

# Online ARIMA Algorithms for Time Series Prediction (supplemental file)

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This document provides the materials of our detailed proofs to supplement our main submission manuscript.

## Proofs of Lemma in Main Manuscript

We re-iterate some necessary assumptions in our theoretical analysis.

1. The coefficients  $\beta_i$  satisfy that a  $q$ -th order difference equation with coefficients  $|\beta_1|, |\beta_2|, \dots, |\beta_q|$  is a stationary process; and
2. The noise terms are stochastically and independently generated, which satisfy  $\mathbb{E}[|\epsilon_t|] < M_{max} < \infty$  and  $\mathbb{E}[\ell_t(X_t, X_t - \epsilon_t)] < \infty$ ; and
3. The loss function  $\ell_t$  is Lipschitz continuous for some Lipschitz constant  $L > 0$ ; and
4. The coefficients  $\alpha_i$  satisfy  $|\alpha_i| < c$  for some  $c \in \mathbb{R}$ .

**Lemma 1.** *From any time series sequence satisfies our assumption, it holds that*

$$\min_{\gamma} \sum_{t=1}^T \ell_t^m(\gamma) \leq \sum_{t=1}^T f_t^m(\alpha^*, \beta^*).$$

*Proof.* Note that if we set  $\gamma_i^* = c_i(\alpha^*, \beta^*)$ , we immediately get that

$$\sum_{t=1}^T \ell_t^m(\gamma^*) = \sum_{t=1}^T f_t^m(\alpha^*, \beta^*).$$

Trivially, it always holds that

$$\min_{\gamma} \sum_{t=1}^T \ell_t^m(\gamma) \leq \sum_{t=1}^T \ell_t^m(\gamma^*),$$

which completes the proof.  $\square$

**Lemma 2.** *Given assumption 1 that a  $q$ -th order difference equation with coefficients  $|\beta_1| \dots, |\beta_q|$  and observations  $\{X_t\}_{t=-(q-1)}^T$  is a stationary process,  $\lambda_1, \dots, \lambda_q$  are the  $q$  roots of this AR characteristic equation. Let we set  $\lambda_{min} = \{|\lambda_1|, \dots, |\lambda_q|\}$ , it holds that*

$$X_t \leq \lambda_{min}^t (X_0 + X_1 + \dots + X_{-(q-1)}).$$

**Lemma 3.** *For any time series sequence satisfies our assumption, it holds that*

$$\left| \sum_{t=1}^T \mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \sum_{t=1}^T \mathbb{E}[f_t^m(\alpha^*, \beta^*)] \right| = O(1),$$

if we choose  $m = \log_{\lambda_{min}} ((TLM_{max}q)^{-1})$ .

*Proof.* For arbitrary  $t$ , we focus on the distance between  $f_t^\infty(\alpha^*, \beta^*)$  and  $f_t^m(\alpha^*, \beta^*)$  in expectation. First, for any  $m \in \{0, -1, \dots, -(1-q)\}$  we have that  $\nabla^d X_t^m(\alpha^*, \beta^*) = \nabla^d X_t$  from definition, and hence

$$\begin{aligned} & |\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)| \\ & \leq |\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*)| \\ & \leq |\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t| + |\epsilon_t|. \end{aligned}$$

From assumption 2, we know  $\mathbb{E}[|\epsilon_t|] < M_{max} < \infty$  for all  $t$  and  $\mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|]$  decays exponentially as proven in lemma 4, and hence we have  $|\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)| < 2M_{max}$ . Next, we show that  $|\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)|$  exponentially decreases as  $m$  increases linearly.

$$\begin{aligned}
& |\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)| \\
&= \left| \sum_{i=1}^q \beta_i^* (\nabla^d X_{t-i} - \nabla^d X_{t-i}^{m-i}(\alpha^*, \beta^*)) \right. \\
&\quad \left. - \sum_{i=1}^q (\nabla^d X_{t-i} - \nabla^d X_{t-i}^\infty(\alpha^*, \beta^*)) \right| \\
&= \left| \sum_{i=1}^q \beta_i^* (\nabla^d X_{t-i}^\infty(\alpha^*, \beta^*) - \nabla^d X_{t-i}^{m-i}(\alpha^*, \beta^*)) \right| \\
&\leq \sum_{i=1}^q |\beta_i^*| |\nabla^d X_{t-i}^\infty(\alpha^*, \beta^*) - \nabla^d X_{t-i}^{m-i}(\alpha^*, \beta^*)|.
\end{aligned}$$

