ODE-Inspired Analysis for the Biological Version of Oja’s Rule in Solving Streaming PCA

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Abstract

Oja’s rule [Oja, Journal of mathematical biology 1982] is a well-known biologically-plausible algorithm using a Hebbian-type synaptic update rule to solve streaming principal component analysis (PCA). Computational neuroscientists have known that this biological version of Oja’s rule converges to the top eigenvector of the covariance matrix of the input in the limit. However, prior to this work, it was open to prove any convergence rate guarantee.

In this work, we give the first convergence rate analysis for the biological version of Oja’s rule in solving streaming PCA. Moreover, our convergence rate matches the information theoretical lower bound up to logarithmic factors and outperforms the state-of-the-art upper bound for streaming PCA. Furthermore, we develop a novel framework inspired by ordinary differential equations (ODE) to analyze general stochastic dynamics. The framework abandons the traditional step-by-step analysis and instead analyzes a stochastic dynamic in one-shot by giving a closed-form solution to the entire dynamic. The one-shot framework allows us to apply stopping time and martingale techniques to have a flexible and precise control on the dynamic. We believe that this general framework is powerful and should lead to effective yet simple analysis for a large class of problems with stochastic dynamics.

1 Introduction

Human brains process an astronomical amount of visual data constantly. In our eyes, 100 millions photoreceptors in the retina receive gigabytes of information per second [A95, WBD77]. To reduce the curse of dimensionality, as a first step, the brain compresses the activities of 100 million photoreceptors into one million retina ganglion cells in optical nerves [GS12]. Neuroscientists have extensively studied the dimensionality reduction in the retina-optical nerve pathway. In particular, Haft and Hemmen [HV98] demonstrated that Principal Component Analysis (PCA) is a likely candidate for the dimensionality reduction in the retina-optical nerve pathway by showing the consistency between theoretical predictions and experiments in the receptive fields of retina ganglion cells. However, their work only proposed PCA as a potential solution to the pathway and did not provide a dynamic to explain the learning process of PCA.

On the other hand, in the seminal work of Oja [Oja82], he proposed a mathematical model for the biological neural network that solves streaming PCA with several biologically-plausible properties: the network not only updates its synaptic weights locally but also normalizes the strength of synapses. This rule, now known as the biological version of Oja’s rule (biological Oja’s rule1 in abbreviation), has been the subject of extensive theoretical [Oja82, OK85, San89, HKP91, Oja92, Plu95, DK96, Zuf02, YYLT05, Duf13, ACS13] and experimental [CL94, KDT94, HP94, Kar96, CKS96, SLY06, SA06, LTYH09, ACS13] studies aimed at understanding its performance. Despite its popularity, the theoretical understanding of the biological Oja’s

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1 Also known as Oja’s rule in the literature. However, many works in the machine learning community use the name “Oja’s rule” for non-biologically-plausible variants of the original Oja’s rule. Thus, in this paper we emphasize the term “biological” to distinguish the two. See Section 1.4 for more discussions on their differences.
rule cannot account for the biologically-realistic time scale in the retina-optical nerve pathway because the state-of-the-art theoretical analysis only provides a guarantee on convergence in the limit [Duf13].

In practice, the time scale of the streaming PCA in the retina-optical nerve pathway is on the order of seconds. For example, when a person is walking from a dark room to a bright room, it only takes a few seconds for the eyes to adapt to the new environment. This suggests that a plausible dynamic for explaining the retina-optical nerve pathway should have little or no dependency on the dimension, i.e., the number of neurons, which in this case is on the order of 100 million. Meanwhile, researchers have observed that the biological Oja’s rule (and its variants) has fast convergence rates [HP94, Kar96, SLY06, SA06, LTYH09] in simulations. Thus, to further our understanding in the retina-optical nerve pathway, it is important to give a theoretical analysis to show that the biological Oja’s rule solves streaming PCA in a biologically-realistic time scale. This is nevertheless a challenging task and has remained elusive for almost 40 years [Oja82].

In this work, we provide the first convergence rate analysis for the biological Oja’s rule in solving streaming PCA.

**Theorem 1.1** (informal). The biological Oja’s rule efficiently solves streaming PCA with (nearly) optimal convergence rate. Specifically, the convergence rate we obtain matches the information theoretical lower bound up to logarithmic factors.

Furthermore, the convergence rate has no dependency on the dimension when the initial weight vector is close to the top eigenvector or has a logarithmic dependency on the dimension when the initial vector is random. Therefore, the biological Oja’s rule solves streaming PCA in a biologically-realistic time scale.

To show the (nearly) optimal convergence rate of biological Oja’s rule in solving streaming PCA, we develop an ODE-inspired framework to analyze stochastic dynamics. Concretely, instead of the traditional step-by-step analysis, our framework analyzes a dynamical system in one-shot by giving a closed-form solution for the entire dynamic. The framework borrows ideas from ordinary differential equations (ODE) and stochastic differential equations (SDE) to obtain a closed-form characterization of the dynamic and uses stopping time and martingale techniques to precisely control the dynamic. This framework provides a more elegant and more general analysis compared with the previous step-by-step approaches. We believe that this novel framework can provide simple and effective analysis on other problems with stochastic dynamics.

We organize the rest of the introduction as follows. We first formally define biological Oja’s rule and streaming PCA in Section 1.1 and state the main results and their biological relevance in Section 1.2. In Section 1.3, we provide a technical overview on the proof and the analysis framework. Finally, we conclude the introduction with a survey and comparison of related works in Section 1.4.

### 1.1 Biological Oja’s rule and streaming PCA

In a biological neural network, two neurons primarily interact with each other via action potentials or instantaneous signals, a.k.a., ”spikes”, through synapses between them. The strength of a synapse might vary from time to time and is called the **synaptic weight**. The ability of a synaptic weight to strengthen or weaken over time is considered as a source for learning and long term memory in our brains. While generally the update of a synaptic weight could depend on the spiking patterns of the end neurons, it is common for neuroscientists to focus on the averaging behaviors of a spiking dynamic. Namely, they simplify the model by only considering the **firing rate**, which is defined as the average number of spikes. This is known as the **rate-based model** [WC72, WC73] and since the biological Oja’s rule was defined on a rate-based model, this setting is going to be the focus of this work.

To understand how the biological Oja’s rule works, consider the following baby example with two neurons $x$ and $y$. Let $x_t, y_t \in \mathbb{R}$ be the firing rates of neurons $x, y$ at time $t \in \mathbb{N}$ and let $w_t \in \mathbb{R}$ be the synaptic weight from $x$ to $y$ at time $t$. In a biological neural network, $w_t$ could change over time and the dynamic is defined locally on the previous synaptic weight as well as the firing rates of the end neurons. Namely, the synaptic weight from the neuron $x$ to $y$ has the following dynamic

$$w_t = w_{t-1} + \eta_t F_t(w_{t-1}, x_t, y_t)$$
where $F_t$ is an update function and $\eta_t$ is the plasticity coefficient, a.k.a., the learning rate. Biologically, the update function should further follow the Hebb postulate, “cells that fire together wire together” \cite{hebb}. One naive way to implement Hebbian learning is to set the update function as $F_t(w_{t-1}, x_t, y_t) = x_t y_t$. However, the values of $w_t$ can grow unboundedly. The biological Oja’s rule is a self-normalizing Hebbian rule with the following synaptic updates.

$$w_t = w_{t-1} + \eta_t y_t (x_t - y_t w_{t-1}) .$$

Using the above synaptic update rule, Oja \cite{Oja82} configured a network that solves streaming PCA while keeping the norm of the weights stable. Before introducing the network, let us formally define the streaming PCA problem.

**Streaming PCA** Principal component analysis (PCA) \cite{Pena01, Hotz33} is a problem to find the top eigenvector of a covariance matrix of a dataset. Let $n$ be the dimension of the data. In the offline setting, one can compute the covariance matrix in $O(n^2)$ space and use the power method to approximate the top eigenvector. As for its variant, the streaming PCA (a.k.a. the stochastic online PCA, see \cite{CG90} for a survey on the literature), the input data arrives in a stream and the algorithm/dynamic only has limited amount of space, e.g., $O(n)$ space. Streaming PCA is important for biological system because the information inherently arrives in a stream in a living system. On the other hand, it is also much more challenging than offline PCA (see for example \cite{AZL17}). In the following, we formally define the streaming PCA problem. \footnote{In related works, some (e.g., \cite{AZL17}) measure the error using $1 - \langle w, v_1 \rangle^2$, some (e.g., \cite{Sha16}) use $1 - w^\top A w/\|A\|$, and some (e.g., \cite{JJK+16}) use $\sin^2(\langle w, v_1 \rangle)$. We remark that all of these error measures (including ours) are the same up to a constant multiplicative factor.

Also, some works emphasize other convergence notions such as the gap-free convergence \cite{Sha16}. Though we do not explicitly study the convergence of biological Oja’s rule under these notions, we believe that our results could be easily extended to other convergence notions with comparable convergence rate and leave this for future work.}

**Problem 1.2** (Streaming PCA). Let $n, T \in \mathbb{N}$ and $D$ be a distribution over the unit sphere of $\mathbb{R}^n$. Suppose the input data $x_1, x_2, \ldots, x_T \overset{i.i.d.}{\sim} D$ are given one by one in a stream. Let $A = \mathbb{E}_{x \sim D}[xx^\top]$ be the covariance matrix and $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$ be the eigenvalues of $A$. Assume $\lambda_1 > \lambda_2$ and let $v_1$ be the top eigenvector of $A$ of unit length. Then the goal of the streaming PCA problem is to output $w \in \mathbb{R}^n$ such that

$$\frac{\langle w, v_1 \rangle^2}{\|w\|^2} \geq 1 - \epsilon .$$

Since the inputs arrive in a stream, usually a streaming PCA algorithm/dynamic would maintain a solution $w_t \in \mathbb{R}^n$ at each time $t \in \mathbb{N}$. Thus, the goal for a streaming PCA algorithm/dynamic would be achieving $\Pr\left[ \frac{\langle w_T, v_1 \rangle^2}{\|w_T\|^2} \geq 1 - \epsilon \right] \geq 1 - \delta$ with small $T$.

**Biological Oja’s rule in solving streaming PCA** Oja \cite{Oja82} proposed a streaming PCA algorithm using $n$ input neurons and one output neuron. The firing rates of the input neurons at time $t$ are denoted by a vector $x_t \in \mathbb{R}^n$ and the firing rate of the output neuron is denoted by a scalar $y_t \in \mathbb{R}$. The synaptic weights at time $t$ from the input neurons to the output neuron are denoted by a vector $w_t \in \mathbb{R}^n$. Note that the weight vector will be the output and ideally it will converge to the top eigenvector $v_1$.

The input stream $x_1, x_2, \ldots, x_T$ arrives in the form of firing rates of the input neurons. The firing rate of the output neuron is simply the inner product of the synaptic weight vector and the firing rate vector of the input neurons, i.e., $y_t = x_t^\top w_{t-1}$. Now, from the biological Oja’s rule, the dynamic of the synaptic weight vector is described by the following equation.

**Definition 1.3** (Biological Oja’s rule). For any initial vector $w_0 \in \mathbb{R}^n$ such that $\|w_0\|_2 = 1$, the dynamic of the biological Oja’s rule is the following. For any $t \in \mathbb{N}$, define

$$w_t = w_{t-1} + \eta_t y_t (x_t - y_t w_{t-1}) \quad (1.4)$$

where $y_t = x_t^\top w_{t-1}$ and $x_t$ is the input at time $t$. See also in Figure 1 for a pictorial definition of biological Oja’s rule in solving streaming PCA.

Follow from the definition, the biological Oja’s rule is automatically biologically-plausible in the following sense. First, the synaptic update rule is local. Namely, each synapse only depends on the previous synaptic
Figure 1: A neural network that uses biological Oja’s rule to solve streaming PCA. The firing rate vector $x_t$ is the input and the weight vector $w_t$ is the output at time $t$.

weight and the firing rates of the two end neurons. Second, with some simple calculations (e.g., Lemma 5.1), biological Oja’s rule achieves the synaptic scaling guarantee [AN00], i.e., $w_{t,i}$ being bounded for all $t \in \mathbb{N}$ and $i \in [n]$. Thus, one can then interpret the convergence results of this work as showing further biological-plausibilities of the biological Oja’s rule in the retina-optical nerve pathway. See Section 1.2 for more discussions.

Oja’s derivation for the biological Oja’s rule Before going into more technical contents, it would be helpful to take a look at the original derivation for the biological Oja’s rule. Initially, Oja wanted to use the following update rule with normalization\(^3\) to solve the streaming PCA problem.

$$w_t = \frac{(I + \eta_t x_t x^\top_t) w_{t-1}}{\| (I + \eta_t x_t x^\top_t) w_{t-1} \|^2_2}. \quad (1.5)$$

However, the normalization term $\| (I + \eta_t x_t x^\top_t) w_{t-1} \|^{-1}_2$ is global\(^4\) and does not seem to have a biologically-plausible implementation. To bypass this issue, Oja applied Taylor’s expansion on the normalization term and truncated the second order terms of $\eta_t$. This exactly results in the biological Oja’s rule (i.e., Equation 1.4). See Appendix A for more details on the derivation.

Also, to see why intuitively biological Oja’s rule could solve streaming PCA, one can check that any eigenvector $v$ of $A$ of unit length with eigenvalue $\lambda$ is a fixed point of the biological Oja’s rule in expectation. Specifically, the expectation of the update term $y_t(x_t - y_t w_{t-1})$ with $w_{t-1} = v$ is the following.

$$\mathbb{E}[x^\top_t v x_t - (x^\top_t v)^2 v] = Av - v^\top Av v = \lambda v - \lambda \|v\|^2_2 v = 0.$$

The first equality follows from for all $i, j \in [n], \mathbb{E}[x_{t,i} x_{t,j}] = \lambda_i \cdot 1_{i=j}$, and the second equality follows from $Av = \lambda v$. By checking the Hessian at the top eigenvector $v_1$, one can even see that $v_1$ is a stable fixed point.

Previous works: Convergence in the limit results There were many previous works on analyzing the convergence of biological Oja’s rule in solving streaming PCA [Oja82, OK85, San89, HKP91, Oja92, Plu95, DK96, Zuf02, YYLT05, Duf13]. However, their works only proved guarantee on convergence in the limit. For example, Duflo [Duf13] showed that $w_t$ converges to the top eigenvector of $A$ in the limit under some constraints on the learning rates.

**Theorem 1.6** ([Duf13], informal). Let $w_0$ be a random unit vector in $\mathbb{R}^n$. If $\eta_t \leq \frac{1}{2}$ for all $t \in \mathbb{N}, \sum_{t=0}^\infty \eta_t = \infty$, and $\sum_{t=0}^\infty \eta_t^2 < \infty$, then $\lim_{t \to \infty} \langle w_t, v_1 \rangle^2 = 1$ almost surely.

The proofs of these previous analyses are usually based on tools from dynamical system such as the Kushner-Clark method or Lyapunov theory. Note that these proof techniques are not sufficient for providing convergence rate guarantee.

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3This update rule is doing a variant of power method with normalization. It is widely used in the machine learning community to solve streaming PCA. See Section 1.4 for more discussion.

4It is global because computing the $\ell_2$ norm requires the information from every neurons.
Prior to this work, there had been no efficiency guarantee for the biological Oja’s rule. The main technical barrier is due to the non-linear terms in the update rule which introduces correlations in the traditional step-by-step analysis and thus naive analysis would not work. We explain the difficulty further in Section 1.3 and Appendix C. Given this situation, natural questions on the frontier would then be:

**Question:** What is the convergence rate of biological Oja’s rule in solving streaming PCA? Is the convergence rate biologically-realistic?

### 1.2 Our results

In this paper, we answer the above questions by giving the first convergence rate guarantee for the biological Oja’s rule in solving streaming PCA. Furthermore, the convergence rate matches the information-theoretic lower bound for streaming PCA up to logarithmic factors. In terms of the techniques, we develop an ODE-inspired framework to analyze stochastic dynamics. We believe this general framework of using tools and insights from ODE and SDE in analyzing stochastic dynamics is elegant and powerful. We provide more details and intuitions on the ODE-inspired framework in the section on the technical overview (see Section 1.3). Also, as a byproduct, our convergence rate guarantee for biological Oja’s rule outperforms the state-of-the-art upper bound for streaming PCA (using other variants of Oja’s rule).

There are two common convergence notions in the streaming PCA literature. The **global convergence** allows the algorithm/dynamic to start from a random initial vector while the **local convergence** allows the algorithm/dynamic to start from an initial vector that is highly correlated to the top eigenvector of the covariance matrix. Now, we are ready to state our main theorem as follows.

**Theorem 1.7** (Global and local convergence). With the setting in Problem 1.2 and dynamic in Definition 1.3, let $\text{gap} := \lambda_1 - \lambda_2 > 0$. For any $\epsilon, \delta \in (0, 1)$, we have the following results.

- **(Global convergence)** Suppose $w_0$ is uniformly sampled from the unit sphere in $\mathbb{R}^n$. For any $T \in \mathbb{N}$ and
  \[ T_0 = \Theta \left( \frac{\lambda_1}{\epsilon \cdot \text{gap}^2} \cdot \log^3 \left( T, n, \frac{1}{\text{gap}^2 \cdot \epsilon \cdot \delta} \right) \right), \]
  there exists $\eta = \tilde{O} \left( \frac{(\epsilon \cdot \text{gap})^2}{\lambda_1} \right)$ such that if for all $t \in \mathbb{N}$, we let $\eta_t = \eta$, then we have
  \[ \Pr \left[ \forall t \in [T_0, T_0 + T], \frac{\langle w_t, v_1 \rangle^2}{\|w_t\|^2} \geq 1 - \epsilon \right] \geq 1 - \delta. \]

- **(Local convergence)** Suppose $\langle w_0, v_1 \rangle^2 = \Omega(1)$. For any $T \in \mathbb{N}$ and
  \[ T_0 = \Theta \left( \frac{\lambda_1}{\epsilon \cdot \text{gap}^2} \cdot \log^3 \left( T, 1, \frac{1}{\epsilon \cdot \delta} \right) \right), \]
  there exists $\eta = \tilde{O} \left( \frac{\epsilon \cdot \text{gap}^2}{\lambda_1} \right)$ such that if for all $t \in \mathbb{N}$, we let $\eta_t = \eta$, then we have
  \[ \Pr \left[ \forall t \in [T_0, T_0 + T], \frac{\langle w_t, v_1 \rangle^2}{\|w_t\|^2} \geq 1 - \epsilon \right] \geq 1 - \delta. \]

The notation $a \land b$ stands for $\min\{a, b\}$ and $\tilde{O}$ hides poly-logarithmic factors in $n, \text{gap}^{-1}, \epsilon^{-1}$, and $\delta^{-1}$.

**Biological perspectives** Our results provide further theoretical evidences for the biological plausibility of biological Oja’s rule to be a likely candidate of the dimensionality reduction in the retina-optical nerve pathway. Specifically, we show that “biological Oja’s rule is a local Hebbian learning rule with bounded synaptic weights that functions in a biologically-realistic time scale.” In particular, in this work we demonstrate that biological Oja’s rule does not have any dependency on the dimension (i.e., $n$, the number of neurons) in the local convergence setting while the dependency is logarithmic in the global convergence setting. Moreover, in the local convergence setting, the dependency of the convergence rate on the failure probability $\delta$ is inverse-logarithmic in stead of $O(1/\delta)$. 

Furthermore, we prove the for-all-time guarantee of the biological Oja’s rule as a corollary of the techniques used in the proof for the main theorems. By for-all-time guarantee we refer to the behavior of a dynamic that always stays around the optimal solution after convergence. Especially, the dynamic would not temporarily leave the neighborhood of the optimal solution. The for-all-time guarantee is of biological importance because a biological system constantly adapts and functions, and it is not enough for a mechanism to hold for only a brief moment. We state the theorem for the for-all-time guarantee as follows.

**Theorem 1.8** (For-all-time guarantee with slowly diminishing rate). With the setting in Problem 1.2 and dynamic in Definition 1.3, let $\text{gap} := \lambda_1 - \lambda_2 > 0$. For any $\epsilon, \delta \in (0, 1)$, suppose $\frac{(w_0, v_1)^2}{\|w_0\|^2} \geq 1 - \epsilon/2$. For any $t \in \mathbb{N}$, let $\eta_t = O \left( \frac{\epsilon \cdot \text{gap}}{\lambda_1 \log(1/\delta)} \right)$, then

$$\Pr \left[ \forall t \in \mathbb{N}, \frac{(w_t, v_1)^2}{\|w_t\|^2} \geq 1 - \epsilon \right] \geq 1 - \delta.$$ 

We should further notice that the learning rate is slowly-diminishing, i.e., $\eta_t = \Theta(1/\log t)$ instead of the commonly used $\eta_t = O(1/t)$, in the for-all-time guarantee (i.e., Theorem 1.8). This suggests the capability of continual adaptation, which is crucial in the biological scenario. For example, if a person walks into a new environment, the retina cells need to quickly adapt to the new environment and this cannot be achieved if the learning rate already diminished too fast in the previous environment.

We remark that prior to this work, the for-all-time guarantee with slowly diminishing learning rates was even unknown to any streaming PCA algorithms. The convergence in the limit result for biological Oja’s rule requires $\eta_t = o(1/\sqrt{t})$ [Duf13] and the convergence rate analysis for non-biologically-plausible variants of Oja’s rule requires $\eta_t = O(1/t)$ [JJK16, AZL17, LWLZ18] or $\eta_t = O(1/\sqrt{t})$ [Sha16]. In particular, all previous works satisfy $\sum_t \eta_t^2 < \infty$ while in this work we can achieve for-all-time convergence with much weaker assumptions $\eta_t = \Theta(1/\log t)$ (hence $\sum_t \eta_t^2 = \infty$) for the biological Oja’s rule.

### 1.3 Technical overview

In this work, we give the first efficiency guarantee for the biological Oja’s rule in solving streaming PCA with an (nearly) optimal convergence rate. In this subsection, we highlight three technical insights of our analysis which lead us to a clean understanding in how the biological Oja’s rule solves streaming PCA. In short, our high-level strategy is to first consider the continuous version of the Oja’s rule where the learning rate $\eta$ is set to be infinitesimal. In the continuous setting, the dynamic can be fully understood by tools from the theory of ordinary differential equations (ODE) or stochastic differential equations (SDE). With the inspiration from the continuous analysis, we are able to identify the right tools (e.g., linearization at two different centers, etc.) to tackle the discrete dynamic.

Before we start, let us recall the problem setting and the goal. For simplicity, here we consider the diagonal case where the covariance matrix $A$ is a diagonal matrix, i.e., $A = \text{diag}(\lambda_1, \ldots, \lambda_n)$ with $\lambda_1 > \lambda_2 \geq \lambda_3 \geq \cdots \geq \lambda_n \geq 0$. Thus the top eigenvector of $A$ is $e_1$, i.e., the indicator vector for the first coordinate, and the goal becomes showing that $w_{t, 1}^2$ efficiently converges to 1 when $t \to \infty$. A reduction from the general case to the diagonal case is provided in Section 5.1.

**Insight 1:** Inspiration from the continuous dynamics The first insight is to analyze the biological Oja’s rule in a way inspired by its continuous analog. The advantage to consider the continuous dynamics is that not only it captures the inherent dynamics but also we can apply the theory of ODE and SDE to obtain closed-form solutions. Thus, the continuous dynamic would serve as a hint on how to derive a tight and closed-form analysis for the discrete dynamic.

