln L_T(\phi^*) < \epsilon = L_T(\phi(0)) - L_T(\phi^*)$. So $L_T(\phi(k)) < L_T(\phi(0))$. It is contradicted to the assumption, this implies that $\Phi_{\phi(0)}$ is closed.

4. Since $Q(\phi|\phi(k))$ is an addition and multiplication of 

$$
\alpha_t(i|\phi(k)), \beta_t(i|\phi(k)), a_{ij}(\phi), \lambda(\phi), \ln \varphi(\phi), \ln \lambda_i(\phi), \ln \gamma_{ij}(\phi),
$$

which are continuous in $\Phi$, then $Q(\phi|\phi(k))$ is continuous in $\Phi$.

\[\square\]

**Corollary 2.1.** The sequence $\{\phi(k)\}$ is well defined in $\Phi$. 

2.2. EM Algorithm

1. Set a value $\phi^{(k)}$ for $k = 0$.

2. E step : compute $Q(\phi|\phi^{(k)}) = E_{\phi^{(k)}}(\ln L_T(\phi)|Y = y)$.

3. M step : find the value $\phi^{(k+1)}$ which maximizes $Q(\phi|\phi^{(k)})$ so that
   
   $Q(\phi^{(k+1)}|\phi^{(k)}) \geq Q(\phi|\phi^{(k)}), \forall \phi \in \Phi$.

4. Replace $k$ by $k+1$ and repeat steps 2 to 4 until $|\ln L_T(\phi^{(k+1)}) - \ln L_T(\phi^{(k)})| < \text{desirable error}$. In other words the sequence $\{\ln L_T(\phi^{(k)})\}$ is convergent.

Lemma 2.1. $\partial_\phi(\ln L_T(\phi)) = E_{\hat{\phi}}(\partial_\phi \ln L_T(\phi)|y)$, $\partial_\phi Q(\phi|\hat{\phi}) = E_{\hat{\phi}}(\partial_\phi \ln L_T^c(\phi)|y)$ and $\partial_\phi H(\phi|\hat{\phi}) = E_{\hat{\phi}}(\partial_\phi \ln f(x|y, \phi)|y)$.

From (5) and Lemma 2.1,

\[
\partial_\phi(\ln L_T(\phi)) = E_{\hat{\phi}}(\partial_\phi \ln L_T(\phi)|y) = E_{\hat{\phi}}(\partial_\phi \ln L_T^c(\phi)|y) - E_{\hat{\phi}}(\partial_\phi \ln f(x|y, \phi)|y).
\]

Define

\[D^{10}Q(\phi|\hat{\phi}) = E_{\hat{\phi}}(\partial_\phi \ln L_T^c(\phi)|y),\]

and

\[D^{10}H(\phi|\hat{\phi}) = E_{\hat{\phi}}(\partial_\phi \ln f(x|y, \phi)|y).
\]

From (6), (7) and (8)

\[\partial_\phi(\ln L_T(\phi)) = D^{10}Q(\phi|\hat{\phi}) - D^{10}H(\phi|\hat{\phi}).\]

Lemma 2.2. For each $\phi, \hat{\phi} \in \Phi$ then $H(\phi|\hat{\phi}) \leq H(\hat{\phi}|\hat{\phi})$.

Lemma 2.3. For each $\hat{\phi} \in \Phi$ then $D^{10}H(\hat{\phi}|\hat{\phi}) = 0$.

Based on Lemma 2.2, Lemma 2.3 and the properties of a maximum and minimum value in a compact metric space (see [4]), it implies the following corollary.

Corollary 2.2. $H(\phi|\hat{\phi})$ attains global maximum at $\hat{\phi}$. 

Theorem 2.2. (see [2]) For each $\phi^{(k)} \in \Psi$ we have $\ln L_T(\phi^{(k+1)}) \geq \ln L_T(\phi^{(k)})$.