We can easily find  $|\nabla^d X_t^m(\alpha^*, \beta^*) - X_t^\infty(\alpha^*, \beta^*)|$  satisfy a  $q$ th order difference inequality with coefficients  $|\beta_1^*|, |\beta_2^*|, \dots, |\beta_q^*|$ . From assumption 1 and Lemma 2, we have

$$\begin{aligned}
& |\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)| \\
&\leq \lambda_{min}^m (|\nabla^d X_{t-m}^0(\alpha^*, \beta^*) - \nabla^d X_{t-m}^\infty(\alpha^*, \beta^*)| \\
&\quad + |\nabla^d X_{t-m-1}^{-1}(\alpha^*, \beta^*) - \nabla^d X_{t-m-1}^\infty(\alpha^*, \beta^*)| + \dots \\
&\quad + |\nabla^d X_{t-m-(q-1)}^{-(q-1)}(\alpha^*, \beta^*) - \nabla^d X_{t-m-(q-1)}^\infty(\alpha^*, \beta^*)|) \\
&\leq 2qM_{max}\lambda_{min}^m.
\end{aligned}$$

Since all  $\nabla^i X_{t-1} (i \in \{1, 2, \dots, d-1\})$  are fixed and hence it follows that

$$\begin{aligned}
& |X_t^m(\alpha^*, \beta^*) - X_t^\infty(\alpha^*, \beta^*)| \\
&= |\nabla^d X_t^m(\alpha^*, \beta^*) + \sum_{i=1}^{d-1} \nabla^i X_{t-1} \\
&\quad - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \sum_{i=1}^{d-1} \nabla^i X_{t-1}| \\
&= |\nabla^d X_t^m(\alpha^*, \beta^*) - \nabla^d X_t^\infty(\alpha^*, \beta^*)| \leq 2qM_{max}\lambda_{min}^m.
\end{aligned}$$

Recall that  $\ell_t$  is assumed to be Lipschitz continuous for some constant  $L > 0$  from our assumption, and hence it

follows that

$$\begin{aligned}
& |\mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \mathbb{E}[f_t^m(\alpha^*, \beta^*)]| \\
&= |\mathbb{E}[\ell_t(X_t, X_t^\infty(\alpha^*, \beta^*))] - \mathbb{E}[\ell_t(X_t, X_t^m(\alpha^*, \beta^*))]| \\
&\leq \mathbb{E}[|\ell_t(X_t, X_t^\infty(\alpha^*, \beta^*)) - \ell_t(X_t, X_t^m(\alpha^*, \beta^*))|] \\
&\leq L \cdot \mathbb{E}[|X_t^m(\alpha^*, \beta^*) - X_t^\infty(\alpha^*, \beta^*)|] \\
&\leq L \cdot 2qM_{max}\lambda_{min}^m,
\end{aligned}$$

where the first inequality follows from Jensen's inequality. By summing the above for all  $t$  we get that

$$\begin{aligned}
& \left| \sum_{t=1}^T \mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \sum_{t=1}^T \mathbb{E}[f_t^m(\alpha^*, \beta^*)] \right| \\
&\leq TL \cdot 2qM_{max}\lambda_{min}^m
\end{aligned}$$

Finally, choosing  $m = \log_{\lambda_{min}}((TLq)^{-1})$  yields

$$\left| \sum_{t=1}^T \mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \sum_{t=1}^T \mathbb{E}[f_t^m(\alpha^*, \beta^*)] \right| = O(1).$$

□

**Lemma 4.** For any time series sequence satisfies our assumption, it holds that

$$\left| \sum_{t=1}^T \mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \sum_{t=1}^T \mathbb{E}[f_t(\alpha^*, \beta^*)] \right| = O(1).$$

*Proof.* First, we prove that  $\mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|]$  decays exponentially as the  $t$  increases linearly.