Interestingly, the continuous SDE of the biological Oja’s rule degenerates into a simple deterministic ODE almost surely (see Section 3 for a derivation). Specifically, for any $t \geq 0$, we have

$$\frac{dw_{t, 1}}{dt} \geq (\lambda_1 - \lambda_2)w_{t, 1}(1 - w_{t, 1}^2) \quad \text{and} \quad \|w_t\|_2 = 1$$

almost surely. Furthermore, observe that the continuous Oja’s rule is non-decreasing and has three fixed points 0 and $\pm 1$ for $w_{t, 1}$ while the first is unstable and the later two are stable. Namely, in the continuous dynamic, $w_t$ will eventually converge to $\pm e_1$, i.e., the top eigenvector of $A$.  

Note that in a discrete stochastic dynamic, there are two sources of the noises: (i) the intrinsic stochasticity from its continuous analog and (ii) the noise due to discretization. Thus, Equation 1.9 suggests that the noise in the biological Oja’s rule only comes from discretization since the continuous Oja’s rule is deterministic.

In addition to the limiting behavior, one can also read out finer structures of the continuous dynamic from Equation 1.9 by solving the differential equation using standard tools from dynamical system. The right hand side (RHS) of the inequality in Equation 1.9 is non-linear which usually does not have a clean solution. A natural idea from dynamical system would then be linearizing the differential equation around fixed points and applying the exact solution for a linear ordinary differential equation. Moreover, as there are three fixed points in Equation 1.9, one can linearize the differential equation with center being either 0 or ±1. For simplicity, we focus on the two fixed points 0 and 1 while −1 can be analyzed similarly due to symmetry.

For example, we can linearize at 0 by lower bounding the RHS of Equation 1.9 by $\epsilon(\lambda_1 - \lambda_2)w_t,1$ for any $w_t,1 \in [0, \sqrt{1-\epsilon}]$ (see Figure 2a). Similarly, we can linearize at 1 by using $w_{0,1}(\lambda_1 - \lambda_2)(1-w_{t,1})$ for any $w_{t,1} \in [w_{0,1},1]$ (see Figure 2b). Another choice would be linearizing at both 0 and 1. Concretely, we linearize at 0 for $w_{t,1} \in [0, 2/3]$ and linearize at 1 for $w_{t,1} \in [2/3, 1]$ (see Figure 2c).

Figure 2: In (a), we only linearize at 0 and use $\epsilon \cdot \text{gap} \cdot w_{t,1}$ to lower bound Equation 1.9 for $w_{t,1} \in [0, \sqrt{1-\epsilon}]$. In (b), we only linearize at 1 and use $(w_{0,1} \cdot \text{gap} \cdot (1-w_{t,1}))$ for $w_{t,1} \in [w_{0,1},1]$. On the other hand, in (c), we linearize at both 0 and 1. For $w_{t,1} \in [0, \frac{2}{3}]$, we use $\frac{2}{5} \text{gap} \cdot w_{t,1}$ while for $w_{t,1} \in [\frac{2}{3}, 1]$ we use $\frac{w_{0,1}}{5} \text{gap} \cdot (1-w_{t,1})$. One can see that the lower bounds in (c) are much tighter than that in (a) and (b) in the sense that the slopes are of order $\Omega(\text{gap})$ instead of $O(\epsilon \cdot \text{gap})$ or $O(w_{0,1} \cdot \text{gap})$.

The main difference between linearizing only at a single fixed point and linearizing at two fixed points is the slope in the linearization. Note that the slopes of the linearizations in Figure 2a and Figure 2b are $\epsilon(\lambda_1 - \lambda_2)$ and $w_{0,1}(\lambda_1 - \lambda_2)$ respectively while the slope is of the order $\Omega(\lambda_1 - \lambda_2)$ in Figure 2c. As the slope corresponds to the speed of the convergence, the extra $\epsilon$ or $w_{0,1}$ in the slope of linearization at a single fixed point would result in an extra $\epsilon^{-1}$ or $w_{0,1}^{-1}$ in the convergence rate. See Figure 2 for a pictorial explanation.

Another key inspiration from the continuous dynamic is the ODE trick which provides a close form characterization of the dynamic in terms of the drifting term captured by the continuous dynamic and the noise term originated from the linearization and discretization. The ODE trick is inspired by the solution to a linear ordinary differential equation (linear ODE). Consider the following simple linear ODE

$$\frac{dy(t)}{dt} = ay(t) + b(t)$$

for some constant $a$ and function $b(t)$. To put into the context, one can think of $a$ as the drifting term and $b(t)$ as the noise term in the continuous Oja’s rule due to the linearization\(^5\). By the standard tool for solving linear ODE, the solution of $y(t)$ at $t = T$ is

$$y(T) = e^{aT} \cdot \left[ y(0) + \int_{0}^{T} e^{-at}b(t)dt \right].$$  \hspace{1cm} (1.10)

\(^5\)In the biological Oja’s rule, the discretization also contributes in the noise term.
From the above equation, one can see that the solution of a linear ODE extracts the drifting term into a multiplier $e^{aT}$ and decouples the initial condition $y(0)$ with the noise term $\int_0^T e^{-a(t)} b(t) dt$. As a consequence, once we can show that the noise term is much smaller than the initial value, then $y(T)$ is dominated by the drifting term $e^{aT} y(0)$ and thus we are able to analyze the progress of $y(T)$.

To sum up, the continuous dynamic informs us to linearize the biological Oja’s rule at different centers in different phases of the analysis. Further, the ODE trick provides us a closed-form approximation to the dynamic. We are then able to analyze the biological Oja’s rule in one-shot rather than doing the traditional step-by-step analysis.

**Insight 2: One-shot analysis instead of step-by-step analysis** The second insight of this work is performing an one-shot analysis instead of the traditional step-by-step analysis (e.g., [AZL17]).

**Traditional step-by-step analysis** To see the difference, let us illustrate how would the step-by-step analysis on the biological Oja’s rule work as follows. Denote the natural filtration as $\{\mathcal{F}_t\}$ where $\mathcal{F}_t$ is the $\sigma$-algebra generated by $x_1, x_2, \ldots, x_t$. For any $t \in \mathbb{N}$, we have

$$E[w_{t,1}] = E\left[ E\left[ w_{t-1,1} + \eta_t(x_t^T w_{t-1}) x_{t,1} - \eta_t(x_t^T w_{t-1})^2 w_{t-1,1} | \mathcal{F}_{t-1} \right] \right]$$

where the second equation is due to the fact that for any $i, j \in [n]$, $E[x_i x_j | \mathcal{F}_{t-1}] = A_{ij} = \lambda_i \cdot 1_{i=j}$ and for any $i \in [n]$, $E[w_{t-1,i} | \mathcal{F}_{t-1}] = w_{t-1,i}$. In a step-by-step analysis, one then argues that the expectation $E[w_{t,1}]$ would be improved from $E[w_{t-1,1}]$ by a certain factor. Then, an induction on each step followed by showing concentration would give some convergence rate guarantee. However, there are two difficulties in getting optimal convergence rate (these difficulties usually also appear in the step-by-step analysis for other problems).

- First, there are some non-linear terms of $w_{t-1,1}$ in the update noise. This usually requires some hacks tailored to the specific problem to enable the analysis.
- Second, the improvement factor at each step can depend on $w_{t-1}$ and at worst case, the dynamic can show no improvement or even deteriorate. Taking expectation loses precise controls of the values of $w_{t-1}$. This makes naive martingale analysis difficult to work and probably requires more ad hoc tricks.

For instance, the first difficulty is exactly what [AZL17] encountered in their analysis for a variant of the biological Oja’s rule. They resolved the first difficulty by decomposing the non-linear term in the dynamic into a multi-dimensional chain and carefully bounding the chain with strong assumptions on learning rates to enable martingale analysis. They used extremely delicate and complicated techniques tailored to the dynamic to achieve optimal convergence rate. The biological Oja’s rule, in addition to having the first difficulty, also has the second difficulty (see Appendix C for more discussions). Therefore, applying the traditional step-by-step analysis on the biological Oja’s rule will encounter great obstacles.

**Our one-shot analysis** In this work, we use an one-shot analysis to avoid the complication of a step-by-step analysis. Namely, instead of looking at the process iteratively, we study the entire dynamic at once. Two key ingredients are needed to implement such an one-shot analysis: (i) a closed-form characterization of the dynamic and (ii) stopping time techniques. As discussed in the previous discussion, the continuous dynamic of the biological Oja’s rule inspires us to get a closed-form lower bound for $w_{t,1}$ by the ODE trick. Concretely, as a simplified example, we have

$$w_{T,1} = H^T \cdot \left( w_{0,1} + \sum_{t=1}^{T} \frac{N_t}{H} \right)$$

\[6\] In general, the multiplier term also varies with respect to time $t$. 


where $H > 1$ is the multiplier term and $\{N_t\}$ is the noise term which forms a martingale on the natural filtration. See Corollary 6.4 and Corollary 7.3 for a precise formulation of $H$ and $\{N_t\}$ in our analysis. Intuitively, one should think of $H^T w_{0,1}$ as the **drifting term** and the other part as the **noise term**. The goal of the ODE trick in the discrete dynamic is to show that the drifting term dominates the noise term.

To show that the noise in Equation 1.11 is small, Azuma’s inequality (see Lemma 2.4) would be a natural tool to start with. However, the **bounded difference** condition in Azuma’s inequality would immediately cause an issue: the noise at time $t$ is correlated with $w_{t-1,1}$ and thus one cannot get a small bounded difference almost surely. For example, suppose the bounded difference of $\{N_t\}$ at time $t$ is at most $w_{t-1,1}^2$. Since we do not yet know the behavior of $w_{t-1,1}$, we can only upper bound the bounded difference of $\{N_t\}$ in the worst case by $1 + o(1)$. In the meantime, both $w_{t,1}^2$ and the noise are expected to be very small in the early stage of the dynamic with high probability.

To circumvent this obstacle, we consider the **stopped process** of the original martingale in which the bounded difference is under control. For example, consider the above situation where the noise term $\{N_t\}$ is a martingale and a stopping time $\tau$ for the event $\{w_{\tau,1}^2 \geq 0.1\}$. The stopped process, denoted by $\{N_{t \wedge \tau}\}$ where $t \wedge \tau = \min\{t, \tau\}$, is a process that simulates $\{N_t\}$ and stops at the first time $t^*$ such that $w_{t^*,1}^2 \geq 0.1$. It is known that a stopped process of a martingale is also a martingale. Furthermore, the bounded difference of the stopped process $\{N_{t \wedge \tau}\}$ would be 0.1 almost surely by the choice of $\tau$. It turns out that this improvement in the bounded difference condition drastically increases the quality of Azuma’s inequality and gives the desiring concentration for the stopped process.

There is one last missing step before showing the dominance of $w_{0,1}$ in Equation 1.11: we have to show that the concentration for the stopped process $\{N_{t \wedge \tau}\}$ can be extended to the original process $\{N_t\}$. We achieve this task by developing a **pull-out lemma** which is able to utilize the structure of the martingale and pull out the stopping time from a concentration inequality.

**Insight 3: Maximal martingale inequality and pull-out lemma** In general, there is no hope to pull out the stopping time from a concentration inequality for the stopped process without blowing up the failure probability. The naive union bound would give a blow-up of factor $T$ in the failure probability and it is undesirable.

Let $M_t = \sum_{\nu=t}^T H^{-\nu} N_\nu$ be the noise term in the ODE trick (i.e., Equation 1.11) and $\tau$ be a stopping time that ensures good bounded difference condition. Note that as $\{N_t\}$ is a martingale, we know that $\{M_{t \wedge \tau}\}$ is also a martingale. There are two key ingredients to pull out the stopping time from $\{M_{t \wedge \tau}\}$, i.e., the stopped process of the noise term.

First, we use the **maximal concentration inequality** (e.g., Lemma 2.5) which gives the following stronger guarantee than the traditional Azuma’s inequality.

\[
\Pr \left[ \sup_{1 \leq t \leq T} \left| M_{t \wedge \tau} - M_0 \right| \geq a \right] < \delta 
\]

(1.12)

for some $a > 0$, $T \in \mathbb{N}$, and $\delta \in (0, 1)$. Note that the maximal concentration inequality gives concentration for any $1 \leq t \leq T$ without paying an union bound.

Second, we identify a **chain structure** on the martingale and the stopping time $\tau$ we are working with. Concretely, we are able to show that for all $t \in [T]$,

\[
\Pr \left[ \tau \geq t + 1 \left| \sup_{1 \leq \nu \leq t} \left| M_\nu - M_0 \right| < a \right] = 1. 
\]

(1.13)

Namely, if the bad event has not happened, then the martingale would not stop immediately. Intuitively, Equation 1.13 holds due to the ODE trick because $\{\sup_{1 \leq \nu \leq t} \left| M_\nu - M_0 \right| < a\}$ implies the noise term to be small and thus the drifting term dominates. As $\tau$ is properly chosen such that the martingale would not stop if the process $w_t$ followed the drifting term, we know that $\tau \geq t + 1$.

Combining the above two ingredients (i.e., Equation 1.12 and Equation 1.13), we are able to show in the pull-out lemma that

\[
\Pr \left[ \sup_{1 \leq t \leq T} \left| M_t - M_0 \right| \geq a \right] < \delta , 
\]

\[\footnote{This is because we are able to upper bound $w_{t-1,1}$ by $1 + o(1)$ almost surely. See Section 5.2. Note that there are ways to get better bounded difference condition in the worst case but this is still not sufficient.} \]
i.e., the stopping time has been pulled out.

Let us end this subsection with a high-level sketch on the proof for the pull-out lemma. The key idea is to consider another stopping time \( \tau' \) for the event \( \{|M_{\tau'} - M_0| \geq a\} \) and partition the probability space of the error event \( \{\sup_{1 \leq t \leq T} |M_t - M_0| \geq a\} \) into two parts \( P_1 \) and \( P_2 \) with the following properties. In \( P_1 \), we can show that

\[
\Pr\left[ \sup_{1 \leq t \leq T} |M_t - M_0| \geq a, \ P_1 \right] = \Pr\left[ \sup_{1 \leq t \leq T} |M_{\tau'} - M_0| \geq a, \ P_1 \right].
\]

As for \( P_2 \), we use the chain condition in Equation 1.13 to show that the probability of error event is 0 based on a diagonal argument. Thus, we have

\[
\Pr\left[ \sup_{1 \leq t \leq T} |M_t - M_0| \geq a \right] = \Pr\left[ \sup_{1 \leq t \leq T} |M_t - M_0| \geq a, \ P_1 \right] + \Pr\left[ \sup_{1 \leq t \leq T} |M_{\tau'} - M_0| \geq a, \ P_2 \right]
\]

\[
= \Pr\left[ \sup_{1 \leq t \leq T} |M_{\tau'} - M_0| \geq a, \ P_1 \right] + 0
\]

\[
\leq \Pr\left[ \sup_{1 \leq t \leq T} |M_{\tau'} - M_0| \geq a \right] < \delta.
\]

See Section 7.4 and Figure 3 for more details on the chain condition for biological Oja’s rule and how to partition the probability space of the error event.

### 1.4 Related works

**Biological Oja’s variants and other Hebbian learning rules** Computational neuroscientists have proposed several variants of the biological Oja’s rule that solve different computational problems. For example, least square learning [OBL00], streaming PCA with \( \ell_1 \) constraint [Apa12], and subspace learning [PHC15]. However, similar to the situation in the biological Oja’s rule, people only showed guarantees on the convergence in the limit and did not provide a convergence rate analysis. Some works also attempted to obtain more than one principal component using variants of Oja’s rule, but these dynamics are less biologically-plausible because they are either not local [San89] [Oja92] or store complicated local variables [PHC15]. Other forms of Hebbian learning rules has also been developed for applications other than PCA. For example, BCM rule [BCM82] and covariance rule [Sej77] are two well-known Hebbian learning rules which were successfully applied to explain the input selectivity in the development of the visual field. A recent work by Lynch and Mallmann-Trenn [LMT19] used Oja’s rule to learn hierarchically structured concepts. They provided theoretical guarantee for the efficiency in a special case where the input is deterministic or nearly deterministic while we can handle arbitrary inputs.

**Oja’s rule in machine learning** Unlike the situation in the biological Oja’s rule, a line of recent exciting results [HP14, DSOR15, BDWY16, Sha16, JJK16, AZL17] showed convergence rate analysis for variants of Oja’s rule in the machine learning community. Since the update rules of these works are not biologically-plausible, we call them ML Oja’s rules to distinguish from the biological Oja’s rule.

To see the difference between the biological Oja’s rule and the ML Oja’s rule, let us take the update rule from [Sha16, JJK16, AZL17] as an example. Note that the other variants of ML Oja’s rule also have the similar fundamental difference to the biological Oja’s rule as illustrated by the following example. Let \( w_t \in \mathbb{R}^n \) be the output vector at time \( t = 0, 1, \ldots, T \), the update rule is

\[
w_t = \prod_{t' = 1}^{t} \left( 1 + \eta_{t'} x_{t'} x_{t'}^T \right) w_0
\]

and the output is \( w_T / \|w_T\|_2 \). Note that the above update rule is equivalent to Equation 1.5, i.e., applying Taylor’s expansion on the ML Oja’s rule and truncating the higher-order terms would result in biological Oja’s rule.
A natural idea would be trying to couple the biological Oja’s rule with the ML Oja’s rule by showing that for all \( t \in \mathbb{N} \), the weight vectors from the two dynamics would be close to each other. However, this seems to be more difficult than direct analysis and we leave it as an interesting open problem to investigate whether this is the case. Moreover, the corresponding continuous dynamics suggest an intrinsic difference between the two: the continuous version of the ML Oja’s rule can be tightly characterized by a single linear ODE while that of the biological Oja’s rule requires two linear ODEs in different regimes for tight analysis. See Section 3 and Appendix C for more details.

To sum up, the biological Oja’s rule and the ML Oja’s rule are similar but the analysis of the later cannot be directly applied to the former. While following the proof idea for the ML Oja’s rule might give some hints on how to analyze the biological Oja’s rule, in this work we develop a completely different framework (as briefly discussed in Section 1.3). This framework not only gives the first and nearly optimal convergence rate guarantee for the biological Oja’s rule, but also could improve the convergence rate of the ML Oja’s rule with better logarithmic dependencies and we leave it as a future work.

Comparing with other streaming PCA algorithms Streaming PCA is a well-studied and challenging computational problem. Many works [DSOR15, Sha16, LWLZ18, JJK+16, AZL17] provided theoretical guarantees for streaming PCA algorithms. Interestingly, all of the streaming PCA algorithms in these works are some variants of the biological Oja’s rule.

Recall that there are two standard convergence notions: the global convergence where \( w_0 \) is an uniformly random unit vector and the local convergence where \( w_0 \) is constantly correlated with the top eigenvector. There are 5 parameters of interest: the dimension \( n \in \mathbb{N} \), the eigenvalue gap \( \text{gap} := \lambda_1 - \lambda_2 \in (0, 1) \), the top eigenvalue \( \lambda_1 \in (0, 1) \), the error parameter \( \epsilon \in (0, 1) \), and the failure probability \( \delta \in (0, 1) \). Ideally, the goal is to achieve the information-theoretic lower bound \( \Omega(\lambda_1 \text{gap}^{-2} \epsilon^{-1} \log(\delta^{-1})) \) given by [AZL17]. Prior to this work, the state-of-the-art for both global and local convergences are achieved by [AZL17] using ML Oja’s rule (see the second to last row of Table 1). In this work, as a byproduct, the convergence rate we get for the biological Oja’s rule outperforms [AZL17] by a logarithmic factor in both settings. See Table 1 for a summary.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Reference</th>
<th>Any Input</th>
<th>Global Convergence</th>
<th>Local Convergence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biological Oja’s Rule</td>
<td>This Work</td>
<td>Y</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}} \cdot \frac{1}{\epsilon^2 \delta^2} \right) )</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td>ML Oja’s Rule</td>
<td>[DSOR15]</td>
<td>N</td>
<td>( \tilde{O} \left( \frac{n}{\text{gap}^2} \cdot \frac{1}{\epsilon^2 \delta^2} \right) )</td>
<td>( \tilde{O} \left( \frac{n}{\text{gap}^2} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td></td>
<td>[Sha16]</td>
<td>Y</td>
<td>( \tilde{O} \left( \frac{n}{\text{gap}^2} \cdot \frac{1}{\epsilon^2 \delta^2} \right) )</td>
<td>( \tilde{O} \left( \frac{n}{\text{gap}^2} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td></td>
<td>[LWLZ18]</td>
<td>N</td>
<td>( \frac{\lambda_1 n}{\text{gap}^2} \cdot \frac{1}{\epsilon^2 \delta^2} )</td>
<td>( \tilde{O} \left( \frac{\lambda_1 n}{\text{gap}^2} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td></td>
<td>[JJK+16]</td>
<td>Y</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}^2} \cdot \frac{1}{\epsilon \delta^2} \right) )</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}^2} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td></td>
<td>[AZL17]</td>
<td>Y</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}^2} \cdot \frac{1}{\epsilon \delta^2} \right) )</td>
<td>( \tilde{O} \left( \frac{\lambda_1}{\text{gap}^2} \cdot \frac{1}{\epsilon} \right) )</td>
</tr>
<tr>
<td>Any Algorithm</td>
<td>[AZL17]</td>
<td></td>
<td>( \Omega \left( \frac{\lambda_1}{\text{gap}^2} \cdot \frac{\log \frac{1}{\delta}}{\epsilon} \right) )</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Convergence rate for biological Oja’s rule and ML Oja’s rule in solving streaming PCA. The “Any Input” column indicates that whether the analysis has higher moment conditions on the unknown distribution \( D \). Note that having higher moment conditions would drastically simplify the problem because the non-linear terms in the update rule can then be non-trivially replaced with the first order term.


Algorithms inspired by biological neural networks In recent years, the study of the algorithmic aspect of mathematical models for biological neural networks is an emerging field in theoretical CS. For example, the efficiency of spiking neural networks in solving the winner-take-all (WTA) problem [LMP17a, LMP17b, LMP17c, LM18, SCL19], the efficiency of spiking neural networks in storing temporal information [WL19, HP19], assemblies [LMPV18, PV18], and spiking neural networks in solving optimization problems [CCL19, Peh19]. Under this context, this work provides an algorithmic insight in a plasticity learning rule that solves streaming PCA.

2 Preliminaries

2.1 Notations

We use \(\mathbb{N} = \{1, 2, \ldots\}\) and \(\mathbb{N}_{\geq 0} = \{0, 1, \ldots\}\). For each \(n \in \mathbb{N}\), denote \([n] = \{1, 2, \ldots, n\}\) and \([n]_{\geq 0} = \{0, 1, \ldots, n\}\). For a vector indexed by time \(t\), e.g., \(w_t\), its \(i^{\text{th}}\) coordinate is denoted by \(w_{i,t}\). The notation \(\tilde{O}\) (similarly, \(\Omega\) and \(\Theta\)) is the same as the big-O notation by ignoring extra poly-logarithmic term. \(1_E\) stands for the indicator function for a probability event \(E\). We sometimes abuse the big \(O\) notation by \(y = O(x)\) meaning \(|y| = O(x)\) and this will be clear in the context. Throughout the paper, \(\lambda\) is used to denote the vector \((\lambda_1, \lambda_2, \ldots, \lambda_n)\) where \(\lambda_1 > \lambda_2 \geq \cdots \geq \lambda_n \geq 0\) are the eigenvalues of the covariance matrix \(A\). \(\text{diag}(\lambda)\) denotes the diagonal matrix with \(\lambda\) on the diagonal.