Proof. It is given an initial value $\phi^{(0)} \in \Phi$. From the EM algorithm, there is $\phi^{(1)} \in \Phi$ so that $\ln L_T(\phi^{(1)}) \geq \ln L_T(\phi^{(0)})$. By obtaining $\phi^{(1)} \in \Phi$, it is obtained $\phi^{(2)}$ so that $\ln L_T(\phi^{(2)}) \geq \ln L_T(\phi^{(1)})$ etc. There is the sequence $\{\phi^{(k)}\}$ which $\ln L_T(\phi^{(k+1)}) \geq \ln L_T(\phi^{(k)})$ and $\{\ln L_T(\phi^{(k)})\}$ which is increasing. It implies for each $\phi^{(k)} \in \Psi$,

$$
\ln L_T(\phi^{(k+1)}) - \ln L_T(\phi^{(k)}) = \left( Q(\phi^{(k+1)}|\phi^{(k)}) - H(\phi^{(k+1)}|\phi^{(k)}) \right) - \left( Q(\phi^{(k)}|\phi^{(k)}) - H(\phi^{(k)}|\phi^{(k)}) \right)
$$

$$
= \left( Q(\phi^{(k+1)}|\phi^{(k)}) - Q(\phi^{(k)}|\phi^{(k)}) \right) - \left( H(\phi^{(k+1)}|\phi^{(k)}) - H(\phi^{(k)}|\phi^{(k)}) \right). \quad (10)
$$

According to the M step, it is defined $Q(\phi^{(k+1)}|\phi^{(k)}) \geq Q(\phi|\phi^{(k)})$ and from Lemma 2.2, $H(\phi^{(k)}|\phi^{(k)}) \geq H(\phi|\phi^{(k)})$ for each $\phi \in \Phi$ and $H(\phi^{(k+1)}|\phi^{(k)}) - H(\phi^{(k)}|\phi^{(k)}) \leq 0$. So it can be said that

$$
\ln L_T(\phi^{(k+1)}) - \ln L_T(\phi^{(k)}) \geq 0
$$

$$
\ln L_T(\phi^{(k+1)}) \geq \ln L_T(\phi^{(k)}). \quad (11)
$$

Theorem 2.3. (see [2]) For each $\phi^{(k)} \notin \Psi$,

$$
\ln L_T(\phi^{(k+1)}) - \ln L_T(\phi^{(k)}).
$$

Proof. From (8), it is known

$$
\partial_{\phi^{(k)}} (\ln L_T(\phi^{(k)})) = D^{10} Q(\phi^{(k)}|\phi^{(k)}) - D^{10} H(\phi^{(k)}|\phi^{(k)}).
$$

Since $D^{10} H(\phi^{(k)}|\phi^{(k)}) = 0$, then $\partial_{\phi^{(k)}} (\ln L_T(\phi^{(k)})) = D^{10} Q(\phi^{(k)}|\phi^{(k)})$. For $\phi^{(k)} \in \Psi$, $\partial_{\phi^{(k)}} (\ln L_T(\phi^{(k)})) \neq 0$ and $D^{10} Q(\phi^{(k)}|\phi^{(k)}) \neq 0$ so that $\phi^{(k)}$ is not a local maximum of $Q(\phi|\phi^{(k)})$. According to the M step, it is defined $Q(\phi^{(k+1)}|\phi^{(k)}) \geq Q(\phi|\phi^{(k)})$ for each $\phi \in \Phi$. Thus, it is obtained $Q(\phi^{(k+1)}|\phi^{(k)}) \geq Q(\phi^{(k+1)}|\phi^{(k)})$ and it implies

$$
\ln L_T(\phi^{(k+1)}) \geq \ln L_T(\phi^{(k)}). \quad (12)
$$
Corollary 2.3. The sequence \( \{ \ln L_T(\phi^{(k)}) \} \) is an increasing sequence.