$$\begin{aligned}
& \mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|] \\
&= \mathbb{E}\left[ \left| \sum_{i=1}^k \alpha_i^* \nabla^d X_{t-i} + \sum_{i=1}^q \beta_i^* \epsilon_{t-i} + \epsilon_t - \sum_{i=1}^k \alpha_i^* \nabla^d X_{t-i} \right. \right. \\
&\quad \left. \left. - \sum_{i=1}^q \beta_i^* (\nabla^d X_{t-i} - \nabla^d X_{t-i}^\infty(\alpha^*, \beta^*)) - \epsilon_t \right| \right] \\
&= \mathbb{E}\left[ \left| \sum_{i=1}^q \beta_i^* (\nabla^d X_{t-i}^\infty(\alpha^*, \beta^*) - \nabla^d X_{t-i} + \epsilon_{t-i}) \right| \right] \\
&\leq \sum_{i=1}^q |\beta_i^*| \mathbb{E}[|\nabla^d X_{t-i} - \nabla^d X_{t-i}^\infty(\alpha^*, \beta^*) - \epsilon_{t-i}|].
\end{aligned}$$

We could regard  $\mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|]$  as a  $q$ th order difference inequality with coefficients

$|\beta_1^*|, |\beta_2^*|, \dots, |\beta_q^*|$ . From assumption 1 and Lemma 2, we have

$$\begin{aligned}
& \mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|] \\
& \leq \lambda_{min}^t (\mathbb{E}[|\nabla^d X_0 - \nabla^d X_0^\infty(\alpha^*, \beta^*) - \epsilon_{-1}|] \\
& \quad + \mathbb{E}[|\nabla^d X_{-1} - \nabla^d X_{-1}^\infty(\alpha^*, \beta^*) - \epsilon_{-1}|] + \dots \\
& \quad + \mathbb{E}[|\nabla^d X_{-(q-1)} - \nabla^d X_{-(q-1)}^\infty(\alpha^*, \beta^*) - \epsilon_{-q}|]) \\
& = \lambda_{min}^t \rho,
\end{aligned}$$

where  $\rho$  represents the right-hand side of  $\lambda_{min}^t$  for simplicity. According to Lemma 2, we know  $|\lambda_{min}| < 1$ , which ends the proof. Since all  $\nabla^i X_{t-1} (i \in \{1, 2, \dots, d-1\})$  are fixed and hence it follows that

$$\begin{aligned}
& \mathbb{E}[|X_t - X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|] \\
& = \mathbb{E}[|\nabla^d X_t + \sum_{i=1}^{d-1} \nabla^i X_{t-1} - \nabla^d X_t^\infty(\alpha^*, \beta^*) \\
& \quad - \sum_{i=1}^{d-1} \nabla^i X_{t-1} - \epsilon_t|] \\
& = \mathbb{E}[|\nabla^d X_t - \nabla^d X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|] \leq \lambda_{min}^t \rho.
\end{aligned}$$

From Assumption 2,  $\epsilon_t$  is stochastic and independent of  $\epsilon_1, \dots, \epsilon_{t-1}$  and hence the best prediction available at time  $t$  will cause a loss of at least  $\ell_t(X_t, X_t - \epsilon_t)$ . The best ARIMA model coefficients  $(\alpha', \beta')$  in hindsight are those have generated signal, which follows that

$$\sum_{t=1}^T f_t(\alpha', \beta') = \sum_{t=1}^T \ell_t(X_t, X_t - \epsilon_t).$$

Recall that  $\ell_t$  is assumed to be Lipschitz continuous for some constant  $L > 0$ , and hence it follows that

$$\begin{aligned}
& |\mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \mathbb{E}[f_t(\alpha^*, \beta^*)]| \\
& = |\mathbb{E}[\ell_t(X_t, X_t^\infty(\alpha^*, \beta^*))] - \mathbb{E}[\ell_t(X_t, X_t - \epsilon_t)]| \\
& = |\mathbb{E}[\ell_t(X_t, X_t^\infty(\alpha^*, \beta^*)) - \ell_t(X_t, X_t - \epsilon_t)]| \\
& \leq \mathbb{E}[|\ell_t(X_t, X_t^\infty(\alpha^*, \beta^*)) - \ell_t(X_t, X_t - \epsilon_t)|] \\
& \leq L \cdot \mathbb{E}[|X_t - X_t^\infty(\alpha^*, \beta^*) - \epsilon_t|] \leq \rho \lambda_{min}^t.
\end{aligned}$$

Finally, summing over all iterations yields

$$\left| \sum_{t=1}^T \mathbb{E}[f_t^\infty(\alpha^*, \beta^*)] - \sum_{t=1}^T \mathbb{E}[f_t(\alpha^*, \beta^*)] \right| = O(1).$$

□