2.2 Probability toolbox

2.2.1 Random unit vector

The following lemma shows that with random initialization, the inner product between \(w_0\) and the top eigenvector of the covariance matrix is of order \(\Omega(1/\sqrt{n})\) with high probability.

Lemma 2.1. For any \(\delta \in (0, 1)\) and unit vector \(v_0 \in \mathbb{R}^n\), let \(v\) be a random unit vector in \(\mathbb{R}^n\). Then

\[
\Pr\left[ |v_0^\top v|^2 \leq \frac{10\delta^2}{n} \right] < \delta.
\]

2.2.2 Random process and concentration inequality

Random process is a central tool in this paper. Let us start with the most general definition on adapted random process.

Definition 2.2 (Adapted random process). Let \(\{X_t\}_{t \in \mathbb{N}_{\geq 0}}\) be a sequence of random variables and \(\{\mathcal{F}_t\}_{t \in \mathbb{N}_{\geq 0}}\) be a filtration. We say \(\{X_t\}_{t \in \mathbb{N}_{\geq 0}}\) is an adapted random process with respect to \(\{\mathcal{F}_t\}_{t \in \mathbb{N}_{\geq 0}}\) if for each \(t \in \mathbb{N}_{\geq 0}\), the \(\sigma\)-algebra generated by \(X_0, X_1, \ldots, X_t\) is contained in \(\mathcal{F}_t\).

In most of the situations, we use \(\mathcal{F}_t\) to denote the natural filtration of \(\{X_t\}_{t \in \mathbb{N}_{\geq 0}}\), namely, \(\mathcal{F}_t\) is defined as the \(\sigma\)-algebra generated by \(X_0, X_1, \ldots, X_t\). One of the most common adapted processes is the martingale.

Definition 2.3 (Martingale). Let \(\{M_t\}_{t \in \mathbb{N}_{\geq 0}}\) be a sequence of random variables and let \(\{\mathcal{F}_t\}_{\mathcal{N}}\) be its natural filtration. We say \(\{M_t\}_{t \in \mathbb{N}_{\geq 0}}\) is a martingale if for each \(t \in \mathbb{N}\), \(\mathbb{E}[M_{t+1} \mid \mathcal{F}_t] = M_t\).

Note that for any adapted random process \(\{X_t\}_{t \in \mathbb{N}_{\geq 0}}\), one can always turn it into a martingale by defining \(M_0 = X_0\) and for any \(t \in \mathbb{N}\), let \(M_t = X_t - \mathbb{E}[X_t \mid \mathcal{F}_{t-1}]\). When the difference of a martingale can be bounded almost surely, the Azuma’s inequality provides an useful concentration inequality with exponential tail.

*Let \(f(\log n, \log(1/\epsilon), \log(1/\delta), \log(1/\text{gap}))\) be the polynomial of the logarithmic dependencies in the convergence rate. We compare the maximum degree of \(f\) among different analyses. Note that this measure makes sense when \(n, 1/\epsilon, 1/\delta, 1/\text{gap}\) are polynomially related.

†Both [DSOR15] and [Sha16] cannot handle arbitrary failure probability so we ignore their \(\delta\) dependency on the table.

‡In [DSOR15, Sha16, LWLZ18], their convergence rates are far from the information-theoretic lower bound. So we do not trace down their logarithmic dependencies.

§In [AZL17], they only stated \(\Omega(\frac{\text{gap}}{\delta})\) lower bound. We observe that their lower bound can be improved by a \(\log(1/\delta)\) factor using the fact that distinguishing a fair coin from a biased coin with probability at least \(\delta\) requires \(\Omega(\log(1/\delta))\) samples.
Lemma 2.4 (Azuma’s inequality [Azu67]). Let \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) be a martingale. Let \( T \in \mathbb{N} \) and \( a, c \geq 0 \) be some constants. Suppose for each \( t = 1, 2, \ldots, T \), \( |M_t - M_{t-1}| \leq c \) almost surely, then we have

\[
\Pr[|M_T - M_0| \geq a] < \exp\left(-\Omega\left(\frac{a^2}{c^2T}\right)\right).
\]

The following maximal Azuma’s inequality shows that one can even get union bound for free with the help of Doob’s inequality.

Lemma 2.5 (Maximal Azuma’s inequality [HMRAR13, Section 3]). Let \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) be a martingale. Let \( T \in \mathbb{N} \) and \( a, c \geq 0 \) be some constants. Suppose for each \( t = 1, 2, \ldots, T \), \( |M_t - M_{t-1}| \leq c \) almost surely and \( \Var[M_t \mid \mathcal{F}_{t-1}] \leq \sigma_t^2 \), then we have

\[
\Pr\left[\sup_{0 \leq t \leq T} |M_t - M_0| \geq a\right] < \exp\left(-\Omega\left(\frac{a^2}{\sigma_T^2 + ca}\right)\right) .
\]

Finally, we state a corollary of Freedman’s inequality for adapted random process with small conditional expectation.

Corollary 2.7. Let \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) be a random process. Let \( T \in \mathbb{N} \) and \( a, c, \sigma_t, \mu_t \geq 0 \) be some constants for all \( t \in [T] \). Suppose for each \( t = 1, 2, \ldots, T \), \( |M_t - M_{t-1}| \leq c \) almost surely, \( \Var[M_t \mid \mathcal{F}_{t-1}] \leq \sigma_t^2 \), and \( |E[M_t - M_{t-1} \mid \mathcal{F}_{t-1}]| \leq \mu_t \), then we have

\[
\Pr\left[\sup_{0 \leq t \leq T} |M_t - M_0| \geq a + \max_{1 \leq t \leq T} \sum_{r=1}^{T} \mu_t\right] < \exp\left(-\Omega\left(\frac{a^2}{\sum_{t=1}^{T} \sigma_t^2 + ca}\right)\right) .
\]

2.2.3 Stopping time

One powerful technique for studying martingale is the notion of stopping time defined as follows.

Definition 2.8 (Stopping time). Let \( \{X_t\}_{t \in \mathbb{N}_{\geq 0}} \) be an adapted random process associated with filtration \( \{\mathcal{F}_t\}_{t \in \mathbb{N}_{\geq 0}} \). An integer-valued random variable \( \tau \) is a stopping time for \( \{X_t\}_{t \in \mathbb{N}_{\geq 0}} \) if for all \( t \in \mathbb{N}, \{\tau = t\} \in \mathcal{F}_t \).

Let \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) be a martingale, the most common stopping time for \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) is of the following form. For any \( a \in \mathbb{R} \), let

\[
\tau := \min_{M_t \geq a} t .
\]

Namely, \( \tau \) is the first time when the martingale becomes at least \( a \). For convenience, in the rest of the paper, we would define stopping time of this form by saying \( \tau \) is the stopping time for the event \( \{M_t \geq a\} \). Given a martingale \( \{M_t\}_{t \in \mathbb{N}_{\geq 0}} \) and a stopping time \( \tau \), it is then natural to consider the corresponding stopped process \( \{M_{t \wedge \tau}\}_{t \in \mathbb{N}_{\geq 0}} \) where \( t \wedge \tau := \min\{t, \tau\} \) is also a random variable. An useful and powerful fact here is that the stopped process of a martingale is also a martingale. See [Wil91, Theorem 10.9] for a proof for this classic result. In the rest of this paper, we sometimes write \( \{M_{t_0 + t \wedge \tau}\} \) to denote martingale starts with time \( t_0 \) and \( \tau \) is used as the stopping time after \( t_0 \) (instead of starting from time \( 0 \)).
2.2.4 Brownian motion

In Section 3, we consider a continuous version of biological Oja’s rule by modeling the input stream as a Brownian motion. Here, we provide background that is sufficient for the readers to understand the discussion there.

First, we introduce the 1-dimensional Brownian motion using the following operational definition. In the following, we use $N(\mu, \sigma^2)$ to denote the Gaussian distribution with mean $\mu$ and variance $\sigma^2$.

**Definition 2.9 (1-dimensional Brownian motion).** Let $\{\beta_t\}_{t \geq 0}$ be a real-valued random process. We say $\{\beta_t\}_{t \geq 0}$ is a 1-dimensional Brownian motion if the following holds.

- For any $0 \leq t_1 < t_2$, $\beta_{t_2} - \beta_{t_1} \sim N(0, t_2 - t_1)$.
- For any $0 = t_0 \leq t_1 < \cdots < t_t$, for each $i \in \{t\}$, $\beta_{t_i} - \beta_{t_{i-1}}$ are independent.

With the above definition, it is then natural to consider some variants such as putting $n$ independent copies of 1-dimensional Brownian motion into a vector, i.e., the $n$-dimensional Brownian motion, or applying linear operations on an $n$-dimensional Brownian motion, or considering the calculus on Brownian motion by looking at $d\beta_t = \lim_{\Delta \to 0} \beta_{t+\Delta} - \beta_t$. The role of Brownian motion in the study of continuous random process is similar to Gaussian random variance in discrete random process and many properties in the discrete world directly extend to the continuous world. One property of Brownian motion though obviously does not hold in the discrete setting and might be counter-intuitive for people who see this in the first time. This is the quadratic variation of Brownian motion as stated below.

**Lemma 2.10 (Quadratic variation of Brownian motion).** Let $\{\beta_t\}_{t \geq 0}$ and $\{\beta'_t\}_{t \geq 0}$ be two independent 1-dimensional Brownian motions. The following holds almost surely.

$$d\beta_t^2 = dt \quad \text{and} \quad d\beta_t d\beta'_t = 0.$$ 

We omit the proof of Lemma 2.10 here and refer the interested readers to standard textbook such as [LG16] for more details on Brownian motion.

2.3 ODE toolbox

**Lemma 2.11 (ODE trick for scalar).** Let $\{X_t\}_{t \geq N \geq 0}$, $\{A_t\}_{t \in \mathbb{N}}$, and $\{H_t\}_{t \in \mathbb{N}}$ be sequences of random variables with the following dynamic

$$X_t = H_t X_{t-1} + A_t \quad (2.12)$$

for all $t \in \mathbb{N}$. Then for all $t_0, t \in \mathbb{N} \geq 0$ such that $t_0 < t$, we have

$$X_t = \prod_{i=t_0+1}^{t} H_i \cdot \left( X_{t_0} + \sum_{i=t_0+1}^{t} \frac{A_i}{\prod_{j=t_0+1}^{i} H_j} \right).$$

**Proof of Lemma 2.11.** For each $t_0 < i \leq t$, dividing Equation 2.12 with $\prod_{j=t_0+1}^{i} H_j$ on both sides, we have

$$\frac{X_i}{\prod_{j=t_0+1}^{i} H_j} = \frac{X_{i-1}}{\prod_{j=t_0+1}^{i-1} H_j} + \frac{A_i}{\prod_{j=t_0+1}^{i} H_j}.$$ 

By telescoping the above equation from $t = t_0 + 1$ to $t$, we get the desiring expression. \qed

**Lemma 2.13 (ODE trick for vector).** Let $m \in \mathbb{N}$ and $\{X_t\}_{t \geq N \geq 0}$, $\{A_t\}_{t \in \mathbb{N}}$ be sequences of $m$-dimensional random variables and $\{H_t\}_{t \in \mathbb{N}}$ be a sequence of random $m \times m$ matrices with the following dynamic

$$X_t = H_t X_{t-1} + A_t \quad (2.14)$$

for all $t \in \mathbb{N}$. Then for all $t_0, t \in \mathbb{N} \geq 0$ such that $t_0 < t$, we have

$$X_t = \prod_{i=t_0+1}^{t} H_i X_{t_0} + \sum_{i=t_0+1}^{t} \prod_{j=t+1}^{i} H_j A_i.$$ 

**Proof of Lemma 2.13.** The proof is a direct induction. \qed
2.4 Approximation toolbox

Here we state some useful inequalities. Since some are quite standard, the proofs are omitted.

**Lemma 2.15.** For any \( x \in (-0.5, 1) \),

\[
1 + x \leq e^x \leq 1 + x + x^2 \leq 1 + 2x .
\]

In fact for all \( x \geq 0 \), the first inequality holds.

**Lemma 2.16.** For any \( x \in (0, 0.5) \) and \( t \in \mathbb{N} \),

\[
1 + \frac{xt}{2} \leq e^{\frac{xt}{2}} \leq (1 + x)^t \leq e^{xt} .
\]

**Lemma 2.17.** For any \( \epsilon \in (0, 0.2) \), we have

\[
\left( \frac{\epsilon}{8} \right)^{1 - \frac{1}{\log 2}} \leq \epsilon .
\]

**Proof.** Rewrite the expression as the follows.

\[
\left( \frac{\epsilon}{8} \right)^{1 - \frac{1}{\log 2}} = \epsilon \cdot \left( \frac{8}{\epsilon} \right)^{\frac{1}{\log 2}} \cdot \frac{1}{8} .
\]

It suffices to show that the product of the last two terms is smaller than 1. Consider the logarithm of them, we have

\[
\log \left( \frac{8}{\epsilon} \right)^{\frac{1}{\log 2}} \cdot \frac{1}{8} = \frac{1}{\log 2} \left( 3 + \log \frac{1}{\epsilon} \right) - 3 = 3 \left( \frac{1}{\log 2} - 1 \right) + 1 .
\]

When \( \epsilon < 0.2 \), we have \( \log(1/\epsilon) > 2 \) and the equation becomes

\[
\leq \left( \frac{1}{2} - 1 \right) 3 + 1 < 0
\]

as desired. \( \square \)

3 Analyzing the Continuous Version of Oja’s Rule

In this section, we introduce the continuous version of Oja’s rule and analyze its convergence rate. The analysis here serves as an inspiration for attacking the discrete dynamic. To model the continuous dynamics, we use Brownian motion to capture the continuous stream of inputs. Surprisingly, it turns out that this continuous version of Oja’s rule is deterministic. Thus, we are able to use the tools from ODE to easily give an exact characterization of how it converges to the top eigenvector of the covariance matrix. As a disclaimer, since the analysis for continuous Oja’s rule is mainly for intuition, we would omit some mathematical details and point the interested readers to the corresponding resources.

3.1 Continuous Oja’s rule is deterministic

In the rest of the section we are going to focus on the diagonal case where the covariance matrix \( A = \text{diag}(\lambda) \) and the goal is showing that \( w_{t,1} \) goes to 1. This is sufficient since there is a reduction from the general case to the diagonal case as explained in Section 5.1.

Intuitively, the continuous dynamic is the limiting process of biological Oja’s rule with learning rate \( \eta \) going to 0. Formally, for each \( i \in [n] \), let \( (\beta_t^{(i)})_{t \geq 0} \) be an independent 1-dimensional Brownian motion and let \( (B_t)_{t \geq 0} \) be an \( n \)-dimensional random process with the \( i \)-th entry being \( B_{t,i} = \sqrt{\lambda_i} \beta_t^{(i)} \) for each \( t \geq 0 \). Now, the difference of \( B_t \) should then be thought of as \( \eta x_t \).
Concretely, to see why \((B_t)_{t \geq 0}\) captures the input behavior of streaming PCA in the continuous setting, let us first discretize \((B_t)_{t \geq 0}\) using constant step size \(\Delta > 0\). Now, observe that for each \(t \geq 0\), \(B_{t+\Delta} - B_t\) is an isotropic Gaussian vector with the variance of the \(i\)th entry being \(\lambda_i \cdot \Delta\). Namely,

\[
\frac{1}{\Delta} \mathbb{E} \left[ (B_{t+\Delta} - B_t) (B_{t+\Delta} - B_t)^\top \right] = \text{diag}(\lambda).
\] (3.1)

Thus, by discretizing \(B_t\) into intervals of length \(\Delta > 0\), \(\left\{ \frac{1}{\sqrt{\Delta}} (B_j - B_{(j-1)\Delta}) \right\}_{j \in \mathbb{N}}\) naturally forms a stream of i.i.d. input\(^8\) with covariance matrix being \(A\). To put this into the context of biological Oja’s rule, one should think of \(\eta = \Delta\), \(x_j = \sqrt{\Delta} B_j\), and \(y_j = x_j \cdot w_{j-1}\) for each \(j \in \mathbb{N}\) where \(\Delta B_j = (B_j - B_{(j-1)\Delta})\) \(^9\). Then, we get the following dynamic.

\[
\begin{align*}
\mathbf{w}_j &= \mathbf{w}_{j-1} + \eta \cdot y_j (x_j - y_j \mathbf{w}_{j-1}) \\
&= \mathbf{w}_{j-1} + \Delta \mathbf{B}_j^\top \mathbf{w}_{j-1} \Delta \mathbf{B}_j - \left[ \Delta \mathbf{B}_j^\top \mathbf{w}_{j-1} \right]^2 \mathbf{w}_{j-1}.
\end{align*}
\]

The above dynamics becomes continuous once we let \(\Delta \to 0\). Formally, we replace\(^10\) \(B_{t+\Delta} - B_t\) with \(dB_t\) and index the weight vector by \(t \geq 0\), i.e., \((\mathbf{w}_t)_{t \geq 0}\). The above dynamic becomes the following SDE.

\[
d\mathbf{w}_t = d\mathbf{B}_t^\top \mathbf{w}_t dB_t - (d\mathbf{B}_t^\top \mathbf{w}_t)^2 \mathbf{w}_t dt. \tag{3.2}
\]

It might look absurd at first glance (for those who have not seen stochastic calculus before) that there is a quadratic term of \(dB_t\) in Equation 3.2. Nevertheless, it is in fact mathematically well-defined and we recommend standard resource such as [LG16] for more details. Intuitively, the quadratic term (which is formally called the quadratic variation of a Brownian motion should be thought of as a deterministic quantity. Concretely, let \((\beta_t)_{t \geq 0}\) be a Brownian motion, we have \(d\beta_t^2 = dt\) almost surely (see Lemma 2.10). Thus, for the \((B_t)_{t \geq 0}\) defined here, we would have

\[
dB_{t,i} dB_{t,j} = \begin{cases} 
\lambda_i dt, & i = j \\
0, & i \neq j
\end{cases}
\]

for each \(i, j \in [n]\). As a consequence, the continuous Oja’s rule defined in Equation 3.2 can be rewritten as the following deterministic process almost surely.

\[
d\mathbf{w}_t = \left[ \text{diag}(\lambda) \mathbf{w}_t - \mathbf{w}_t^\top \text{diag}(\lambda) \mathbf{w}_t \right] dt. \tag{3.3}
\]

With the continuous Oja’s rule being deterministic as in Equation 3.3, it is then not difficult to have a tight analysis on its convergence using tools from ODE as explained in the next subsection.

### 3.2 One-sided versus two-sided linearization

In this subsection, we analyze Equation 3.3 by linearizing the dynamic at 0 and 1 respectively and get two incomparable convergence rates (Theorem 3.4 and Theorem 3.5).

**Theorem 3.4** (Linearization at 0). Suppose \(\mathbf{w}_{0,1} > 0\). For any \(\epsilon \in (0,1)\), when \(t \geq \Omega \left( \frac{\log(1/\epsilon)}{\epsilon (\lambda_1 - \lambda_2)} \right)\), we have \(w_{t,1}^2 > 1 - \epsilon\).

**Theorem 3.5** (Linearization at 1). Suppose \(\mathbf{w}_{0,1} > 0\). For any \(\epsilon \in (0,1)\), when \(t \geq \Omega \left( \frac{\log(1/\epsilon)}{\mathbf{w}_{0,1}^2 (\lambda_1 - \lambda_2)} \right)\), we have \(w_{t,1}^2 > 1 - \epsilon\).

---

\(^8\)Though here is a caveat that the length of the input vector might not be 1. Nevertheless, the point of continuous dynamic is not to exactly characterize the limiting behavior of discrete Oja’s rule. Instead, the goal here is to capture the intrinsic properties of the biological Oja’s rule.

\(^9\)Here we abuse the notation of \(\Delta\). When we write \(\Delta B_j\), the \(\Delta\) is regarded as an operator instead of the interval length.

\(^{10}\)This replacement might look weird for those who have not seen Brownian motion before. But this is standard and can be found in textbook such as [LG16].
The proofs for Theorem 4.1 and Theorem 4.2 are based on applying Taylor’s expansion on Equation 3.3 with center either being 0 or 1. Then, we approximate the dynamics with linear differential equations and use tools from ODE to get an tight analysis. See Appendix B for the details on the linearizations of continuous Oja’s rule.

When starting with a random vector, i.e., \( w_{0,1} = \Omega(1/\sqrt{n}) \) with high probability, the above convergence rates become \( O\left(\frac{\log n}{\delta(\lambda_1 - \lambda_2)}\right) \) and \( O\left(\sqrt{n}\log(1/\epsilon)\right) \) respectively. This indicates that linearizing only on one side (either at 0 or at 1) would not give tight analysis. Nevertheless, if we invoke Theorem 3.4 with the error parameter being 0.5, then for some \( t_1 = O\left(\frac{\log n}{\lambda_1 - \lambda_2}\right) \), we have \( w_{t_1,1} > 0.5 \). Next, we invoke Theorem 3.5 starting from \( w_{t_1} \) and with the error parameter being \( \epsilon \), then for some \( t_2 = O\left(\frac{\log(1/\epsilon)}{\lambda_1 - \lambda_2}\right) \), we have \( w_{t_1+t_2,1} > 1 - \epsilon \). Putting these together, we have the following theorem combining the linearizations on both sides.

**Theorem 3.6 (Linearization at both 0 and 1).** Suppose \( w_{0,1} > 0 \). For any \( \epsilon \in (0, 1) \), when

\[
t > \Omega\left(\frac{1}{w_{0,1}} + \log \frac{1}{\epsilon} \right),
\]

we have \( w^2_{t,1} > 1 - \epsilon \).

The above theorem for the convergence rate of the continuous Oja’s rule gives three key insights. First, it suggests that one should linearize at 0 in the beginning of the process and switch to linearizing at 1 when \( w_{t,1} \) becomes \( \Omega(1) \). Second, after the linearization, using linear ODE to give exact characterization of the dynamic would give tight analysis. Finally, the continuous dynamic is deterministic and will stay around the optimal region for all time after certain point. This suggests that the for-all-time guarantee could potentially happen in the original discrete setting.

## 4 Main Result

Now, let us state the formal version of the main theorem for the biological Oja’s rule. In the following, all of the theorems and lemmas are stated with respect to the setting of Problem 1.2 and Definition 1.3. Thus, for simplicity, we would not repeat the setup in their statements.

In Theorem 4.1, we show that it would not take too much time for the biological Oja’s rule to achieve both constant error and arbitrary small error. Next, in Theorem 4.2 we show that once \( w_t \) becomes \( \epsilon \)-close to the top eigenvector \( v_1 \), it will stay in the neighborhood of \( v_1 \) for a long time. Thus, combining Theorem 4.1 and Theorem 4.2, we can get the standard convergence notions as stated in Theorem 1.7 and Theorem 1.8.