Theorem 2.4. Let \( E_{\phi^{(k)}}(\ln L_T^r(\phi)|Y = y) = Q(\phi|\phi^{(k)}) \), then

\[
Q(\phi|\phi^{(k)}) = \sum_{i \in S_X} \frac{\alpha_1(i|\phi^{(k)}) \beta_1(i|\phi^{(k)})}{\sum_{l \in S_X} \alpha_t(l|\phi^{(k)}) \beta_t(l|\phi^{(k)})} \ln \varphi_i(\phi)
\]

\[
+ \sum_{i \in S_X} \sum_{t=1}^{T} \frac{\alpha_t(i|\phi^{(k)}) \beta_t(i|\phi^{(k)})}{\sum_{l \in S_X} \alpha_t(l|\phi^{(k)}) \beta_t(l|\phi^{(k)})} \ln f(Y_t = y_t|X_t = i, \phi)
\]

\[
+ \sum_{i \in S_X} \sum_{j \in S_X} \sum_{t=1}^{T-1} \frac{a_{ij}(\phi^{(k)}) \alpha_t(i|\phi^{(k)}) \beta_{t+1}(j|\phi^{(k)}) J(y)}{\sum_{l \in S_X} \alpha_t(l|\phi^{(k)}) \beta_t(l|\phi^{(k))} \ln a_{ij}(\phi)},
\]

where \( J(y) = f(Y_{t+1} = y_{t+1}|X_{t+1} = j, \phi^{(k)}) \).

Theorem 2.5. Let \( \phi = (A, \lambda) \) be the parameter of \( Q(\phi|\phi^{(k)}) \) with \( A = [a_{ij}] \) and \( \lambda = \lambda_i \), then

\[
a_{ij}(\phi^{(k+1)}) = \frac{\sum_{t=1}^{T-1} a_{ij}(\phi^{(k)}) \alpha_t(i|\phi^{(k)}) \beta_{t+1}(j|\phi^{(k)}) J(y)}{\sum_{t=1}^{T-1} \alpha_t(i|\phi^{(k)}) \beta(i|\phi^{(k)})},
\]

where \( J(y) = f(Y_{t+1} = y_{t+1}|X_{t+1} = j, \phi^{(k)}) \) and

\[
\lambda(\phi^{(k+1)}) = \frac{\sum_{t=1}^{T} \alpha_t(i|\phi^{(k)}) \beta_t(i|\phi^{(k)}) (y_t)}{\sum_{t=1}^{T} \alpha_t(i|\phi^{(k)}) \beta_t(i|\phi^{(k)})}.
\]

3. Convergence of Parameter Estimator EHMM

Let \( \{ \phi^{(k)} \} \) be the sequence which is obtained from the EM algorithm. It will be proven that the sequence \( \{ \ln L_T(\phi^{(k)}) \} \) converges to \( \ln L_T(\phi^*) \) which \( \phi^* \) is a stationary point of \( \ln L_T(\phi) \).

Based on the properties of a continuous function in a compact metric space (see [4]), we have the following corollaries.

Corollary 3.1. Let \( h : \Phi \to \mathbb{R}^1 \) be a function with \( h(\phi) = \ln L_T(\phi) \). Then the range of \( h(\phi) \) is a compact metric space in \( \mathbb{R}^1 \).

Corollary 3.2. The range of \( h(\phi) \) is bounded.
Corollary 3.3. The sequence \( \{\ln L_T(\phi^{(k)})\} \) is an increasing and convergent sequence in \( h(\phi) \) which is convergent. Since \( h(\phi) \) is compact, there is \( \phi^* \in \Phi \) such that \( \lim_{k \to \infty} \ln L_T(\phi^{(k)}) = \ln L_T(\phi^*) \).

Theorem 3.1. (see [2]) Let \( g(\hat{\phi}) = \{\delta' \in \Phi : Q(\delta'|\hat{\phi}) \geq Q(\delta|\hat{\phi}) \text{ for each } \delta \in \Phi\} \) then \( g \) is a closed set in \( \Phi \setminus \Psi \).