**Theorem 4.1.** For any \( \epsilon, \delta \in (0, 1) \), we have the following results.

- (Phase 1: Toward constant error) Suppose \( w_0 \) is uniformly sampled from the unit sphere of \( \mathbb{R}^n \). Let \( \tau \) to be the stopping time for the event \( \left\{ \frac{(w, v_1)^2}{\|w\|^2} \geq 2/3 \right\} \) and let \( \eta_t = \eta = O\left(\frac{\delta^2(\lambda_1 - \lambda_2)}{\lambda_1 \log^2 \frac{n}{\delta(\lambda_1 - \lambda_2)}}\right) \), then there exists \( t_1 = O\left(\frac{\log(n/\delta)}{\eta(\lambda_1 - \lambda_2)}\right) \) such that \( \Pr[\tau \leq t_1] \geq 1 - \delta \). Specifically, we have

\[
t_1 = O\left(\frac{\lambda_1 \log \frac{n}{\delta} \log^2 \frac{n}{\delta(\lambda_1 - \lambda_2)}}{\delta(\lambda_1 - \lambda_2)^2}\right).
\]

- (Phase 2: Toward arbitrarily small error) Suppose \( \frac{(w_0, v_1)^2}{\|w_0\|^2} = \Omega(1) \). For any \( t \in \mathbb{N} \), let \( \eta_t = \eta = O\left(\frac{\epsilon(\lambda_1 - \lambda_2)}{\lambda_1 \log \log \frac{1}{\epsilon}}\right) \), then there exists \( t_2 = O\left(\frac{\log(1/\epsilon)}{\eta(\lambda_1 - \lambda_2)}\right) \) such that \( \Pr\left[\frac{(w_{t_2}, v_1)^2}{\|w_{t_2}\|^2} \geq 1 - \epsilon\right] \geq 1 - \delta \). Specifically, we have

\[
t_2 = O\left(\frac{\lambda_1 \log \frac{1}{\epsilon} \log \log \frac{1}{\epsilon}}{\epsilon(\lambda_1 - \lambda_2)^2}\right).
\]
Proof structure of Theorem 4.1 To prove Theorem 4.1, we first reduce the general setting where the covariance matrix $A$ being PSD to the special case where $A = \text{diag}(\lambda)$ in Section 5.1. Next, an important property of biological Oja’s rule showing the boundedness of $\|w_t\|_2^2$ is provided in Section 5.2. The rest of the proof proceeds in two phases: In Phase 1 (see Section 6), we analyze the speed of biological Oja’s rule getting constant error using linearization at 0. This is summarized in Theorem 6.1. In Phase 2 (see Section 7), we analyze how fast does biological Oja’s rule go from constant error regime to the $\epsilon$ error regime. This is summarized in Theorem 7.1.

Theorem 4.2. For any $\epsilon, \delta \in (0, 1)$, suppose $\frac{(w_0, v_1)^2}{\|w_0\|_2^2} \geq 1 - \epsilon/2$, we have the following results.

• (Fixed learning rate) For any $T, t \in \mathbb{N}$, let $\eta_t = \eta = O\left(\frac{\epsilon (\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{T}{\delta}}\right)$, then
  \[
  \Pr \left[ \forall t \leq T, \frac{(w_t, v_1)^2}{\|w_t\|_2^2} \geq 1 - \epsilon \right] \geq 1 - \delta.
  \]

• (Slowly diminishing learning rate) For any $t \in \mathbb{N}$, let $\eta_t = O\left(\frac{\epsilon (\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{T}{\delta}}\right)$, then
  \[
  \Pr \left[ \forall t \in \mathbb{N}, \frac{(w_t, v_1)^2}{\|w_t\|_2^2} \geq 1 - \epsilon \right] \geq 1 - \delta.
  \]

Proof structure of Theorem 4.2 The proof of Theorem 4.2 is a direct application of Lemma 7.4 from Phase 2. Since there is no new technique involves except properly setting the parameters, we postpone the whole proof to Appendix F.

5 Preprocessing

Before the main analysis of biological Oja’s rule, we provide two useful observations on the dynamic in this section. Specifically, we show in Section 5.1 that considering the covariance matrix being diagonal is sufficient for the analysis and in Section 5.2 that $\|w_t\|_2^2 = 1 \pm O(\eta)$ almost surely for all $t \in \mathbb{N}$.

5.1 A reduction to the diagonal case

In this subsection, we show that it suffices to analyze the case where the covariance matrix $A$ is a diagonal matrix $D$. Recall that $A$ is defined as the expectation of $xx^\top$ and thus it is positive semidefinite. Namely, there exists an orthonormal matrix $U$ and a diagonal matrix $D$ such that $A = UDU^\top$. Especially, the eigenvalues of $A$, i.e., $1 \geq \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \geq 0$, are the entries of $D$ from top left to bottom right on the diagonal. Thus, by a change of basis, we can focus on the case where $A = D$ without loss of generality.

To see this, consider $\tilde{w}_t = Uw_t$ and $\tilde{x}_t = UX_t$. As $U^\top U = UU^\top = I$, we have $\tilde{x}_t^\top \tilde{w} = x_t^\top w$ and $\mathbb{E}[\tilde{x}\tilde{x}^\top] = D$. Let $v_1$ be the top eigenvector of $A$ (i.e., the first row of $U$), we also have

$$\|w_t - v_1\|_2 = \|Uw_t - Uv_1\|_2 = \|\tilde{w}_t - e_1\|_2$$

where $e_1$ is the indicator vector for the first coordinate. Namely, it suffices to analyze how fast does $\tilde{w}_t$ converge to $e_1$. Thus, in the rest of this paper, we without loss of generality consider the diagonal case where the goal would then be showing that $w_{t,1}^2 \geq 1 - \epsilon$.

5.2 Bounded conditions of Oja’s rule

In this subsection, we show that the $\ell_2$ norm of the weight vector is always close to 1 almost surely.

Lemma 5.1. For any $\eta \in (0, 0.1)$, if for all $t \in \mathbb{N}$, $\eta_t \leq \eta$, then for all $t \in \mathbb{N}_{\geq 0}$, $1 - 10\eta \leq \|w_t\|_2^2 \leq 1 + 10\eta$ almost surely.
Proof. Here we only prove the upper bound while the lower bound can be proved using the same argument. The proof is based on induction. For the base case where \( t = 0 \), we have \( \|w_0\|_2^2 = 1 \) from the problem setting. For the induction step, consider any \( t \in \mathbb{N} \) such that \( w_{t-1} \) satisfies the bounds, we have

\[
\|w_t\|_2^2 = \|w_{t-1}\|_2^2 + 2\eta_t \cdot w_{t-1}^\top \left[ x_t^\top w_{t-1} x_t - (x_t^\top w_{t-1})^2 w_{t-1} \right] + \eta_t^2 \cdot \|x_t^\top w_{t-1} x_t - (x_t^\top w_{t-1})^2 w_{t-1}\|_2^2
\]

\[
= \|w_{t-1}\|_2^2 - 2\eta_t (x_t^\top w_{t-1})^2 \cdot (\|w_{t-1}\|_2^2 - 1) + 2\eta_t^2 (x_t^\top w_{t-1})^2 \cdot \max\{\|x_t\|_2^2, (x_t^\top w_{t-1})^2\|w_{t-1}\|_2^2\}.
\]

Consider two cases: (i) \( \|w_{t-1}\|_2^2 \leq 1 + 8\eta \) and (ii) \( 1 + 8\eta < \|w_{t-1}\|_2^2 \leq 1 + 10\eta \). Note that \( \|w_t\|_2^2 \leq 1 + 10\eta \) in both cases. This completes the induction and the proof.

\[\square\]

6 Phase 1: Toward Constant Error

In this section, we study the stopping time \( \tau \) for the event \( \{w_{t,1}^2 \geq \frac{4}{\delta}\} \). We show that for any failure probability \( \delta \in (0, 1) \), we have \( \Pr[\tau > t_1] < \delta \) for some \( t_1 = \tilde{O}(\lambda_2^{-2} \text{gap}^{-2}) \). The following is the formal theorem statement.

**Theorem 6.1.** For any \( n \in \mathbb{N} \), \( \delta \in (0, 1) \), \( w_0 \) a random unit vector in \( \mathbb{R}^n \), and

\[
\eta = O\left( \frac{\delta^2 (\lambda_1 - \lambda_2)}{\lambda_1 \log^{\frac{n}{\delta(\lambda_1 - \lambda_2)}}} \right)
\]

there exists

\[
t_1 = O\left( \frac{\log^2 \frac{\delta}{\eta}}{\frac{\delta}{\eta}} \right)
\]

such that if for all \( t \in \mathbb{N} \), \( \eta_t = \eta \), then

\[
\Pr[\tau > t_1] < \delta.
\]

Specifically, the stopping time \( \tau \) is of order \( O\left( \frac{\lambda_1 \log \frac{\delta}{\eta} \log^2 \frac{n}{\delta(\lambda_1 - \lambda_2)}}{\delta^2 (\lambda_1 - \lambda_2)} \right) \) with probability at least \( 1 - \delta \).

The proof of Theorem 6.1 contains three steps. First, we linearize the biological Oja’s rule and apply the ODE trick to get a closed-form expression for the updates in Section 6.1. Next, in Section 6.2 we use the corollary of Freedman’s inequality (i.e., Corollary 2.7) to show that the the stopped process of the noise term in this closed-form expression is small and thus the updates will be dominated by the drifting term. Finally, we wrap up the proof in Section 6.3 using stopping time arguments.

**Dictionary for parameters in Phase 1** Since the analysis is recursive, some of the parameters, *e.g.*, the failure probability \( \delta \), are scaled by \( \delta / \log(n/\delta) \) in some of the lemmas. Also, we use \( T \) instead of \( t_1 \) in most of the lemmas because some parameters depend on \( T \) so in the end we will fix \( T = t_1 \) and show that all the conditions hold. In Table 2, we provide a dictionary of parameters for the reader to recall from time to time during the reading.

<table>
<thead>
<tr>
<th>Time length</th>
<th>Stopping time</th>
<th>Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_1 ) and ( T )</td>
<td>( \tau ) and ( \xi )</td>
<td>( w_{t,1}^2 ) from ( \frac{\xi^2}{\eta} ) to ( \frac{4}{\delta} )</td>
</tr>
<tr>
<td>( t_1' = \frac{t_1}{10\log(n/\delta)} )</td>
<td>( \tau' ) and ( \tau_i )</td>
<td>( w_{t,1}^2 ) from ( a ) to ( 4a )</td>
</tr>
</tbody>
</table>

Table 2: Some potentially confusing parameters in Phase 1.
6.1 Linearization and ODE trick centered at 0

In this subsection, we describe the linearization of biological Oja’s rule and ODE trick with center at 0. The point here is to get a closed-form expression in Equation 6.5 where the initial point \( w_{t_0,1} \) is decoupled with the noise terms. Specifically, the noise terms are martingales (or submartingales) with well-controlled bounded difference and conditional variance.

**Lemma 6.2** (Linearization in Phase 1). For any \( t \in \mathbb{N} \) and \( \eta \in (0, 0.1) \), we have

\[
 w_{t,1} = H_t \cdot w_{t-1,1} + \eta D_t + \eta F_t + \eta^2 Q_t
\]

almost surely where \( H_t, D_t, F_t, Q_t \) are some random processes depend on \( w_{t-1} \) and \( x_t \). Specifically,

\[
 D_t = \sum_{i=2}^{n} x_{t,i} x_{t-1,i} \quad \text{and} \quad H_t = \exp\left(\eta(\lambda_1 - \lambda_2)(1 - w_{t-1,1}^2) + \eta E_t\right).
\]

Furthermore, the following hold.

- **(Bounded difference)** For any \( t \in \mathbb{N} \), \( E_t \geq 0 \), \( |F_t| = O(w_{t-1,1}) \), and \( |Q_t| = O(w_{t-1,1}) \) almost surely.
- **(Conditional expectation)** For any \( t \in \mathbb{N} \), \( \mathbb{E}[F_t \mid F_{t-1}] = 0 \) and \( \mathbb{E}[Q_t \mid F_{t-1}] = O(\lambda_1 w_{t-1,1}) \).
- **(Conditional variance)** For any \( t \in \mathbb{N} \), \( \text{Var}[F_t \mid F_{t-1}] = O(\lambda_1^2 w_{t-1,1}^2) \) and \( \text{Var}[Q_t \mid F_{t-1}] = O(\lambda_1^2 w_{t-1,1}^2) \).

**Proof of Lemma 6.2.** The proof is based on Taylor’s expansion and Cauchy-Schwarz inequality. See Appendix E for the full proof.

It turns out that the cross term, i.e., \( D_t \), is the most annoying term and we need the following extra lemma to control its bounded difference as well as its conditional variance. The way we handle \( D_t \) is introducing another stopping time \( \xi \) and a time parameter \( T \) such that (i) the bounded difference and the conditional variance of the stopped process \( D_{t\wedge \xi} \) is under control and (ii) \( \xi \geq T \) with high probability. Intuitively, \( \xi \) is the stopping time for some “bad events” and we want the probability of the “bad events” happening before \( T \) to be small.

Throughout the proof, the reader should think of \( T \) as \( t_1 \). We decide not to directly state the lemma in terms of \( t_1 \) because there are some recursive dependencies between \( T \) and other parameters (e.g., \( \eta \)). In the end of the proof of Theorem 6.1, we will fix \( T \) to be \( t_1 \) and show that every conditions hold.

**Lemma 6.3** (Bounds for \( D_t \)). Let \( w_0 \) be a random unit vector in \( \mathbb{R}^n \). For any \( T \in \mathbb{N} \), \( \delta \in (0, 1) \), if \( \eta = O\left(\frac{\sqrt{\lambda_1^2 - \lambda_2^2}}{\lambda_1 \log^2 \frac{nT}{\delta}}\right) \), then there exists a stopping time \( \xi \) such that the following hold.

1. \( \Pr[\xi \geq T] \geq 1 - \delta \).
2. **(Bounded difference)**

\[
 \Pr\left[|D_{t\wedge \xi}| = O\left(\frac{w_{(t\wedge \xi)-1,1}}{\delta} \sqrt{\log \frac{nT}{\delta}}\right)\right] = 1, \quad \forall t \in [T].
\]

3. **(Conditional variance)**

\[
 \text{Var}[D_{t\wedge \xi} \mid F_{t-1}] = O\left(\frac{\lambda_1 w_{(t\wedge \xi)-1,1}^2 \log \frac{nT}{\delta}}{\delta^2}\right), \quad \forall t \in [T].
\]

**Proof of Lemma 6.3.** The proof of Lemma 6.3 improves on the Markov-type inequality on a multi-dimensional chain of [AZL17] by considering a different multi-dimensional chain and using a vector form of ODE trick to gain a tight exponential bound in one-shot. Since the basic strategy is similar to the techniques in phase 2, we postpone the proof to Appendix D.
Finally, apply the ODE trick (i.e., Lemma 2.11) on Lemma 6.2, we get the following corollary.

**Corollary 6.4** (ODE trick in Phase 1). For any \( t_0 \in \mathbb{N}_{\geq 0} \), \( t \in \mathbb{N} \), and \( \eta \in (0, 0.1) \), we have

\[
\mathbf{w}_{t_0+t,1} = \left( \prod_{i=t_0+1}^{t_0+t} H_i \right) \cdot \left( \mathbf{w}_{t_0,1} + \sum_{i=t_0+1}^{t_0+t} \frac{\eta D_i + \eta F_i + \eta^2 Q_i}{\prod_{j=t_0+1}^{i} H_j} \right). \tag{6.5}
\]

### 6.2 Concentration of the noise terms

After using the ODE trick to rewrite the dynamic of biological Oja’s rule, we would like to show that the second parenthesis of Equation 6.5 is dominated by \( \mathbf{w}_{0,1} \). In that case, it is then not difficult to argue that \( \mathbf{w}_{t,1} \) grows as fast as one can expect. Let us start with the following lemma analyzing the concentration of the noise terms (i.e., the \( D_i \), \( F_i \), and \( Q_i \) term in the second parenthesis). Note that since we do not have good control on the bounded difference and conditional variance on the noise terms, we are going to consider the stopped processes of them.

**Lemma 6.6** (Concentration of noise in an interval). Let \( \mathbf{w}_0 \) be a random unit vector in \( \mathbb{R}^n \). For any \( T \in \mathbb{N} \), \( \delta \in (0, 0.5) \), choose \( \eta, \delta' \in (0, 0.5) \) such that \( \delta' = \Omega(\delta/nT) \) and \( \eta = O\left( \frac{\delta^2(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{1}{\delta'}} \right) \). Let \( \xi \) be the stopping time from Lemma 6.3 with the corresponding parameters \((T, \eta, \delta)\). For any \( a \in (0, 1/9) \), and \( t_0 \in \mathbb{N} \) such that \( \mathbf{w}_{t_0,1}^2 \in [a, 4a] \), let \( \tau' \) be the stopping time for the event \( \{\mathbf{w}_{t_0,1}^2 \geq 4a\} \). For all \( t \in \mathbb{N} \) such that \( t_0 + t \leq T \), we have

1. \[
\Pr \left[ \sum_{i=t_0+1}^{(t_0+t)\wedge \xi} \frac{\eta^2 Q_i}{\prod_{j=t_0+1}^{i} H_j} \geq \Omega \left( \frac{\eta \lambda_1 \sqrt{a}}{\lambda_1 - \lambda_2} + \eta \sqrt{\frac{\eta a \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}} \right) \right] < \delta',
\]

2. \[
\Pr \left[ \sum_{i=t_0+1}^{(t_0+t)\wedge \xi} \frac{\eta F_i}{\prod_{j=t_0+1}^{i} H_j} \geq \Omega \left( \sqrt{\frac{\eta \lambda_1 a \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}} \right) \right] < \delta', \quad \text{and}
\]

3. \[
\Pr \left[ \sum_{i=t_0+1}^{(t_0+t)\wedge \xi} \frac{\eta D_i}{\prod_{j=t_0+1}^{i} H_j} \geq \Omega \left( \frac{1}{\delta} \sqrt{\frac{\eta \lambda_1 a \log \frac{1}{\delta'} \log \frac{2T}{\delta}}}{\lambda_1 - \lambda_2} \right) \right] < \delta'.
\]

We state Lemma 6.6 in a very general form because we are going to apply it for several times in the later interval analysis. Concretely, the final analysis will start from setting \( a_1 = \mathbf{w}_{0,1}^2 \) and look at the stopping time for the event \( \{\mathbf{w}_{t_1,1}^2 \geq 4a_1\} \). We show that the concentration lemma (i.e., Lemma 6.6) and the ODE trick (i.e., Corollary 6.4) imply \( \tau_1 \) being small with high probability. Then, we are going to set \( a_2 = 4a_1 \) and repeat the same argument until some \( a_\ell \) reaches 1/9. From Lemma 2.1, such \( \ell \) could be \( O(\log(n/\delta)) \) with high probability. We will pick \( \delta' = \Theta(\delta/(\log(n/\delta))) \) in the end and apply union bound.

To see why Lemma 6.6 would be helpful, the following lemma plugs in the parameters we are going to use later and show that the deviations in the concentration inequalities are small.

**Lemma 6.7** (Parameters for Phase 1). For any \( n \in \mathbb{N} \) and \( \delta \in (0, 1) \), let \( \eta \) and \( t_1 \) be the parameters chosen in Theorem 6.1. For any \( \delta' = \Omega(\delta/nt_1) \), there exists \( C > 0 \) such that for any \( t \geq \frac{C}{\eta(\lambda_1 - \lambda_2)t} \), the following holds.

- (Drifting term)

\[
\exp \left( \frac{5}{9} \eta (\lambda_1 - \lambda_2) t \right) \geq 16.
\]
• (Deviation terms) For any \( a > 0 \)
\[
O\left(\sqrt[4]{\frac{\eta \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}}\right), \quad O\left(\frac{\eta \lambda_1 \sqrt{a}}{\lambda_1 - \lambda_2} + \eta \sqrt[4]{\frac{\eta \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}}\right), \quad O\left(\frac{1}{\delta'} \sqrt[4]{\frac{\eta \lambda_1 \log \frac{1}{\delta'} \log \frac{M}{\delta}}}{\lambda_1 - \lambda_2}\right) \leq \frac{\sqrt{a}}{10},
\]
where all the \( O \) terms are from the concentration inequalities in Lemma 6.6.

Proof of Lemma 6.7. Both statements immediately follow from checking the parameters.

From Lemma 6.7, one can see that the deviations in the concentration inequalities for the noise terms are quite small (\( \leq \sqrt{a}/10 \)) compared with \( |w_{t_0,1}| \geq \sqrt{a} \). The rest of this subsection is devoted to the proof of the concentration lemma. Reader should feel comfortable to skip it during the first reading.

Proof of the concentration lemma

Proof of Lemma 6.6. Recall that the definition of \( H_j \) is \( H_j = \exp\left(\eta (\lambda_1 - \lambda_2)(1 - w_{j-1,1}^2) + \eta E_j\right) \) and \( \tau' \) is the stopping time for the event \( \{w_{t_0+\tau',1} \geq 4a\} \).

Let us start with the following observation on the multiplier term \( \{w_{t_0+\tau',1} \geq 4a\} \).

Now by the corollary of Freedman’s inequality (i.e., Corollary 2.7), we have

\[
\text{Pr}\left[\sum_{j=1}^{t_0+\tau'} \eta^2 Q_i \geq \Omega\left(\frac{\eta \lambda_1 \sqrt{a}}{\lambda_1 - \lambda_2} + \eta \sqrt[4]{\frac{\eta \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}}\right)\right] < \exp\left(-\Omega\left(\frac{\eta^3 \lambda_1 a \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2} + \eta^2 a \sqrt[4]{\frac{\eta^3 \lambda_1 a \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}}\right)\right) < \delta'.
\]

Note that the \( \eta \sqrt{a} \) term in the deviation is due to the sum of conditional expectation and \( \eta \sqrt[4]{\frac{\eta \lambda_1 \log (1/\delta')}{\lambda_1 - \lambda_2}} \) is due to the bounded difference and conditional variance.

2. Similarly, for the \( F_i \) term, define \( M_0 = 0 \) and
\[
M_t = \sum_{i=t_0+1}^{t_0+t} \frac{\eta F_i}{\prod_{j=t_0+1}^{j} H_j}, \quad \forall t \geq 1.
\]
Note that \( \{M_t\} \) is a martingale and so is its stopped process \( \{M_{t\wedge \tau'}\} \). Since the process stops when \( w_{t_0+t (\wedge \tau')} \geq 4a \), we can upper bound the difference of \( \{M_{t\wedge \tau'}\} \) by \( O(\eta \sqrt{\alpha}) \) almost surely and by Equation 6.8 upper bound the sum of the conditional variance by \( O\left( \frac{\eta^2 \lambda_1 a \log \frac{\delta}{\alpha}}{\eta(\lambda_1 - \lambda_2)} \right) \). By Freedman’s inequality (see Lemma 2.6), we have

\[
\Pr \left[ \sum_{i=1}^{t\wedge \tau'} \eta F_i \prod_{j=1}^{t} H_j \right] \geq \Omega \left( \sqrt{\frac{\eta \lambda_1 a \log \frac{\delta}{\alpha}}{\lambda_1 - \lambda_2}} \right) < \exp \left( -\Omega \left( \frac{\eta \lambda_1 a \log \frac{2}{\alpha}}{\lambda_1 - \lambda_2} \right) \right) < \delta'.
\]

3. Similarly, for the \( D_t \) term, define \( M_0 = 0 \) and

\[
M_t = \sum_{i=t_0+1}^{t} \frac{\eta D_i}{\prod_{j=t_0+1}^{t} H_j}, \ \forall t \leq T - t_0.
\]

Note that \( \{M_t\} \) is a martingale and so is its stopped process \( \{M_{t\wedge \tau'}(\wedge (t-t_0)) \} \). By Lemma 6.3, Equation 6.8, and the definition of \( \tau' \), we can upper bound the difference of \( \{M_{t\wedge \tau'}(\wedge (t-t_0)) \} \) by \( O\left( \eta \sqrt{\alpha \log \frac{nT}{\delta}} \right) \) almost surely and upper bound the sum of the conditional variance by \( O\left( \frac{\eta^2 \lambda_1 a \log \frac{nT}{\delta}}{\delta^2 \eta(\lambda_1 - \lambda_2)} \right) \). By Freedman’s inequality (see Lemma 2.6), we have

\[
\Pr \left[ \sum_{i=t_0+1}^{(t_0+\tau')\wedge \xi} \frac{\eta D_i}{\prod_{j=t_0+1}^{t} H_j} \right] \geq \Omega \left( \frac{1}{\delta^2} \sqrt{\frac{\eta \lambda_1 a \log \frac{2}{\alpha} \log \frac{nT}{\delta}}{\lambda_1 - \lambda_2}} \right)
< \exp \left( -\Omega \left( \frac{\eta^2 \lambda_1 a \log \frac{\delta}{\alpha} \log \frac{nT}{\delta}}{\delta^2 \eta(\lambda_1 - \lambda_2)} \right) \right) < \delta'.
\]

\]

6.3 Wrap up

To prove Theorem 6.1, we do an interval analysis by looking at the stopping time of the form \( \{w_{t_0+t \wedge \tau'} \geq 4a\} \) with \( \alpha \) geometrically growing from \( w_{t_0,1} \) to \( 4/9 \). The following lemma summarizes how the analysis works in a single interval. We will prove Theorem 6.1 after stating this lemma and provide the proof for the lemma in the rest of the section.

**Lemma 6.9** (Interval analysis in Phase 1). For any \( n, T \in \mathbb{N} \) and \( \delta \in (0, 0.5) \), choose any \( \delta' \in (0, 0.5) \) such that \( \delta' = \Omega(\delta/nT) \). For any

\[
\eta = O \left( \frac{\delta^2 (\lambda_1 - \lambda_2)}{\lambda_1 \log^2 \frac{nT}{\delta}} \right)
\]

there exists

\[
t_1' = \Theta \left( \frac{1}{\eta(\lambda_1 - \lambda_2)} \right)
\]

such that the following holds. For any \( a \in (0, 1/9) \) and \( t_0 + t_1' \leq T \) such that \( w_{t_0,1} \in [a, 4a) \), let \( \tau' \) be the stopping time for the event \( \{w_{t_0+t \wedge \tau'} \geq 4a\} \). Then, we have

\[
\Pr [\tau' > t_1'] < \delta'.
\]
Proof of the main theorem in Phase 1

Proof of Theorem 6.1. Now, the proof of Theorem 6.1 follows from recursively invoking Lemma 6.9 for $O(\log \frac{n}{\delta})$ times. First, we need to set the parameter $T$. Let $T = t_1 = 10 \log \frac{n}{\delta} t_1'$. Then for

$$\eta = O \left( \frac{\delta^2(\lambda_1 - \lambda_2)}{\lambda_1 \log^2 \frac{n}{\delta(\lambda_1 - \lambda_2)}} \right),$$

it satisfies the condition of Lemma 6.9.

Recall that $\tau$ is the stopping time for the event $\{w_{i,1}^2 \geq 4/9\}$. Let us first invoke Lemma 6.9 with $a_1 = w_{i,1}^2$ and failure probability $\delta' = \frac{\delta}{10 \log(n/\delta)}$. Let $\tau_1$ be the stopping time for $\{w_{i,1}^2 \geq 4a_1\}$, this gives

$$\Pr[\tau_1 > t_1'] < \frac{\delta}{10 \log \frac{n}{\delta}}.$$

Next, for each $i \in \mathbb{N}$, let $a_{i+1} = 4a_i$ if $4a_i < 1/9$ and let $a_{i+1} = 1/9$ otherwise. Also, define $\tau_{i+1}$ inductively to be the stopping time for the event $\{w_{i+1,1}^2 \geq 4a_{i+1}\}$. By invoking Lemma 6.9 with $a_{i+1}$, $\tau_{i+1}$, and failure probability $\delta' = \frac{\delta}{10 \log(n/\delta)}$, we have

$$\Pr[\tau_{i+1} > t_1'] < \frac{\delta}{10 \log \frac{n}{\delta}}.$$

Now, by Lemma 2.1, we have $a_1 = w_{0,1}^2 = \delta^2/100n$ with probability at least $1 - \delta/10$. Let $\ell$ be the index such that $a_\ell = \frac{1}{5}$, we have $\ell \leq 9 \log(n/\delta)$ with probability at least $1 - \delta/10$. Finally, by union bound, we have

$$\Pr[\tau > t_1] \leq \Pr \left[ \tau > 9 \log \frac{n}{\delta} \right] \leq \Pr \left[ \ell > 9 \log \frac{n}{\delta} \lor \bigvee_{i=1}^{\ell} \tau_i > \ell \cdot t_1' \right]$$

$$= \Pr \left[ \ell > 9 \log \frac{n}{\delta} \right] + \Pr \left[ \ell \leq 9 \log \frac{n}{\delta} \land \bigwedge_{i=1}^{\ell} \tau_i > \ell \cdot t_1' \right]$$

$$< \frac{\delta}{10} + 9 \log \frac{n}{\delta} \cdot \frac{\delta}{10 \log \frac{n}{\delta}} = \delta.$$

This completes the proof of Theorem 6.1. \qed

Proof of the interval analysis

Proof of Lemma 6.9. Denote the failure event $\{\tau' > t_1'\}$ as BAD, the goal is to show that $\Pr[\text{BAD}] < \delta'$. The high-level strategy here is to use the concentration of (the stopped process of) the noise terms and ODE trick to guarantee $w_{i,1}$ is going to follow the drifting term with high probability. To formalize this idea, we have to get rid of the stopping time in Lemma 6.6. Nevertheless, it turns out that in Phase 1 we do not need pull-out lemma to achieve this.

First, denote the good event where the noise terms in the ODE trick are small as follows.

$$\text{GOOD} := \left\{ \left| \sum_{i=t_0+1}^{t_0+(t_1' \wedge \tau')} \eta F_i \right| \leq \frac{\delta}{10}, \left| \sum_{i=t_0+1}^{t_0+(t_1' \wedge \tau')} \eta^2 Q_i \right| \leq \frac{\delta}{10}, \left| \sum_{i=t_0+1}^{t_0+(t_1' \wedge \tau')} \eta D_i \right| \leq \frac{\delta}{10} \right\}.$$

Note that with the parameter settings, from Lemma 6.7, the good events are exactly the events from the concentration inequalities in Lemma 6.6. Thus, we have $\Pr[\text{GOOD}] \geq 1 - \delta/2$. Also, by Lemma 6.3, we have $\Pr[\{\xi \geq T\}] \geq 1 - \delta/2$. The following claim shows that the events GOOD, BAD, and $\{\xi \geq T\}$ cannot happen simultaneously due to ODE trick.

Claim 6.10. $\Pr[\text{GOOD} \land \text{BAD} \land \{\xi \geq T\}] = 0$. Namely, $\Pr[\text{BAD}] \leq 1 - \Pr[\text{GOOD} \land \{\xi \geq T\}]$. 

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Theorem 7.1. For some analysis of biological Oja’s rule. Let us first state the main theorem in this section as follows.

Namely, the convergence rate is of order \( \eta D_1 + \eta F_1 + \eta^2 Q_1 \) for some \( \eta \). Combine the above three, we have

\[
\eta D_1 + \eta F_1 + \eta^2 Q_1 = \left( \frac{t_0 + t_1'}{t_0 + t_1'} \right) \cdot \left( \frac{t_0 + t_1'}{t_0 + t_1'} \right) \cdot \left( \frac{t_0 + t_1'}{t_0 + t_1'} \right).
\]

Also, because \( i \leq \tau' \) for all \( i \in [t_1'] \), we have \( \eta D_1 + \eta F_1 + \eta^2 Q_1 \leq 4a \leq 4/9 \) and thus \( H_i \geq \exp (\frac{5}{9} \eta (\lambda_1 - \lambda_2) t_1') \). By the choice of parameters (i.e., Lemma 6.7), we have

\[
\frac{t_0 + t_1'}{t_0 + t_1'} \cdot \exp (\frac{5}{9} \eta (\lambda_1 - \lambda_2) t_1') \geq 16.
\]

Further, the events GOOD implies

\[
\left| \sum_{i=t_0}^{t_0 + t_1'} \eta D_i + \eta F_i + \eta^2 Q_i \right| \leq \frac{\sqrt{\lambda}}{2}.
\]

Combine the above three, we have

\[
\eta D_1 + \eta F_1 + \eta^2 Q_1 \geq \left( \frac{t_0 + t_1'}{t_0 + t_1'} \right)^2 \cdot \left( \frac{t_0 + t_1'}{t_0 + t_1'} \right)^2 \geq 16 \cdot \frac{a}{4} \geq 4a
\]

which implies \( \tau' \leq t_1' \) and contradicts to the happening of BAD. Thus, we conclude that the events \( \text{GOOD, BAD, and } \{\xi \geq T\} \) cannot happen simultaneously and this completes the proof for the claim.

Proof of Claim 6.10. For the sake of contradiction, assume \( \text{GOOD, BAD, and } \{\xi \geq T\} \) happen simultaneously. Note that \( t_1' \land \tau' = t_1' \) and \( (t_0 + (t_1' \land \tau')) \land \xi = t_1' \) under this assumption. Intuitively, the stopping times were pulled out in this situation.

Now, by the ODE trick (i.e., Corollary 6.4), we have

\[
w_{t_0+t_1'} = \left( \prod_{i=t_0+1}^{t_0+t_1'} H_i \right) \cdot \left( \prod_{i=t_0+1}^{t_0+t_1'} H_i \right) \cdot \left( \prod_{i=t_0+1}^{t_0+t_1'} H_i \right).
\]

Finally, Lemma 6.6 immediately follows from Claim 6.10. Concretely,

\[
\Pr[\tau' > t_1'] = \Pr[\text{BAD}] \leq 1 - \Pr[\text{GOOD} \land \{\xi \geq T\}] \leq \Pr[\neg \text{GOOD}] + \Pr[\neg \{\xi \geq T\}] < \frac{\delta}{2} + \frac{\delta}{2} = \delta.
\]

This completes the proof of Lemma 6.6.

7 Phase 2: Toward Arbitrarily Small Error

Suppose \( w_{t_0,1} \geq 2/3 \) for some \( t_0 \in \mathbb{N} \). For any \( \epsilon \in (0, 1) \), the goal of this section is to show that \( 1 - w_{t_0+t,1}^2 \leq \epsilon \) for some \( t = O\left( \frac{\lambda_1 \log (1/\epsilon) \log \log \log (1/\epsilon) + \log (1/\delta)}{\epsilon (\lambda_1 - \lambda_2)^2} \right) \). Note that analogous result that starts from \( w_{t_0,1} \leq -2/3 \) is an immediate corollary. Thus, combining with the previous section we would be able to complete the analysis of biological Oja’s rule. Let us first state the main theorem in this section as follows.

Theorem 7.1. For some \( t_0 \in \mathbb{N} \), suppose \( w_{t_0,1} \geq 2/3 \). For any \( n \in \mathbb{N} \), \( \epsilon, \delta \in (0, 1) \), there exists

\[
\eta = O\left( \frac{\epsilon (\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{\log \log (1/\epsilon) + \log (1/\delta)}{\delta}} \right), \quad t_2 = O\left( \frac{\log (1/\epsilon)}{\eta (\lambda_1 - \lambda_2)} \right)
\]

such that

\[
\Pr[w_{t_0+t_2,1} < 1 - \epsilon] < \delta.
\]

Namely, the convergence rate is of order \( t_0 + O\left( \frac{\lambda_1 \log \frac{1}{\epsilon} \log \log \log (1/\epsilon) + \log (1/\delta)}{\epsilon (\lambda_1 - \lambda_2)^2} \right) \) with probability at least \( 1 - \delta \).
The proof structure of Theorem 7.1 is the same as that of the main theorem in Phase 1. However, each step requires some non-trivial modifications. First, we derive a different linearization and ODE trick in Section 7.1 using center at 1 instead of 0. Next, in Section 7.2 we state the lemma showing that the noise terms in the ODE trick are small and further use the lemma to wrap up the proof for the main theorem in Section 7.3. Nevertheless, it turns out that the noise terms in Phase 2 are more difficult to handle. We develop a pull-out lemma to get rid of the stopping time in the concentration inequality. The details of how we handle the noise is provided in Section 7.4.

**Dictionary for parameters in Phase 2** Similarly, the analysis in Phase 2 is recursive and thus some of the parameters, e.g., the failure probability \( \delta \), are scaled by \( \delta/\log\log(1/\epsilon) \) in some of the lemmas. We provide a dictionary of parameters for the reader to recall from time to time during the reading.

<table>
<thead>
<tr>
<th>Failure probability</th>
<th>Time length</th>
<th>Error</th>
<th>Goal</th>
</tr>
</thead>
<tbody>
<tr>
<td>The whole analysis</td>
<td>( \delta )</td>
<td>( t_2 = \sum_{k=1}^{\ell} t_{2,k} )</td>
<td>( \epsilon )</td>
</tr>
<tr>
<td>An interval analysis</td>
<td>( \delta' = \frac{\delta}{7} )</td>
<td>( t_{2,k} )</td>
<td>( \epsilon' = \frac{\epsilon}{8} )</td>
</tr>
</tbody>
</table>

Table 3: Some potentially confusing parameters in Phase 2. The parameter \( \ell = [\log\log(1/\epsilon)] \) is the number of intervals we are going to use in the whole analysis.

### 7.1 Linearization and ODE trick centered at 1

In the analysis of Phase 2, we use a different linearization for the biological Oja’s rule. The main difference from the linearization in Phase 1 is that here we do Taylor expansion with center at 1 instead of 0. The idea is inspired from the analysis of the continuous dynamics as explained in Section 3.

To ease the notation, we define \( w_{t,1}' = w_{t,1} - 1 \) and the goal becomes showing that \( w_{t_0+t_2,1}' > -\epsilon \) with probability at least \( 1 - \delta \). The following lemma states the linearization for \( w_{t,1}' \).

**Lemma 7.2** (Linearization in Phase 2). For any \( t \in \mathbb{N} \) and \( \eta \in (0,0.1) \), we have

\[
w_{t,1}' = H \cdot w_{t-1,1}' + \eta F_t + \eta P_t + \eta^2 Q_t
\]

almost surely, where the multiplier is

\[
H = \exp \left( -\frac{3}{4} \eta (\lambda_1 - \lambda_2) \right).
\]

Moreover, \( F_t, P_t, Q_t \) satisfy the following properties.

- **(Bounded difference)** For any \( t \in \mathbb{N} \), \( |F_t| = O(\sqrt{w_{t-1}'} + \eta) \), and \( |Q_t| = O(1) \) almost surely. If \( w_{t-1,1}' \geq 0.5 \), then \( P_t \geq -O(\eta \lambda_1) \) almost surely.

- **(Conditional expectation)** For any \( t \in \mathbb{N} \), \( \mathbb{E}[F_t \mid \mathcal{F}_{t-1}] = 0 \) and \( |\mathbb{E}[Q_t \mid \mathcal{F}_{t-1}]| = O(\lambda_1) \).

- **(Conditional variance)** For any \( t \in \mathbb{N} \), \( \mathbb{V}[F_t \mid \mathcal{F}_{t-1}] = O(\lambda_1 (w_{t-1,1}' + \eta)) \) and \( \mathbb{V}[Q_t \mid \mathcal{F}_{t-1}] = O(\lambda_1) \).

**Proof of Lemma 7.2.** The proof is based on Taylor’s expansion and Cauchy-Schwarz inequality. See Appendix E for the full proof.

Similarly, we apply the ODE trick (see Lemma 2.11) on Lemma 7.2 and get the corollary as follows. Note that one major difference between the ODE trick in the two phases is that here the multiplier \( H \) is a constant and does not depend on \( w_t \).

**Corollary 7.3** (ODE trick in Phase 2). For any \( t_0 \in \mathbb{N}_{\geq 0}, \ t \in \mathbb{N}, \) and \( \eta \in (0,0.1) \), we have

\[
w_{t_0+t,1}' = H^t \cdot \left( \frac{\sum_{i=t_0+1}^{t_0+t} \eta F_i + \eta P_i + \eta^2 Q_i}{H^{t-t_0}} \right).
\]
### 7.2 Concentration of noise

The following key lemma shows the concentration of noise in Phase 2. Similarly, since we are doing an interval analysis so the lemma is stated in a general form.

**Lemma 7.4** (Concentration of noise in an interval). For any $\epsilon', \delta', \eta \in (0, 0.5)$ and $k \in \mathbb{N}_{\geq 0}$ such that $\eta = O\left(\frac{\epsilon'(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{1}{\eta}}\right)$, let $t_{2,k} \in \mathbb{N}$ be

$$t_{2,k} = \frac{4}{3} \cdot \frac{2^{-k} \log \frac{1}{\eta}}{\eta(\lambda_1 - \lambda_2)} + \Theta\left(\frac{2^{-k}}{\eta(\lambda_1 - \lambda_2)}\right).$$

Suppose there exists some $t_0 \in \mathbb{N}$ and $\gamma \in (0, 0.5)$ where $\gamma = \Omega((\epsilon')^{1 - 2^{-k}})$ such that $w_{t_0,1} \geq 1 - \frac{\gamma}{2}$. Then,

$$H^{t_{2,k}} = \exp\left(-\frac{3}{4} \eta(\lambda_1 - \lambda_2) t_{2,k}\right) \leq \frac{(\epsilon')^{2^{-k}}}{10}$$

and

$$\Pr\left[\min_{1 \leq t \leq t_{2,k}} \sum_{i=t_0+1}^{t_0+t} \eta F_i + \eta P_i + \eta^2 Q_i \leq H^{t-t_0} < -\frac{\gamma}{2}\right] < \delta'.$$

The proof of Lemma 7.4 involves stopping time analysis and maximal martingale inequality and is provided in Section 7.4. Let us first take a look at how to use Lemma 7.4 to prove the main theorem in Phase 2.

### 7.3 Wrap up

Now we are ready to prove the main theorem of this section.

**Proof of Theorem 7.1.** Recall that we have $w_{\tau,1} \geq 2/3$ and the goal is to show that $w_{\tau + t_2,1} \geq 1 - \epsilon$ with probability at least $1 - \delta$ for some $t_2 = O\left(\frac{\log(1/\epsilon)}{\eta(\lambda_1 - \lambda_2)}\right)$.

We use an interval analysis to achieve the goal. Specifically, there are going to be $\ell = \lceil \log(1/\epsilon) \rceil$ stages of the analysis. Let $\epsilon' = \epsilon/8$ and $\delta' = \delta/\ell$ be the error and failure probability parameters in each stage. For each $k \in [\ell]$, in the $k$th stage, we are going to show that $\eta F_i$ improve from $1 - (\epsilon')^{1 - 2^{-k}}$ to $1 - (\epsilon')^{1 - 2^{-k}}$ in $t_{2,k}$ steps with probability at least $1 - \delta'$. The following is the formal statement of the guarantee we want to get for each stage in the interval analysis.

**Lemma 7.5** (Interval analysis in Phase 2). Let $n, \epsilon, \delta, \eta$ be the parameters from Theorem 7.1 and $\epsilon', \delta'$ be the parameters as defined above. For each $k \in [\ell]$, let $t_{2,k} = \frac{4}{3} \cdot \frac{2^{-k} \log \frac{1}{\eta}}{\eta(\lambda_1 - \lambda_2)} + \Theta\left(\frac{2^{-k}}{\eta(\lambda_1 - \lambda_2)}\right)$. Then we have

$$\Pr\left[w_{\tau + t_{2,k},1} < 1 - (\epsilon')^{1 - 2^{-k}}\right] < k \cdot \delta'.$$

With the lemma for each interval, we are ready to prove Theorem 7.1. Recall that $\epsilon' = \epsilon/8$ and thus by Lemma 2.17, we have

$$(\epsilon')^{1 - 2^{-\ell}} \leq \left(\frac{\epsilon}{8}\right)^{1 - \frac{\ell}{\log(1/\epsilon)}} \leq \epsilon.$$

Pick $t_2 = \sum_{j=1}^{\ell} t_{2,j}$, we have

$$t_2 = \sum_{j=1}^{\ell} \frac{4}{3} \cdot \frac{2^{-j} \log \frac{1}{\eta}}{\eta(\lambda_1 - \lambda_2)} + \Theta\left(\frac{2^{-j}}{\eta(\lambda_1 - \lambda_2)}\right) = O\left(\frac{\log \frac{1}{\eta}}{\eta(\lambda_1 - \lambda_2)}\right)$$

as desired. Finally, recall that $\delta' = \delta/\ell$ and thus Lemma 7.5 gives

$$\Pr\left[w_{\tau + t_{2,1}} > 1 - \epsilon\right] \leq \Pr\left[w_{\tau + t_{2,1}} > 1 - (\epsilon')^{1 - 2^{-\ell}}\right] < \ell \cdot \delta' = \delta.$$

This completes the proof of Theorem 7.1. The rest of this subsection is devoted to the proof of Lemma 7.5 on the interval analysis.
Proof of the interval analysis

Proof of Lemma 7.5. The proof is based on induction on \( k \in [\ell] \geq 0 \). For the base case where \( k = 0 \), we have \( w_{\tau,1} \geq 2/3 \) by the definition of \( \tau \).

For the induction step, for any \( k \in [\ell] \), let \( \text{GOOD}_k \) denote the event \( \{ w_{\tau+\sum_{j=1}^{k-1} t_{2,j},1} \geq 1 - (\epsilon')^{1-2^{-(k-1)}} \} \). The induction hypothesis gives

\[
\Pr \left[ \neg \text{GOOD}_k \right] \leq (k - 1) \cdot \delta'.
\]

Now, invoke Lemma 7.4 with \( t_0 = \tau + \sum_{j=1}^{k-1} t_{2,j}, \gamma = 2(\epsilon')^{1-2^{-(k-1)}}, \) and \( \epsilon', \delta' \) as chosen before. We have

\[
\Pr \left[ \min_{1 \leq t' \leq t_{2,k}} \sum_{i=t_0+1}^{t_0+t_{2,k}} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{t'-t_0}} \leq -\gamma \frac{10}{10} \bigg| \text{GOOD}_k \right] < \delta'
\]

and

\[
\Pr \left[ H^{t_{2,k}} \leq \left( \frac{(\epsilon')^{2^k}}{10} \right)^{2-k} \bigg| \text{GOOD}_k \right] = 1.
\]

Thus, by the ODE trick (i.e., Corollary 7.3), we have

\[
w'_{t_0+t_{2,k},1} = H^{t_{2,k}} \cdot \left( w_{t_0,1} + \sum_{i=t_0+1}^{t_0+t_{2,k}} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{t'-t_0}} \right).
\]

Condition on the event \( \text{GOOD}_k \), we have

\[
\geq \frac{(\epsilon')^{2^k}}{10} \cdot \left( \frac{-\gamma}{2} \right) \geq (\epsilon')^{2^{-k}} \cdot (\epsilon')^{1-2^{-(k-1)}} \geq -\epsilon')^{1-2^{-k}}
\]

happens with probability at least \( 1 - \delta' \). Namely,

\[
\Pr \left[ w_{\tau+\sum_{j=1}^{k-1} t_{2,j},1} < 1 - (\epsilon')^{1-2^{-k}} \right] = \Pr \left[ w'_{\tau+\sum_{j=1}^{k-1} t_{2,j},1} < -\epsilon')^{1-2^{-k}} \right]
\]

\[
\leq \Pr \left[ w'_{\tau+\sum_{j=1}^{k-1} t_{2,j},1} < -\epsilon')^{1-2^{-k}} \bigg| \text{GOOD}_k \right] + \Pr[\neg \text{GOOD}_k]
\]

\[
< \delta' + (k - 1) \cdot \delta' = k \cdot \delta'.
\]

This completes the induction and the proof for the interval analysis.