Proof. Since \( g \) is a set value function (see [5]), from \( Q(\delta'|\phi') \) it is known that \( \delta' \in g(\phi') \) for \( \delta', \phi' \in \Phi \). For each \( \hat{\phi} \in \Phi \setminus \Psi \) and from Theorem 2.1 (4), \( Q(\delta|\phi) \) is a continuous function for \( \delta \) and \( \phi \) in \( \Phi \times \Phi \), if \( \phi^{(k)} \to \hat{\phi} \) and \( \delta^{(k)} \to \bar{\delta} \) then \( Q(\delta^{(k)}|\phi^{(k)}) \to Q(\bar{\delta}|\hat{\phi}) \) for \( k \to \infty \). So that, it is obtained \( \delta^{(k)} \in g(\phi^{(k)}) \) for \( k = 1, 2, \ldots \) and it satisfies if \( \phi^{(k)} \to \hat{\phi} \) and \( \delta^{(k)} \to \bar{\delta} \), then \( \bar{\delta} \in g(\hat{\phi}) \), for \( k \to \infty \). So that \( g \) is a closed function, it is satisfied by the EM algorithm i.e \( \delta^{(k)} \) corresponding to \( \phi^{(k+1)} \).

Theorem 3.2. (see [2]) Let \( Q(\phi|\phi^{(k)}) \) be a continuous function of \( \phi, \phi^{(k)} \in \Phi \times \Phi \). Let \( \{\phi^{(k)}\} \) be the EHMM estimator sequence which is obtained from the EM algorithm,

1. \( \lim_{k \to \infty} \ln L_T(\phi^{(k)}) = \ln L_T(\phi^*) \), which the convergence is increasing.

2. If \( \lim_{k \to \infty} \phi^{(k)} = \phi^* \), then \( \phi^* \) is a stationary point of \( \ln L_T(\phi) \).

Proof. 1. From Corollary 3.1, Theorem 2.2 and Theorem 2.3,

\[
\lim_{k \to \infty} \ln L_T(\phi^{(k)}) = \ln L_T(\phi^*).
\]

The sequence \( \{\ln L_T(\phi^{(k)})\} \) is an increasing sequence.

2. Let \( \lim_{k \to \infty} \phi^{(k)} = \phi^* \), if \( \phi^* \) is not a stationary point \( (\phi^* \notin \Psi) \). We consider a sequence \( \{\phi^{(k+1)}\} \) so that \( \phi^{(k+1)} \in g(\phi^{(k)}) \) for each \( k \) and the sequence \( \{\phi^{(k+1)}\} \) in a compact set according to Theorem 2.1 (3). It implies that there is the sequence \( \{\phi^{(k+1)}\} \) so that for \( m \to \infty \) then \( \phi^{(k+1)m} \to \hat{\phi} \) and for \( k \to \infty \) then \( \phi^{(k+1)} \to \hat{\phi} \). From Theorem 3.1, \( g \) is a closed function in \( \Phi \setminus \Psi \) and the assumption \( \phi^* \notin \Psi \) thus \( \hat{\phi} \in g(\phi^*) \). From (12), it implies

\[
\ln L_T(\hat{\phi}) > \ln L_T(\phi^*). \quad (13)
\]

Since \( \ln L_T(\phi) \) in a continuous function, from Theorem 3.2 (1) and \( \phi^{(k+1)} \to \hat{\phi} \) for \( k \to \infty \), then \( \lim_{k \to \infty} \ln L_T(\phi^{(k)}) = \lim_{k \to \infty} \ln L_T(\phi^{(k+1)}) \). It implies
\[ \ln L_T(\phi^*) = \ln L_T(\hat{\phi}) \] and it is contradicted by (13). So \( \phi^* \) is not a stationary point.

\[ \square \]

References