\( \square \)

7.4 Proof of Lemma 7.4

Now, the only missing part in this section is the proof of Lemma 7.4. Recall that the goal is to show that the noise term in the ODE trick (Corollary 7.3) is small with high probability.

High-level idea on the proof of Lemma 7.4 The most natural way to prove such statement is using martingale concentration inequality as the noise term is a martingale by construction. However, the difficulty here is that \( w_{t,1} \) might go back to the small region (e.g., \( w_{t,1} < 1/2 \)) and thus the bounded difference might be large and ruin the condition of Freedman’s inequality. Note that this “going back phenomenon” is the major difference between Phase 1 and Phase 2 and thus the simple proof of the former cannot be applied to the later. Nevertheless, the continuous dynamic (see Section 3) suggests that this situation should happen with small probability. To enforce the analysis, we consider a stopped process where the dynamic stops once \( w_{t,1} < 1/2 \). Concretely, let \( t_0 \) be the time when we enter Phase 2, i.e., \( w_{t_0,1} \geq 2/3 \), and let \( \tau \) be the stopping time for the event \( \{ w_{t_0+\tau,1} < 1/2 \} \). Denote the noise term in Corollary 7.3 as \( \{ M_{t_0+t'} \}_{t' \in \mathbb{N}} \), which is a martingale by construction. Consider its stopped process \( \{ M_{t_0+t'} \}_{t' \in \mathbb{N}} \), which is also a martingale due to
the property of stopping time. Moreover, the stopped process satisfies good bounded difference condition by its construction and thus Freedman’s inequality works well. See Lemma 7.6 for a formal and more general statement on the above intuition.

After obtaining a good control on the noise term in the stopped process, we would like to remove the stopping time and get back to the original non-stopped process in order to prove Lemma 7.4. This can be done by Lemma 7.9 which pulls out the stopping time from the concentration inequality for the stopped process. In general, pulling out the stopping time is impossible, however, there are some structures in the martingale we are looking at. Intuitively, suppose \( \tau \geq t \) for some \( t \), then this would imply that all the noise terms before time \( t_0 + t \) are small with high probability (using maximal martingale inequality). Next, the noise being small at time \( t_0 + t \) would further imply that \( \tau \geq t + 1 \) (using ODE trick). This would form a chain of implications as pictured in Figure 3.

\[
\begin{align*}
\tau \geq t & \quad \text{Definition} \quad \text{noises before time } t_0 + t \text{ are small} \\
\tau \geq t + 1 & \quad \text{Definition} \quad \text{noises before time } t_0 + t + 1 \text{ are small}
\end{align*}
\]

Figure 3: Intuition on why it is possible to pull out stopping time in Phase 2.

With the above chain structure in the noise terms, we are then able to pull out the stopping time in Lemma 7.6 by introducing another stopping time to help us properly partition the probability space. The rest of this subsection is devoted to formalize the above intuition and complete the proof for Lemma 7.4.

**Noise concentration for the stopped process** The first step towards proving Lemma 7.4 is showing the concentration of the noise terms in the stopped process.

**Lemma 7.6** (Bounds for the noise terms in the stopped process in Phase 2). For any \( t \in \mathbb{N} \), \( \eta, \epsilon, \delta \in (0,1) \), \( t_0 \in \mathbb{N} \) and \( \gamma \in (0, 0.5) \) such that \( \eta = O \left( \frac{\lambda_1 - \lambda_2}{\lambda_2 \log(1/\delta)} \right) \), define stopping time \( \tau \) to be the first time of the event \( \{w_{t_0+\tau} < 1 - \gamma\} \).

Then, we have

1. \[
\Pr \left[ \min_{1 \leq t' \leq t} \sum_{i=t_0+1}^{t_0+(t' \wedge \tau)} \eta P_i \frac{H_{i-t_0}}{H_{i-t_0}^i} \geq -O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \frac{\eta \lambda_1}{\lambda_1 - \lambda_2} \right) \right] = 1,
\]

2. \[
\Pr \left[ \max_{1 \leq t' \leq t} \sum_{i=t_0+1}^{t_0+(t' \wedge \tau)} \eta F_i \frac{H_{i-t_0}}{H_{i-t_0}^i} \geq \Omega \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \sqrt{\eta \gamma + \eta} \frac{\lambda_1}{\lambda_1 - \lambda_2} \log \frac{1}{\delta} \right) \right] < \delta, \quad \text{and}
\]

3. \[
\Pr \left[ \max_{1 \leq t' \leq t} \sum_{i=t_0+1}^{t_0+(t' \wedge \tau)} \eta^2 Q_i \frac{H_{i-t_0}}{H_{i-t_0}^i} \geq \Omega \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \sqrt{\eta \gamma + \eta} \frac{\lambda_1}{\lambda_1 - \lambda_2} \log \frac{1}{\delta} + \frac{\eta \lambda_1}{\lambda_1 - \lambda_2} \right) \right] < \delta.
\]

To see why Lemma 7.6 would be helpful, the following lemma plugs in the parameters we are going to use later and show that the deviations in the concentration inequalities are small.
Lemma 7.7. For any $k \in \mathbb{N}$, let $\epsilon', \delta', \gamma, \eta, t_{2,k}$ be the parameters from Lemma 7.4. Then we have

1. 
\[
O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t_{2,k} \right) \frac{\eta \lambda_1}{\lambda_1 - \lambda_2} \right) \leq \frac{\gamma}{10},
\]

2. 
\[
O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t_{2,k} \right) \sqrt{\frac{\eta (\gamma + \eta) \lambda_1}{\lambda_1 - \lambda_2} \log \frac{1}{\delta}} \right) \leq \frac{\gamma}{10},
\]

3. 
\[
O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t_{2,k} \right) \left( \sqrt{\frac{\eta^2 \lambda_1}{\lambda_1 - \lambda_2} \log \frac{1}{\delta} + \frac{\eta \lambda_1}{\lambda_1 - \lambda_2}} \right) \right) \leq \frac{\gamma}{10}, \text{ and}
\]

4. 
\[
H^{t_{2,k}} = \exp \left( -\frac{3}{4} \eta (\lambda_1 - \lambda_2) t_{2,k} \right) \leq (\epsilon')^{2^{-k}}.
\]

All the $O$ terms are from the concentration inequalities of Lemma 7.4.

Proof of Lemma 7.7. These items directly follow from the choice of parameters $\epsilon', \delta', \gamma, \eta, t_{2,k}$. \qed

Proof of Lemma 7.6. The proof is based on using the properties of these martingales (see Lemma 7.2) and maximal martingale concentration inequality (e.g., Freedman’s inequality as stated in Lemma 2.6). First, notice that by $\eta (\lambda_1 - \lambda_2) = O(1)$, for any $1 \leq t' \leq t$, we have

\[
\sum_{i=t_0+1}^{t_0 + t'} \frac{1}{H^{i-t_0}} = O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \right) \cdot \text{Lemma 2.15} = O \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \right).
\]

1. From Lemma 7.2, we know that $P_{t_0 + t'} \geq -O(\eta \lambda_1)$ for all $1 \leq t' \leq t$. Combine with Equation 7.8, for any $1 \leq t' \leq t$, we have

\[
\sum_{i=t_0+1}^{t_0 + (t' \wedge \tau)} \frac{\eta P_i}{H^{i-t_0}} \geq -O \left( \frac{\eta \lambda_1 \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right)}{\lambda_1 - \lambda_2} \right)
\]

almost surely.

2. Let $M_0 = 0$ and for each $1 \leq t' \leq t$, let $M_{t'} = \sum_{i=t_0+1}^{t_0 + t'} \frac{\eta F_i}{H^{i-t_0}}$. Note that both $\{M_t\}$ and $\{M_{t' \wedge \tau}\}$ form martingales. Also, recall that $H = \exp(-3\eta (\lambda_1 - \lambda_2)/4)$. Moreover, by Lemma 7.2, the bounded difference of $\{M_{t' \wedge \tau}\}$ is $O(\eta \sqrt{\gamma + \eta} \exp(\frac{3}{4} \eta (\lambda_1 - \lambda_2) t))$ and the sum of the conditional variance of $\{M_{t' \wedge \tau}\}$ can be upper bounded by $O \left( \frac{(\gamma + \eta) \lambda_1 \exp(\frac{3}{4} \eta (\lambda_1 - \lambda_2) t)}{\eta (\lambda_1 - \lambda_2)} \right)$. Now, by the Freedman’s inequality (see Lemma 2.6), we have

\[
\Pr \left[ \max_{1 \leq t' \leq t} \left| \sum_{i=t_0+1}^{t_0 + (t' \wedge \tau)} \frac{\eta F_i}{H^{i-t_0}} \right| \geq \Omega \left( \exp \left( \frac{3}{4} \eta (\lambda_1 - \lambda_2) t \right) \sqrt{\frac{\eta (\gamma + \eta) \lambda_1}{\lambda_1 - \lambda_2} \log \frac{1}{\delta}} \right) \right] < \exp \left( \frac{\eta (\gamma + \eta) \lambda_1 \exp(\frac{3}{4} \eta (\lambda_1 - \lambda_2) t)}{\lambda_1 - \lambda_2} \log \frac{1}{\delta} \right) + \frac{\eta \sqrt{\gamma + \eta} \exp(\frac{3}{4} \eta (\lambda_1 - \lambda_2) t)}{\eta (\gamma + \eta) \lambda_1 \exp(\frac{3}{4} \eta (\lambda_1 - \lambda_2) t) \log \frac{1}{\delta}} < \delta.
\]

The last inequality holds because $\eta = O(\frac{\lambda_1 - \lambda_2}{\lambda_1 \log(1/\delta)})$ and thus the first term in the denominator dominates the second term.
3. Let $M_0 = 0$ and for each $1 \leq t' \leq t$, let $M_{t'} = \sum_{i=t_0+1}^{t_0+t'} \frac{\eta^2 Q_{i}}{H_{t_0+t}}$. By Lemma 7.2, the bounded difference of $\{M_{t',\tau}\}$ is $O(\eta^2 \exp(\frac{3}{4}(\eta(\lambda_1 - \lambda_2)t)))$, the sum of the absolute value of the conditional expectation is bounded by $O\left(\frac{\eta^2 \lambda_1 \exp(\frac{3}{4}\eta(\lambda_1 - \lambda_2)t)}{\eta(\lambda_1 - \lambda_2)}\right)$ and the sum of conditional variance of can be upper bounded by $O\left(\frac{\eta^2 \lambda_1 \exp(\frac{3}{4}\eta(\lambda_1 - \lambda_2)t)}{\eta(\lambda_1 - \lambda_2)}\right)$. Now, by the corollary of Freedman’s inequality (i.e., Corollary 2.7), we have

$$\Pr\left[\max_{1 \leq t' \leq t} \left| \sum_{i=t_0+1}^{t_0+t'} \frac{\eta^2 Q_{i}}{H_{t_0+t'}} - \frac{\eta^2 \lambda_1 \exp(\frac{3}{4}\eta(\lambda_1 - \lambda_2)t)}{\eta(\lambda_1 - \lambda_2)} \log \frac{1}{\delta} \right| - \frac{\eta^2 \lambda_1 \exp(\frac{3}{4}\eta(\lambda_1 - \lambda_2)t)}{\eta(\lambda_1 - \lambda_2)} \log \frac{1}{\delta} \right] < \delta.$$

Similarly, the last inequality holds because $\eta = O\left(\frac{\lambda_1 - \lambda_2}{\lambda_1 \log(1/\delta)}\right)$ and thus the first term in the denominator dominates the second term.

Pulling out the stopping time In the second step towards proving Lemma 7.4, we are going to pull out the stopping time $\tau$ in Lemma 7.6. The following lemma shows that under certain chain condition, it is possible to pull out the stopping time.

**Lemma 7.9.** Let $\{M_i\}_{t \in \mathbb{N}^+}$ be an adapted stochastic process and $\tau$ be a stopping time. Let $\{M_i^*\}_{t \in \mathbb{N}^+}$ be the maximal process of $\{M_i\}_{t \in \mathbb{N}^+}$ where $M_i^* = \max_{1 \leq t' \leq t} M_{t'}$. For any $t \in \mathbb{N}^+$, $a \in \mathbb{R}$, and $\delta \in (0, 1)$, suppose

1. $\Pr[M_i^* \geq a] < \delta$ and
2. $\Pr[\tau \geq t' + 1 \mid M_i^* < a] = 1$ for any $1 \leq t' < t$.

Then, we have

$$\Pr[M_i^* \geq a] < \delta.$$

**Proof of Lemma 7.9.** The key idea is to introduce another stopping time which helps us partition the probability space. Let $\tau'$ be the stopping time for the event $\{M_i^* \geq a\}$. The following claim shows that if $\tau$ stopped before time $t$, then $\tau'$ should stop earlier than $\tau$.

**Claim 7.10.** Let $\tau$ and $\tau'$ be stopping times as defined above. Suppose the conditions in Lemma 7.9 hold. Then we have

$$\Pr[\tau < t, \tau' > \tau] = 0.$$

**Proof of Claim 7.10.** The claim can be proved by contradiction as follows. Suppose both $\tau < t$ and $\tau' > \tau$. By the definition of $\tau'$, we know that $M_i^* < a$ since $\tau < \tau'$. However, by the second condition of the lemma, we then have

$$\Pr[\tau \geq t + 1 \mid M_i^* < a] = 1$$

which is a contradiction.

Next, we would like to show that $\Pr[M_i^* \geq a] \leq \Pr[M_{i,\tau}^* \geq a]$. The idea is partitioning the probability space as follows.

$$\Pr[M_i^* \geq a] = \Pr[M_i^* \geq a, \ \tau \geq t] + \Pr[M_i^* \geq a, \ \tau < t, \ \tau' \leq \tau] + \Pr[M_i^* \geq a, \ \tau < t, \ \tau' > \tau]. \tag{7.11}$$

For the first term of Equation 7.11, when $\tau \geq t$, we have $t = t \land \tau$ and thus $M_i^* = M_{i,\tau}^*$. As for the second term, when $\tau' \leq \tau < t$, we have both $M_i^*, M_{i,\tau}^* \geq a$. Thus, Equation 7.11 becomes

$$= \Pr[M_{i,\tau}^* \geq a, \ \tau \geq t] + \Pr[M_{i,\tau}^* \geq a, \ \tau < t, \ \tau' \leq \tau] + \Pr[M_i^* \geq a, \ \tau < t, \ \tau' > \tau].$$

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Combining the first two terms, we have
\[ \leq \Pr[M_{t_1,\tau}^* \geq a] + \Pr[M_{t,\tau}^* \geq a, \tau < t, \tau' > \tau]. \]
Finally, from Claim 7.10, we know that \( \Pr[\tau < t, \tau' > \tau] = 0 \). Thus, we conclude that \( \Pr[M_{t,\tau}^* \geq a] \leq \Pr[M_{t_1,\tau}^* \geq a] < \delta \) as desired.

Wrap up the proof of Lemma 7.4. Finally, we are ready to prove Lemma 7.4 by using Lemma 7.6 which bounds the the stopped process of the noise terms and Lemma 7.9 which pulls out the stopping time from the concentration inequalities. Let us restate the lemma as follows for the completeness.

Lemma 7.4 (Concentration of noise in an interval). For any \( \epsilon', \delta', \eta \in (0,0.5) \) and \( k \in \mathbb{N}_{\geq 0} \) such that \( \eta = O\left(\frac{\epsilon' \log 1}{\lambda_1 - \lambda_2}\right) \), let \( t_{2,k} \in \mathbb{N} \) be
\[ t_{2,k} = \frac{4}{3} \cdot \frac{2^{-k} \log \frac{1}{\eta}}{(\lambda_1 - \lambda_2)} + \Theta\left(\frac{2^{-k}}{\eta(\lambda_1 - \lambda_2)}\right). \]
Suppose there exists some \( t_0 \in \mathbb{N} \) and \( \gamma \in (0,0.5) \) where \( \gamma = \Omega((\epsilon')^{1-2^{-k}}) \) such that \( w_{t_0,1} \geq 1 - \frac{\gamma}{2} \). Then,
\[ H^{t_{2,k}} = \exp\left(-\frac{3}{4} \eta(\lambda_1 - \lambda_2)t_{2,k}\right) \leq \left(\frac{\epsilon'}{2}\right)^{2^{-k}} \]
and
\[ \Pr\left[ \min_{1 \leq i \leq t_{2,k}} \sum_{i=t_{0}+1}^{t_{0}+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{i-t_{0}}} < -\frac{\gamma}{2} \right] < \delta'. \]

Proof of Lemma 7.4. The first statement of the lemma directly follows from the forth item of Lemma 7.7. For the second statement of the lemma, the proof is based on Lemma 7.9 which pulls out the stopping time.

Let \( \tau \) be the stopping time for the event \( \{w_{t_0+\tau,1} < 1 - \gamma\} \) as defined in Lemma 7.6. Also, define
\[ M_t = -\sum_{i=t_{0}+1}^{t_{0}+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{i-t_{0}}} \]
for any \( t \in \mathbb{N} \). Now by Lemma 7.6 and Lemma 7.7, we have
\[ \Pr\left[ \max_{1 \leq i \leq t_{2,k}} M_i > \frac{\gamma}{2} \right] < \delta. \tag{7.12} \]
Now in order to apply Lemma 7.9 to pull out the stopping time, we need to check the following.
\[ \Pr\left[ \tau \geq j + 1 \mid \max_{1 \leq i \leq j} M_i \leq \frac{\gamma}{2} \right] = 1 \tag{7.13} \]
for any \( 1 \leq j < t_{2,k} \). By the ODE trick (i.e., Corollary 7.3) we have
\[ w'_{t_{0}+j,1} = H^j \left( w'_{t_{0},1} + \sum_{i=t_{0}+1}^{t_{0}+j} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{i-t_{0}}} \right). \]
By the condition in Equation 7.13 and \( w'_{t_{0},1} \geq -\frac{\gamma}{2} \), the ODE trick gives us
\[ \geq H^j \left( -\frac{\gamma}{2} - \frac{\gamma}{2} \right) \geq -\gamma. \]
Note that the above implies that \( w_{t_0+j,1} \geq 1 - \gamma \) which means that \( \tau \geq j + 1 \) as desired. This shows that Equation 7.13 holds.

Finally, invoke the pull-out lemma (i.e., Lemma 7.9) with Equation 7.12 and Equation 7.13, we have the desiring bound as follows.
\[ \Pr\left[ \min_{1 \leq i \leq t_{2,k}} \sum_{i=t_{0}+1}^{t_{0}+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{i-t_{0}}} < -\frac{\gamma}{2} \right] = \Pr\left[ \max_{1 \leq i \leq t_{2,k}} M_i > \frac{\gamma}{2} \right] \leq \Pr\left[ \max_{1 \leq i \leq t_{2,k}} M_i > \frac{\gamma}{2} \right] < \delta. \]
This completes the proof of Lemma 7.4.
8 Conclusions and Future Directions

In this work, our contributions are two-fold. First, we give the first convergence rate analysis for the biological Oja’s rule in solving streaming PCA. In particular, the rate we show is nearly optimal. This provides theoretical evidences for a biologically-plausible streaming PCA mechanism to converge in a biologically-realistic time scale in the retina-optical nerve pathway. Second, we introduce a novel one-shot framework to analyze stochastic dynamics. The framework is simple and captures the intrinsic behaviors of the dynamics. Finally, as a byproduct, the convergence rate we get for the biological Oja’s rule outperforms the state-of-the-art upper bound for streaming PCA (using ML Oja’s rule).

In this section, we discuss the biological and algorithmic significance of our results and point out potential future directions.

8.1 Biological aspect

**Spiking Oja’s Rule** In this paper, we simplify the biological dynamic using a rate-based model. It would be interesting to design a spiking version of the learning rule to solve streaming PCA. On the other hand, it has been shown that Spike Timing Dependent Plasticity (STDP) has self-normalizing behaviors [AN00], so the higher order terms in the biological Oja’s rule might not be needed for the normalization in the spiking version.

**Convergence rate analysis for other biological-plausible learning rules** As mentioned in Section 1.4, there are plenty of Hebbian-type learning rules that had been proposed to solve some computational problems [Sej77, BCM82, San89, OBL00, Apa12, PHC15]. Nevertheless, most of them do not have efficiency guarantee and we think it would be of interest to use our frameworks to systematically analyze the convergence rates of these update rules. This is not only a natural theoretical question but also could potentially provide insights on how these biologically-plausible algorithms are different from standard algorithms.

**Designing biologically-plausible learning rule for online k-PCA** In this work, we focus on the biological Oja’s rule in finding the top eigenvector of the covariance matrix. It is a natural question to ask: whether there is a biologically-plausible algorithm for finding top k eigenvectors (a.k.a. the k-PCA problem)? In the setting of ML Oja’s rule, this can be achieved by QR decomposition [AZL17] while it is unclear how to implement such decomposition in a biologically-plausible way. Another standard way to solve k-PCA is performing the Gram–Schmidt process after having a good enough approximation to the top eigenvectors. Nevertheless, it is also unclear how to implement Gram–Schmidt using a simple plasticity update rule. Thus, in our opinion, it would be very exciting to have a variant of biological Oja’s rule that solves the streaming k-PCA problem.

8.2 Algorithmic aspect

**Improving the guarantees for biological Oja’s rule** In this paper, we mainly focus on the situation when $\lambda_1 > \lambda_2$ while some of the previous works also considered the gap-free setting. We believe our framework can be easily extended to the gap-free setting and leave it as a future work. Also, there are some logarithmic terms (e.g. additive log log log(1/ϵ) in the local convergence) in the convergence rate and do not seem to be inherent. It would be interesting to find out the optimal logarithmic dependency.

On the other hand, we suspect the log(1/ϵ) term in the convergence rate of biological Oja’s rule might be necessary. Thus, showing a lower bound with log(1/ϵ) would be of great interest. Note that there exists (non-streaming) algorithm which solves PCA using only $O(\lambda_1^{-1} \text{gap}^{-2})$ samples so the lower bound should be tailored to the dynamic.

**Tighter analysis for ML Oja’s rule** Using the objective function from [AZL17], one can also easily generalize our framework to ML Oja’s rule and tighten the bounds for both the local and global convergence rates.
Other Stochastic Dynamics  There are many stochastic optimization problems in machine learning where the optimal analysis still remains elusive, e.g., stochastic gradient dynamics of matrix completion, low-rank approximation, nonnegative matrix factorization, etc. It is of great interest to apply our one-shot framework to analyze other important stochastic dynamics.

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A Oja’s derivation for the biological Oja’s rule

Recall that Oja wanted to use the following normalized update rule to solve the streaming PCA problem.

\[ w_t = \frac{(I + \eta_t x_t x_t^\top)w_{t-1}}{\| (I + \eta_t x_t x_t^\top)w_{t-1} \|_2}. \] (A.1)

Oja applied Taylor’s expansion on the normalization term and truncated the higher-order term of \( \eta_t \). Concretely, we have

\[
\| (I + \eta_t x_t x_t^\top)w_{t-1} \|_2^{-1} = \left( \sum_{i=1}^{n} (w_{t-1,i} + \eta_t y_t x_{t,i})^2 \right)^{-1/2} \approx \left( \sum_{i=1}^{n} w_{t-1,i}^2 + 2\eta_t y_t x_{t,i}w_{t-1,i} + O(\eta_t^2) \right)^{-1/2}.
\]

As \( y_t = x_t^\top w_{t-1} \) and \( \| w_{t-1} \|_2 \) is expected to be 1, the equation approximately becomes

\[
= (1 + 2\eta_t y_t^2 + O(\eta_t^2))^{-1/2} = 1 - \eta_t y_t^2 + O(\eta_t^2). \] (A.2)

Replace the denominator of Equation A.1 with Equation A.2 and truncate the \( O(\eta_t^2) \) term, one gets exactly Equation 1.4.

B Details of the Linearizations in Continuous Oja’s Rule

Recall that the dynamic of the continuous Oja’s rule is the following.

\[ \frac{dw_t}{dt} = \text{diag}(\lambda)w_t - w_t^\top \text{diag}(\lambda)w_t w_t. \]

Before proving the two convergence theorems of continuous Oja’s rule using different linearizations, let us first prove the following lemma on some basic properties.

**Lemma B.1** (Properties of continuous Oja’s rule). Let \( w_0 \in \mathbb{R}^n \) such that \( \|w_0\|_2 = 1 \) and \( w_{0,1} > 0 \). For any \( t \geq 0 \), we have

1. \( \|w_t\|_2 = 1 \),
2. \( \frac{dw_{t,1}}{dt} \geq (\lambda_1 - \lambda_2)w_{t,1}(1 - w_{t,1}^2) \), and
3. \( w_{t,1} \) is non-decreasing almost surely.
Proof of Lemma B.1. In the following, everything holds almost surely so we would not mention this condition every time. First, consider
\[
\frac{d\|w_t\|^2}{dt} = 2w_t^T \frac{dw_t}{dt} = 2w_t^T (\text{diag}(\lambda)w_t - \text{diag}(\lambda)w_tw_t) = 2w_t^T \text{diag}(\lambda)w_t \cdot (1 - \|w_t\|^2).
\]
As $1 - \|w_t\|^2 = 0$, by induction, we have $\|w_t\|^2 = 1$ for all $t \geq 0$.

For the second item of the lemma, we have
\[
\frac{dw_{t,1}}{dt} = \left(\lambda_1 - \left(\sum_{i \in [n]} \lambda_i w_{t,i}^2\right)\right)w_{t,1} \geq (\lambda_1 - \lambda_2)w_{t,1}(1 - w_{t,1}^2)
\]
\[
= \lambda_1(w_{t,1} - w_{t,1}^3) - \sum_{i=2}^n \lambda_i w_{t,i}^2 w_{t,1}.
\]
From the first item, we have $\sum_{i=2}^n w_{t,i}^2 = 1 - w_{t,1}^2$. Thus, we have
\[
\geq \lambda_1(w_{t,1} - w_{t,1}^3) - \lambda_2(1 - w_{t,1}^2)w_{t,1} = (\lambda_1 - \lambda_2)w_{t,1}(1 - w_{t,1}^2).
\]
The last item of the lemma is then an immediate corollary of the first two items.

Now, we restate and prove Theorem 3.4 as follows.

**Theorem 3.4 (Linearization at 0).** Suppose $w_{0,1} > 0$. For any $\epsilon \in (0, 1)$, when $t \geq \Omega\left(\frac{\log(1/w_{0,1}^2)}{\epsilon(\lambda_1 - \lambda_2)}\right)$, we have $w_{t,1}^2 > 1 - \epsilon$.

**Proof of Theorem 3.4.** Observe that for any $t \geq 0$ such that $w_{t,1}^2 \leq 1 - \epsilon$, by the second item of Lemma B.1, we have
\[
\frac{dw_{t,1}}{dt} \geq (\lambda_1 - \lambda_2)w_{t,1}(1 - w_{t,1}^2) \geq \epsilon(\lambda_1 - \lambda_2)w_{t,1}.
\]
Let $\tau = \frac{10\log(1/w_{0,1}^2)}{\epsilon(\lambda_1 - \lambda_2)}$ and assume $w_{t,1}^2 \leq 1 - \epsilon$ for the sake of contradiction. From the above linearization and $w_{t,1}$ being non-decreasing (the third item of Lemma B.1), we have
\[
w_{\tau,1} \geq e^{\epsilon(\lambda_1 - \lambda_2)\tau} \cdot w_{0,1} > 1,
\]
which is a contradiction to the first item of Lemma B.1. Thus, we conclude that for any $t = \Omega\left(\frac{\log(1/w_{0,1}^2)}{\epsilon(\lambda_1 - \lambda_2)}\right)$, $w_{t,1}^2 > 1 - \epsilon$.

Now, we restate and prove Theorem 3.5 as follows.

**Theorem 3.5 (Linearization at 1).** Suppose $w_{0,1} > 0$. For any $\epsilon \in (0, 1)$, when $t \geq \Omega\left(\frac{\log(1/\epsilon)}{w_{0,1}(\lambda_1 - \lambda_2)}\right)$, we have $w_{t,1}^2 > 1 - \epsilon$.

**Proof of Theorem 3.5.** Observe that for any $t \geq 0$, by the second item of Lemma B.1, we have
\[
\frac{d(w_{t,1} - 1)}{dt} \geq (\lambda_1 - \lambda_2)w_{t,1}(1 - w_{t,1}^2) = -(\lambda_1 - \lambda_2)(w_{t,1} - 1)(w_{t,1} + w_{t,1}^2).
\]
As $w_{t,1}$ is non-decreasing (the third item of Lemma B.1) and at most 1, we have
\[
\geq -(\lambda_1 - \lambda_2)w_{0,1}(w_{t,1} - 1).
\]
By solving the linear ODE, we have
\[
w_{t,1} - 1 \geq (w_{0,1} - 1) \cdot e^{-(\lambda_1 - \lambda_2)w_{0,1}t}.
\]
Thus, for any $t \geq \Omega\left(\frac{\log(1/\epsilon)}{w_{0,1}(\lambda_1 - \lambda_2)}\right)$, we have $w_{t,1}^2 > 1 - \epsilon$. \hfill $\square$
C Why the Analysis of ML Oja’s Rule Cannot be Applied to Biological Oja’s Rule?

In this section, we would like to discuss what makes biological Oja’s rule much harder to analyze comparing to the previous approaches for ML Oja’s rule. We study this problem through the lens of their corresponding continuous dynamics. Observe that, to study ML Oja’s rule, it suffices to study the following dynamic

\[
\frac{dw_t}{dt} = \text{diag}(\lambda)w_t.
\]

The dynamic of the objective function \(\sum_{i=2}^{n} \frac{w_{t,i}^2}{w_{t,1}^2}\) would be

\[
\frac{d\sum_{i=2}^{n} \frac{w_{t,i}^2}{w_{t,1}^2}}{dt} = -2\sum_{i=2}^{n} \frac{w_{t,i}^2}{w_{t,1}^2} \lambda_1 w_{t,1} + \sum_{i=2}^{n} \frac{2w_{t,i}}{w_{t,1}^2} \lambda_i w_{t,i} \\
\leq -2(\lambda_1 - \lambda_2) \sum_{i=2}^{n} \frac{w_{t,i}^2}{w_{t,1}^2}.
\]

Namely, the continuous dynamic is just a linear ODE with slope being independent to the value of \(w_t\). In comparison, the dynamic of the biological Oja’s rule is the following.

\[
\frac{d\omega_{t,1}}{dt} \geq (\lambda_1 - \lambda_2)\omega_{t,1}(1 - \omega_{t,1}^2)
\]

where you have to use at least two objective functions with different linearizations to get tight analysis. Furthermore, for any linearization, there exist some values of \(w_t\) that make the improvement extremely small or even vanishing. It is also not obvious to choose which two objective functions to analyze unless you are guided by the continuous dynamics.

We remark that the discussion here only suggests the difficulty of applying previous techniques of ML Oja’s rule to biological Oja’s rule. It might still be the case that the two dynamics are coupled but we argue here that even this is the case, previous techniques cannot show this.

D Proof of Lemma 6.3

Let us start with the definition of the central object of this section.

**Definition D.1.** For each \(j \in [n]\), \(t \in [T]\), and \(w \in \mathbb{R}^n\), define

\[
f_{t,j}(w) = \frac{\sum_{i=2}^{j} x_{t,i}w_i}{w_1}.
\]

The goal of this section is to prove the following lemma which implies Lemma 6.3.

**Lemma D.2.** Let \(w_0\) be a random unit vector in \(\mathbb{R}^n\). For any \(n, T \in \mathbb{N}\) and \(\delta \in (0, 1)\) and \(\eta = O\left(\frac{\delta^2(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{nT}{\delta}}\right)\). There exists a stopping time \(\xi\) such that the following hold.

1. \(\Pr[\xi \geq T] \geq 1 - \delta\),

2. \(\Pr \left[f_{t \wedge \xi, n}(w_{t \wedge \xi - 1}) = O\left(\frac{1}{\delta} \sqrt{\log \frac{nT}{\delta}}\right)\right] = 1\)

for \(t \in [T]\).

Note that Lemma 6.3 would be an immediate corollary of Lemma D.2.
Proof of Lemma 6.3. Pick exactly the same $\xi$ as in Lemma D.2 and the first item holds directly. As for the second item, we have

$$|D_{t\wedge \xi}| = \left| \sum_{i=2}^{n} x_{t\wedge \xi,i} w_{t\wedge \xi-1,i} \right| \leq \sum_{i=2}^{n} x_{t\wedge \xi,i} w_{t\wedge \xi-1,i} = |f_{t\wedge \xi,n}(w_{t\wedge \xi-1}) : w_{t\wedge \xi-1,1}|.$$  

By the second item in Lemma D.2, we have

$$= O\left(\frac{w_{t\wedge \xi-1,1}}{\delta} \sqrt{\log \frac{nT}{\delta}}\right)$$

almost surely. As for the third item, we have

$$\begin{align*}
\text{Var}[D_{t\wedge \xi} | F_{t-1}] &\leq \mathbb{E} \left[ x_{t\wedge \xi,1}^2 \left( \sum_{i=2}^{n} x_{t\wedge \xi,i} w_{t\wedge \xi-1,i} \right)^2 | F_{t-1} \right] \\
&= \mathbb{E} \left[ x_{t\wedge \xi,1}^2 f_{t\wedge \xi,n}(w_{t\wedge \xi-1})^2 : w_{t\wedge \xi-1,1} | F_{t-1} \right].
\end{align*}$$

By the second item in Lemma D.2, we have

$$\begin{align*}
&\leq \mathbb{E} \left[ x_{t\wedge \xi,1}^2 w_{t\wedge \xi-1,1}^2 | F_{t-1} \right] \cdot O \left( \frac{1}{\delta^2} \log \frac{nT}{\delta} \right) \\
&= O \left( \frac{\lambda_1 w_{t\wedge \xi-1,1}^2}{\delta^2} \log \frac{nT}{\delta} \right).
\end{align*}$$

Organization of this section The goal of the rest of this section is to prove Lemma D.2. In Section D.1, we first use an initialization lemma from [AZL17] and design the stopping time $\xi$. Specifically, we show in Lemma D.4 that proving Equation D.5 would be sufficient for the goal. Next, we introduce the linearization and ODE trick for handling $f_{t,j}(w_s)$ in Section D.2. In particular, we use a vector form of the ODE trick to get tight characterization. Then, we are able to show the concentration of the stopped process in Section D.3 and wrap up the proof in Section D.4.

D.1 Initialization

Before describing the stopping time $\xi$ we are going to use, let us first introduce an useful initialization lemma (due to [AZL17]) which shows that some nice initial conditions hold with good probability (over the randomness of $w_0$). We then embed the nice initial conditions into the stopping time $\xi$ to enable future analysis.

Lemma D.3 (Initialization lemma in [AZL17, Lemma 5.1]). For any $n, T \in \mathbb{N}$, and $\mathcal{D}$ a distribution over unit vectors in $\mathbb{R}^n$. Let $w_0 \in \mathbb{R}^n$ be a random unit vector, then for any $j \in [n]$ and $p, \delta' \in (0,1)$, we have

$$\frac{\sum_{i=2}^{n} w_{0,i}^2}{w_{0,1}^2} \leq O \left( \frac{n \log n}{p^2} \right)$$

and

$$\Pr_{x_1,\ldots,x_T \sim \mathcal{D}} \left[ \exists j \in [n], t \in [T], |f_{t,j}(w_0)| > \Omega \left( \frac{1}{p} \sqrt{\log \frac{nT}{\delta'}} \right) \right] < \delta'$$

with probability at least $1 - p - \delta'$ where the randomness is over $w_0$.  

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Fixing parameters There are plenty of parameters here and might be confusing. So let us fix them before moving on. Recall that \( n, T \in \mathbb{N}, \delta \in (0, 1), \) and \( \eta = O \left( \frac{\delta^2(\Lambda_1 - \lambda_2)}{\lambda_1 \log n} \right) \) are given and we are going to specify the deviation \( \Lambda \) and another auxiliary failure probability \( \delta' \). First, take \( \delta' = \frac{\delta}{32n^2T} \) and \( p = \delta/4 \) and let the deviation inside the Lemma D.3 be \( \frac{\Lambda}{10} = O \left( \frac{\delta}{\frac{1}{2} \sqrt{\log \frac{nT}{3\delta}} } \right) = O \left( \frac{\delta}{\frac{1}{2} \sqrt{\log \frac{nT}{\delta}} } \right) \).

The choice of stopping time Now, we are able to formally define the stopping time \( \xi \) as follows. First, consider the initialization lemma (i.e., Lemma D.3) with \( p = \delta/4 \) and \( \delta' \ll \delta \) chosen later. If \( w_0 \) does not satisfy the conditions in Lemma D.3, then we define \( \xi = 0 \). Note that \( \{ \xi = 0 \} \) happens with probability at most \( p + \delta' \leq \delta/2 \). Next, if \( w_0 \) satisfies the conditions, then define \( \xi \) to be the first time \( t \) such that \( |f_{t,n}(w_{t-1})| > \Lambda \). Observe that the event \( \{ \xi = 0 \} \) only depends on the randomness from \( w_0 \) (not on that from \( x_1, x_2, \ldots, x_T \)). Thus, \( \xi \) is well-defined with respect to the natural filtration.

Note that \( \xi \) satisfies the second item of Lemma D.2 immediately from its definition. To achieve the first condition and complete the proof, the following lemma shows that it suffices to show the concentration for a bunch of events described in Equation D.5.

**Lemma D.4.** For any \( n, T \in \mathbb{N} \) and \( \delta \in (0, 1) \), suppose for any \( t \in [T] \) and \( j \in [n] \), we have

\[
\Pr \left[ |f_{t,j}(w_{(t-1)\wedge \xi})| > \Lambda \mid \xi > 0 \right] < \frac{\delta}{4nT}.
\]

Then

\[
\Pr[\xi < T] < \delta.
\]

**Proof of Lemma D.4.** The proof is based on induction on \( T \). Our induction hypothesis is that for any \( t \in [T] \)

\[
\Pr[\xi < t] < \frac{\delta}{2} + \frac{\delta t}{2T}.
\]

For the base case where \( t = 1 \), we have

\[
\Pr[\xi < 1] = \Pr[\xi = 0] = \Pr[w_0 \text{ does not satisfy the conditions in Lemma D.3}] < \frac{\delta}{2}.
\]

For the induction step, assume the induction hypothesis holds for \( t - 1 \) for some \( 1 < t \leq T \). Consider

\[
\Pr[\xi < t] = \Pr[\xi < t - 1] + \Pr[\xi = t - 1].
\]

By the induction hypothesis, the first term can be bounded by \( \frac{\delta}{2} + \frac{\delta(t-1)}{2T} \). The second term can also be upper bounded from definition as follows.

\[
< \frac{\delta}{2} + \frac{\delta(t-1)}{2T} + \Pr[\exists j \in [n], |f_{t,j}(w_{t-1})| > \Lambda, \xi \geq t - 1]
= \frac{\delta}{2} + \frac{\delta(t-1)}{2T} + \Pr[\exists j \in [n], |f_{t,j}(w_{(t-1)\wedge \xi})| > \Lambda, \xi \geq t - 1].
\]

Finally, from the assumption (i.e., Equation D.5) in the lemma statement, the second term can be union bounded by \( n \cdot \frac{1}{\Pr[\xi > 0]} \cdot \frac{\delta}{4nT} \). As \( \Pr[\xi > 0] \geq 0.5 \), the inequality becomes

\[
\leq \frac{\delta}{2} + \frac{\delta(t-1)}{2T} + n \cdot \frac{1}{\Pr[\xi > 0]} \cdot \frac{\delta}{4nT} \leq \frac{\delta}{2} + \frac{\delta t}{2T}.
\]

This completes the induction. Thus, \( \Pr[\xi < T] \leq \delta \) as desired. \( \Box \)

To get Equation D.5, we need to show the concentration of \( f_{t,j}(w_{t-1}) \) and as before the linearization and ODE trick would be our main tools. In the end, we prove Equation D.5 in Section D.4.
D.2 Linearization and ODE trick

Let us start with the linearization and ODE trick for function \( f_{t,j} \) in this subsection.

**Lemma D.6 (Linearization).** For any \( t \in [T] \) and \( j \in [n] \). For any \( s \in [t] \), write \( \mathbf{w}_s = \mathbf{w}_{s-1} + \eta \mathbf{z}_s \) where \( \mathbf{z}_s = \mathbf{y}_s (\mathbf{x}_s - \mathbf{y}_s \mathbf{w}_{s-1}) \). There exists \( \mathbf{w}_{s-1} = \mathbf{w}_{s-1} + c \mathbf{z}_s \) for some \( c \in [0, 1] \) such that

\[
f_{t,j}(\mathbf{w}_s) = (1 - \eta (\lambda_1 - \lambda_j))f_{t,j}(\mathbf{w}_{s-1}) + \eta A_{t,s,j} + \eta B_{t,s,j} + \eta^2 C_{t,s,j}
\]

where

\[
A_{t,s,j} = \sum_{i=2}^{j-1} (\lambda_i - \lambda_{i+1})f_{t,i}(\mathbf{w}_{s-1}) ,
\]

\[
B_{t,s,j} = \sum_{i=1}^{n} \frac{\partial f_{t,j}}{\partial \mathbf{w}_i} (\mathbf{w}_{s-1}) \cdot (\mathbf{z}_{s,i} - E[\mathbf{z}_{s,i} | \mathcal{F}_{s-1}]) , \text{ and}
\]

\[
C_{t,s,j} = \sum_{i,i'=1}^{n} \frac{\partial^2 f_{t,j}}{\partial \mathbf{w}_i \partial \mathbf{w}_{i'}} (\mathbf{w}_{s-1}) \cdot \mathbf{z}_{s,i} \mathbf{z}_{s,i'} .
\]

**Vector form of linearization** For any \( t \in [T] \), let \( f_t(\mathbf{w}), B_{t,s,i}, C_{t,s,i} \in \mathbb{R}^{n-1} \) be \((n-1)\)-dimensional vectors where the \( i^{th} \) coordinates of them are \( f_{t,i+1}(\mathbf{w}), B_{t,i+1}, C_{t,i+1} \) respectively. The following is an immediate corollary of Lemma D.6 by rewriting everything into a vector form.

**Corollary D.7 (Linearization in vector form).** For any \( t \in [T] \) and \( s \in [t] \), we have

\[
f_t(\mathbf{w}_s) = Hf_t(\mathbf{w}_{s-1}) + \eta B_{t,s} + \eta^2 C_{t,s}
\]

where

\[
H = \begin{pmatrix}
1 - \eta (\lambda_1 - \lambda_2) & 0 & 0 & \cdots & 0 \\
\eta (\lambda_2 - \lambda_3) & 1 - \eta (\lambda_1 - \lambda_3) & 0 & \cdots & 0 \\
\eta (\lambda_3 - \lambda_4) & \eta (\lambda_4 - \lambda_5) & 1 - \eta (\lambda_1 - \lambda_4) & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\eta (\lambda_2 - \lambda_3) & \eta (\lambda_3 - \lambda_4) & \eta (\lambda_4 - \lambda_5) & \cdots & 1 - \eta (\lambda_1 - \lambda_n)
\end{pmatrix}.
\]

It turns out that the multiplier matrix \( H \) in Corollary D.7 is well-behaved: it is invertible and we can explicitly write down its eigenvectors as follows. For each \( i \in [n-1] \), the \( i^{th} \) eigenvalue-eigenvector pair \((\mu_i, \mathbf{v}_i)\) is

\[
\mu_i = 1 - \eta (\lambda_1 - \lambda_{i+1}) \quad \text{and} \quad \mathbf{v}_i = [0, \ldots, 0, 1, \ldots, 1]^T.
\]

With the eigenvectors, we can easily diagonalize \( H \) as follows. Let \( V \in \mathbb{R}^{(n-1) \times (n-1)} \) be the matrix with the \( i^{th} \) column being \( \mathbf{v}_i \), we have \( H = VDV^{-1} \) where

\[
D = \text{diag}(1 - \eta (\lambda_1 - \lambda_2), 1 - \eta (\lambda_1 - \lambda_3), \ldots, 1 - \eta (\lambda_1 - \lambda_n)).
\]

Thus, the inverse of \( H \) is \( H^{-1} = VD^{-1}V^{-1} \).

By the ODE trick for vector (see Lemma 2.13), we immediately have the following corollary for a closed-form solution to \( f_t(\mathbf{w}_s) \).

**Corollary D.8 (ODE trick).** For any \( t \in [T] \), \( s \in [t-1] \), and \( \eta > 0 \), we have

\[
f_t(\mathbf{w}_s) = H^s f_t(\mathbf{w}_0) + \sum_{s'=1}^{s} H^{s-s'} (\eta B_{t,s'} + \eta^2 C_{t,s'}) .
\]
D.3 Concentration of the noise terms

In this subsection, we prove Equation D.5. However, same as the situation before, we cannot get concentration for the noise terms of the ODE trick (see Corollary D.8) directly. As a consequence, we have to introduce a new stopping time $\tau_t$ to make sure the stopped processes are in a good shape for the martingale concentration inequality.

D.3.1 Stopping time

For a fixed $t \in [T]$, we define a stopping time $\tau_t$ for the noise terms from $s = 1, 2, \ldots, t - 1$ as follows. First, we work on a slightly different filtration $\{F_t^{(s)}\}_{s \in [t-1]}$ than the natural filtration $\{F_t\}_{s \in [t-1]}$. The key idea is that the stopping time can depend on $x_t$ since we only look at the noise term up to $t-1$. Concretely, for each $s \in [t-1]$, let $F_t^{(s)}$ be the $\sigma$-algebra generated by $\{x_1, x_2, \ldots, x_s\} \cup \{x_t\}$. Note that $\{F_t^{(s)}\}_{s \in [t-1]}$ is well-defined and both $\{B_{t,s,j}\}_{s \in [t-1]}$ and $\{C_{t,s,j}\}_{s \in [t-1]}$ are adapted random processes with respect to $\{F_t^{(s)}\}_{s \in [t-1]}$, i.e., $B_{t,s,j}$ and $C_{t,s,j}$ lie in $F_t^{(s)}$ for all $s \in [t-1]$. Also, note that $E[z_s | F_{s-1}] = E[z_s | F_s]$. That is, the conditional expectation and conditional variance of $z$ are the same with respect to $\{F_s\}$ and $\{F_s^{(s)}\}$.

Now we define $\tau_t$ to be the stopping time for the event $\{\|f_t(w_{\tau_t})\|_\infty > \Lambda\}$. Note that the stopped process $\left\{\sum_{s=1}^{s} H^{(s'-s_0)} B_{t,(s'-1)\wedge \tau_t} \right\}_{s \in [t-1]}$ is a martingale and $\left\{\sum_{s'=1}^{s} H^{(s'-s_0)} C_{t,(s'-1)\wedge \tau_t} \right\}_{s \in [t-1]}$ is an adapted stochastic process with respect to $\{F_s^{(s)}\}_{s \in [t-1]}$. Furthermore, both of them have small bounded difference, conditional expectation, and conditional variance. Concretely, we have the following lemma.

Lemma D.9 (Structure of the stopped processes). Let $T, \eta, \Lambda$ be the parameters and $\xi, \tau_t$ be the stopping times as chosen before. For any $t \in [T]$, $s \in [t-1]$, and $j \in [n]$, let $M_{t,s,j}^B$ and $M_{t,s,j}^C$ be the $j^{th}$ entry of $\sum_{s'=1}^{s} H^{s-s'} B_{t,s'\wedge \xi \wedge \tau_t}$ and $\sum_{s'=1}^{s} H^{s-s'} C_{t,s'\wedge \xi \wedge \tau_t}$ respectively. The following hold.

- **(Bounded difference)** For any $j \in [n]$, we have

$\left| M_{t,s,j}^{B} - M_{t,s-1,j}^{B} \right| = O(\Lambda^2)$ and $\left| M_{t,s,j}^{C} - M_{t,s-1,j}^{C} \right| = O(\Lambda^3)$ almost surely.

- **(Conditional expectation)** For any $s \in [t-1]$ and $j \in [n]$, we have

$E \left[ M_{t,s,j}^{B} - M_{t,s-1,j}^{B} \mid F_{s-1}^{(s)} \right] = 0$ and $\sum_{s'=1}^{s} E \left[ M_{t,s',j}^{C} - M_{t,s'-1,j}^{C} \mid F_{s'-1}^{(s')} \right] = O \left( \frac{\lambda_1 \Lambda^3}{\eta (\lambda_1 - \lambda_2)} \right)$.

- **(Conditional variance)** For any $s \in [t-1]$ and $j \in [n]$, we have

$\sum_{s'=1}^{s} \text{Var} \left[ M_{t,s,j}^{B} \mid F_{s-1}^{(s)} \right] = O \left( \frac{\lambda_1 \Lambda^4}{\eta (\lambda_1 - \lambda_2)} \right)$ and $\sum_{s'=1}^{s} \text{Var} \left[ M_{t,s,j}^{C} \mid F_{s-1}^{(s')} \right] = O \left( \frac{\lambda_1 \Lambda^6}{\eta (\lambda_1 - \lambda_2)} \right)$.

**Proof of Lemma D.9.** Before looking at $M_{t,s,j}^B$ and $M_{t,s,j}^C$, which are weighted by some factor of $H$, let us first understand the structure of the unweighted version in the following lemma.

Lemma D.10. Let $T, \eta, \Lambda$ be the parameters and $\xi, \tau_t$ be the stopping times as chosen before. For any $t \in [T]$, $s \in [t-1]$, and $j \in [n]$, the following hold.

- **(Bounded difference)** We have

$\left| B_{t,s\wedge \xi \wedge \tau_t,j} \right| = O(\Lambda^2)$ and $\left| C_{t,s\wedge \xi \wedge \tau_t,j} \right| = O(\Lambda^3)$ almost surely.

- **(Conditional expectation)** We have

$E \left[ B_{t,s\wedge \xi \wedge \tau_t,j} \mid F_{s-1}^{(s)} \right] = 0$ and $E \left[ C_{t,s\wedge \xi \wedge \tau_t,j} \mid F_{s-1}^{(s')} \right] = O(\lambda_1 \Lambda^3)$.

- **(Conditional variance)** We have

$\text{Var} \left[ B_{t,s\wedge \xi \wedge \tau_t,j} \mid F_{s-1}^{(s')} \right] = O(\lambda_1 \Lambda^4)$ and $\text{Var} \left[ C_{t,s\wedge \xi \wedge \tau_t,j} \mid F_{s-1}^{(s')} \right] = O(\lambda_1 \Lambda^6)$.
Proof of Lemma D.10. The proof is based on properly expanding the noise terms and utilizes the stopping time condition. We postpone the details to Section E.3.

To move the unweighted structure (i.e., Lemma D.10) to the desiring weighted structure (i.e., for $M_{t,s,j}^{B}$ and $M_{t,s,j}^{C}$), we need the following claim on translating the bounded difference and variance after being multiplied by some power of $H$.

**Claim D.11.** Let $H \in \mathbb{R}^{(n-1)\times(n-1)}$ be the matrix from Corollary D.7. For any $s \in \mathbb{N}$, $c, \mu, \sigma^2 > 0$, and random vector $u \in \mathbb{R}^{n-1}$ such that (i) $\|u\|_\infty \leq c$ almost surely, (ii) $\|E[u]\|_\infty \leq \mu$, and (ii) $\text{Var}(u_i) \leq \sigma^2$ for each $i \in [n-1]$. The following hold.

- (Bounded difference) For any $s \in \mathbb{N}$, $\|H^s u\|_\infty \leq (1 - \eta(\lambda_1 - \lambda_2))^s \cdot c$ almost surely.
- (Expectation) $\|E[H^s u]\|_\infty \leq (1 - \eta(\lambda_1 - \lambda_2))^s \cdot \mu$.
- (Variance) $\text{Var}(H^s u)_i \leq (1 - \eta(\lambda_1 - \lambda_2))^{2s} \cdot \sigma^2$ for each $i \in [n-1]$.

**Proof of Claim D.11.** Recall that $H = VDV^{-1}$ is invertible where

$$V = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & \cdots & 1 \end{pmatrix} \quad \text{and} \quad V^{-1} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ -1 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}.$$  

Also, observe that for any diagonal matrix $D' = \text{diag}(d_1, d_2, \ldots, d_{n-1})$, we have

$$VD'V^{-1} = \begin{pmatrix} d_1 & 0 & 0 & \cdots & 0 \\ d_1 - d_2 & d_2 & 0 & \cdots & 0 \\ d_1 - d_2 & d_2 - d_3 & d_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_1 - d_2 & d_2 - d_3 & d_3 - d_4 & \cdots & d_{n-1} \end{pmatrix}.$$  

Note that if $d_1 \geq d_2 \geq \cdots \geq d_{n-1}$, the $\ell_1$ norm of each row of $VD'V^{-1}$ is exactly $d_1$ and the $\ell_2$ norm is at most $d_1$. To see the bound for the $\ell_2$ norm, for any $i \in [n-1]$, the square of the $\ell_2$ norm of the $i^{th}$ row of $VD'V^{-1}$ is

$$\sum_{j=1}^{i-1} (d_j - d_{j+1})^2 + d_i^2 \leq \left( \sum_{j=1}^{i-1} (d_j - d_{j+1}) + d_1 \right)^2 = d_1^2.$$  

The first inequality holds because $d_j - d_{j+1} \geq 0$ for all $j \in [n-2]$.

Now, let us go back to $H^s = VD^sV^{-1}$ and recall that the $i^{th}$ entries of $D$ are $(1 - \eta(\lambda_1 - \lambda_{i+1}))$ for each $i \in [n-1]$. Namely, the diagonal entries of $D^s$ from top left to bottom right are non-increasing and the corresponding $d_1 = (1 - \eta(\lambda_1 - \lambda_2))^s$.

Finally, let $u \in \mathbb{R}^{n-1}$ be a random vector with the properties as stated in the claim, for any $i \in [n-1]$, we have

$$(H^s u)_i = (VD^sV^{-1} u)_i = v_{s,i}^T u$$

where $v_{s,i}$ is the $i^{th}$ row of $VD^sV^{-1}$. By the above discussion, $\|v_{s,i}\|_1, \|v_{s,i}\|_2 \leq d_1 = (1 - \eta(\lambda_1 - \lambda_2))^s$.

Thus, we have both

$$|(H^s u)_i| = |v_{s,i}^T u| \leq \|v_{s,i}\|_1 \cdot \|u\|_\infty$$

and

$$|(H^s u)_i| = |v_{s,i}^T u| \leq \|v_{s,i}\|_2 \cdot \|u\|_2$$

almost surely due to Hölder’s inequality. This gives $|(H^s u)_i| \leq (1 - \eta(\lambda_1 - \lambda_2))^s \cdot c$ almost surely and $\text{Var}((H^s u)_i) \leq (1 - \eta(\lambda_1 - \lambda_2))^{2s} \cdot \sigma^2$. The expectation of $(H^s u)_i$ is handled by linearity as follows.

$$E[(H^s u)_i] = E[v_{s,i}^T u] = |v_{s,i}^T E[u]| \leq \|v_{s,i}\|_1 \cdot \|E[u]\|_\infty.$$  

This completes the proof of the claim. □
Now, the structure for the vector form (i.e., Lemma D.9) immediately follows from the structure of the individual noise term (i.e., Lemma D.10), Claim D.11, Cauchy-Schwarz inequality, and the following formula.

\[
\sum_{s=0}^{\infty} (1 - \eta(\lambda_1 - \lambda_2))^s = \frac{1}{\eta(\lambda_1 - \lambda_2)}.
\]

\[\square\]

D.3.2 Concentration for the stopped processes

As a consequence of Lemma D.10, we are able to prove the following concentration for the stopped processes of the noise terms.

Lemma D.12 (Concentration for the stopped process of the noise vectors). Let \( T, \eta, \Lambda \) be the parameters and \( \xi, \tau \) be the stopping times as chosen before. For any \( t \in [T] \), \( s \in [t-1] \), and \( i \in [n-1] \), the following hold.

1.

\[
\Pr \left[ \sup_{s' \in [s]} \sum_{s''=1}^{s'} \eta \left( H^{s''-s'} B_{t,s'' \land \xi \land \tau_i} \right)_i \geq \Omega \left( \Lambda^2 \sqrt{\frac{\eta \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}} \right) \right] < \delta'.
\]

2.

\[
\Pr \left[ \sup_{s' \in [s]} \sum_{s''=1}^{s'} \eta^2 \left( H^{s''-s'} C_{t,s'' \land \xi \land \tau_i} \right)_i \geq \Omega \left( \frac{\eta^3 \lambda_1 \Lambda^3}{\lambda_1 - \lambda_2} + \eta \Lambda^3 \sqrt{\eta \lambda_1 \log \frac{1}{\delta'}} \frac{1}{(\lambda_1 - \lambda_2)} \right) \right] < \delta'.
\]

Proof of Lemma D.12. The proof is based on applying the corollary of Freedman’s inequality (see Corollary 2.7) on each coordinate using Lemma D.9. Since the calculation is similar to that of Lemma 6.6 and Lemma 7.6, we omit the details here for simplicity. \[\square\]

The following lemma calculates the deviation in Lemma D.12 after fixing the parameters and weighting the noise terms with \( \eta \).

Lemma D.13. With the parameter settings in Section D.1, by direct verification we have

\[
O \left( \Lambda^2 \sqrt{\frac{\eta \lambda_1 \log \frac{1}{\delta'}}{\lambda_1 - \lambda_2}} \right), \quad O \left( \frac{\eta^3 \lambda_1 \Lambda^3}{\lambda_1 - \lambda_2} + \eta \Lambda^3 \sqrt{\eta \lambda_1 \log \frac{1}{\delta'}} \frac{1}{(\lambda_1 - \lambda_2)} \right) < \frac{\Lambda}{10}
\]

where the \( O \) terms are from the concentration inequalities of Lemma D.12.

D.3.3 Pull-out lemma

Now that we have good concentration on the stopped process of the noise vector in the ODE trick, the last step is pulling out the stopping time. Note that there are two differences between the setting here and the setting in Phase 2: here we are working on a vector of random processes instead of a single one and there is an initial condition (i.e., Lemma D.3) we have to condition on throughout the analysis. Thus, we have to develop the following generalization of Lemma 7.9.

Lemma D.14. Let \( m \in \mathbb{N} \) and \( \{M_{s,j}\}_{s \in \mathbb{N} \geq 0} \) be \( m \)-dimensional random processes indexed by \( j \in [m] \). Denote its maximal process as \( \{M_{s,j}\}_{s \in \mathbb{N} \geq 0} \) where \( M_{s,j} = \sup_{s' \in [s]} M_{s',j} \) for any \( s \in \mathbb{N} \) and \( j \in [m] \).

For any \( s \in \mathbb{N} \), \( a \in \mathbb{R} \), \( \delta \in (0, 1) \), stopping time \( \tau \), and an event \( \mathcal{E} \), suppose

1. \( \Pr[\exists j \in [n], M_{s,\tau,j} \geq a \mid \mathcal{E}] < \delta \) and

2. \( \Pr[\tau \geq s' + 1 \mid \forall j \in [n], M_{s',j} < a, \mathcal{E}] = 1 \) for any \( 1 \leq s' < s \).
Then, we have
\[ \Pr[\exists j \in [n], M^*_s_{i,j} \geq a] < \delta . \]

**Proof.** Let stopping time \( \tau' \) be the first time \( t \) such that \( \exists j \in [n], M_{t \wedge \tau, j} \geq a \). Similarly, we first have the following observation.

**Claim D.15.** For any \( s \in \mathbb{N} \), we have
\[ \Pr[\tau < s, \tau' > \tau \mid \mathcal{E}] = 0 . \]

**Proof of Claim D.15.** Let us assume both \( \tau < s \) and \( \tau' > \tau \) for the sake of contradiction. Since \( \tau' > \tau \), we know that for any \( j \in [n] \) and \( s'' \leq \tau, M_{s'', j} < a \). From the second condition of Lemma D.14, we have \( \tau \geq \tau + 1 \) almost surely, which is a contradiction. Thus, we conclude that the two events cannot simultaneously happen.

Now, let us partition the probability space of the error event as follows.
\[ \Pr[\exists j \in [n], M^*_s_{i,j} \geq a \mid \mathcal{E}] = \Pr[\exists j \in [n], M^*_s_{i,j} \geq a, \tau \geq s \mid \mathcal{E}] + \Pr[\exists j \in [n], M^*_s_{i,j} \geq a, \tau < s, \tau' \leq \tau \mid \mathcal{E}] + \Pr[\exists j \in [n], M^*_s_{i,j} \geq a, \tau < s, \tau' > \tau \mid \mathcal{E}] . \]

Note that when \( \tau \geq s \), we have \( s = s \wedge \tau \) and thus \( M^*_s_{i,j} = M^*_s_{s \wedge \tau, j} \) for all \( j \in [n] \). Also, when \( \tau' \leq \tau < s \), we know that there exists \( j \in [n] \) such that both \( M^*_s_{i,j}, M^*_s_{s \wedge \tau, j} \geq a \). Thus, the equation becomes
\[ = \Pr[\exists j \in [n], M^*_s_{s \wedge \tau, j} \geq a, \tau \geq s \mid \mathcal{E}] + \Pr[\exists j \in [n], M^*_s_{s \wedge \tau, j} \geq a, \tau < s, \tau' \leq \tau \mid \mathcal{E}] + \Pr[\exists j \in [n], M^*_s_{s \wedge \tau, j} \geq a, \tau < s, \tau' > \tau \mid \mathcal{E}] . \]

Moreover, by Claim D.15, we know that the last term is 0. Finally, we have
\[ \leq \Pr[\exists j \in [n], M^*_s_{s \wedge \tau, j} \geq a \mid \mathcal{E}] < \delta . \]

This completes the proof of the pull-out lemma.

**D.4 Wrap up**

Now, let us formally prove Equation D.5 and thus by Lemma D.4 and Lemma D.2 this would finish the proof of Lemma 6.3 and fulfill the goal of this section.

**Proof of Equation D.5.** Recall that the goal is to show that
\[ \Pr[|f_{t,j}(w_{(t-1)\wedge \xi})| > A] < \frac{\delta'}{4nT} \]
for all \( t \in [T] \) and \( j \in [n] \). The high-level idea is first showing that the stopped process of the noise vectors would concentrate (using Lemma D.12) and then using the pull-out lemma (i.e., Lemma D.14) to get the concentration for the original noise vectors.

For the ease of notation, for any \( t \in [T] \), let us define
\[ \text{BAD}_t := \left\{ \exists s' \in [t-1], i \in [n-1], \left| \sum_{s''=1}^{s'} \eta \left( H^{s'-s''} B_{t,s'', \wedge \xi} \right)_i + \eta^2 \left( H^{s'-s''} C_{t,s'', \wedge \xi} \right)_i \right| > \frac{\Lambda}{5} \right\} \]
and
\[ \text{BAD}_{t, \tau_t} := \left\{ \exists s' \in [t-1], i \in [n-1], \left| \sum_{s''=1}^{s'} \eta \left( H^{s'-s''} B_{t,s'', \wedge \xi \wedge \tau_t} \right)_i + \eta^2 \left( H^{s'-s''} C_{t,s'', \wedge \xi \wedge \tau_t} \right)_i \right| > \frac{\Lambda}{5} \right\} . \]
As \(\xi > 0\), any \(1 \leq s \leq t - 1\), assume for any \(i \in [n - 1]\) and \(s' \in [s]\), we have
\[
\sum_{s''=1}^{s'} \eta \left( H^{s''-s'} B_{t,s'',\xi} \right)_i + \eta^2 \left( H^{s''-s'} C_{t,s'',\xi} \right)_i < \frac{\Lambda}{5}.
\]
Now, we would like to bound each coordinate of \(f(w_{s,\xi})\). Specifically, we only care about the case where \(\xi > 0\). By the ODE trick (i.e., Corollary 2.7) can show that the noise terms in Section D.1, thus we get Equation D.5. Finally, using the ODE trick, we have
\[
\Pr \left[ \exists j \in [n], \ |f_{i,j}(w_{t-1,\xi})| > \Lambda \mid \xi > 0 \right] \leq \Pr[\text{BAD}_{t} \mid \xi > 0] \leq \frac{\Pr[\text{BAD}_{t,\tau_t} \mid \xi > 0]}{\Pr[\xi > 0]} < 8n\delta'.
\]
where the last inequality is due to \(\Pr[\xi > 0] \geq 0.5\) and Equation D.16. Finally, using the ODE trick, we have
\[
\Pr \left[ \exists j \in [n], \ |f_{i,j}(w_{t-1,\xi})| > \Lambda \mid \xi > 0 \right] \leq \Pr[\text{BAD}_{t} \mid \xi > 0] \leq \frac{\delta}{4nT^3}.
\]
Recall that the last inequality holds because we piked \(\delta' = \frac{\delta}{32n^2T}\) in Section D.1, thus we get Equation D.5. This completes the proof.

E Details of Linearizations in Biological Oja’s Rule

In this section, we provide the full proofs for the linearization lemmas for biological Oja’s rule. In Section E.1 we provide the proof of the linearization in Phase 1, in Section E.2 we provide the proof of the linearization in Phase 2, and in Section E.3 we provide the proof of the linearization used in Appendix D for the proof of Lemma 6.3.

We remark that all of these linearization lemmas are based on Taylor’s expansion and the proofs are elementary. The key of the proofs is to identify the right way to rearrange the terms so that everything is analyzable. The rule of thumb is separating the drifting terms and the noise terms where in most of the case the later are either (i) martingales or (ii) something with small bounded difference and small conditional expectation. Namely, martingale concentration inequality (e.g., Corollary 2.7) can show that the noise terms are small with high probability and thus the dynamic is dominated by the drifting terms.

E.1 Linearization in Phase 1

In this subsection, we prove Lemma 6.2 using Lemma E.1 and Lemma E.3.

**Lemma E.1 (Linearization in Phase 1).** For any \(t \in \mathbb{N}\) and \(\eta \in (0, 0.1)\), we have
\[
w_{t,1} = H_t \cdot w_{t-1,1} + \eta D_t + \eta F_t + \eta^2 Q_t
\]
almost surely, where
\[
A_t = -\sum_{i\neq j} x_{t,i} x_{t,j} w_{t-1,i} w_{t-1,j}, \quad B_t = \sum_{i=3}^{n} (x_{t,i}^2 - (\lambda_2 - \lambda_i)^2) w_{t-1,i}^2, \\
C_t = (1 - w_{t-1,1}^2) \left( x_{t,1}^2 - x_{t,2}^2 - (\lambda_1 - \lambda_2) \right), \quad D_t = \sum_{i=2}^{n} x_{t,i} x_{t,1} w_{t-1,i}, \\
E_t = \sum_{i=3}^{n} (\lambda_2 - \lambda_i) w_{t-1,i}, \quad F_t = w_{t-1,1} (A_t + B_t + C_t), \\
Q_t = O(x_{t,1}^2 w_{t-1,1}^2 + \lambda_1 w_{t-1,1}).
\]

**Proof of Lemma E.3.** Recall that from Equation 1.4, we have
\[
w_{t,1} = w_{t-1,1} + \eta \cdot \left[ \sum_{i=1}^{n} x_{t,i} w_{t-1,i} x_{t,1} - \left( \sum_{i=1}^{n} x_{t,i} w_{t-1,i} \right)^2 w_{t-1,1} \right]
= w_{t-1,1} + \eta \cdot \left[ x_{t,1}^2 w_{t-1,1} + D_t - \left( x_{t,1}^2 w_{t-1,1}^2 + x_{t,2}^2 w_{t-1,2}^2 + \sum_{i=3}^{n} x_{t,i}^2 w_{t-1,i}^2 - A_t \right) w_{t-1,1} \right]
\]

From Lemma 5.1, we can replace \( w_{t-1,2}^2 \) with \( 1 - w_{t-1,1}^2 - \sum_{i=3}^{n} w_{t-1,i}^2 + O(\eta) \). Let \( B'_t = \sum_{i=3}^{n} (x_{t,i}^2 - x_{t,i}^2) w_{t-1,i} \), we have
\[
w_{t-1,1} + \eta \cdot \left[ (x_{t,1}^2 - x_{t,2}^2) w_{t-1,1}^2 + w_{t-1,1} B'_t + w_{t-1,1} A_t + D_t \right] + O(\eta^2 x_{t,2}^2 w_{t-1,1}).
\]

By adding and subtracting \( \eta(w_1 - w_2)w_{t-1,1}^2 \) and \( \eta w_{t-1,1} E_t \), we have
\[
w_{t-1,1} + \eta \cdot \left[ (w_1 - w_2) w_{t-1,1}^2 + w_{t-1,1} (A_t + B_t + C_t + E_t) + D_t \right] + O(\eta^2 x_{t,2}^2 w_{t-1,1}).
\]

Let \( F_t = w_{t-1,1} (A_t + B_t + C_t) \) and \( Q_t = O(x_{t,1}^2 w_{t-1,1} + \lambda_1 w_{t-1,1}) \). By Lemma 2.16, we have
\[
w_{t-1,1} \cdot \exp \left( \eta(w_1 - w_2)(1 - w_{t-1,1}^2) + \eta E_t \right) + \eta D_t + \eta F_t + \eta^2 Q_t.
\]

Finally, let \( H_t = \exp \left( \eta(w_1 - w_2)(1 - w_{t-1,1}^2) + \eta E_t \right) \), we have
\[
H_t \cdot w_{t-1,1} + \eta D_t + \eta F_t + \eta^2 Q_t.
\]

\[\square\]

**Lemma E.3** (Bounded difference and conditional variance in Phase 1). For each \( t \in \mathbb{N} \), we have the following.

- (Bounded difference) For any \( t \in \mathbb{N} \), \( E_t \geq 0 \), \( |F_t| = O(w_{t-1,1}) \), and \( |Q_t| = O(w_{t-1,1}) \) almost surely.
- (Conditional expectation) For any \( t \in \mathbb{N} \), \( \mathbb{E}[F_t | \mathcal{F}_{t-1}] = 0 \) and \( \mathbb{E}[Q_t | \mathcal{F}_{t-1}] = O(\lambda_1 w_{t-1,1}) \).
- (Conditional variance) For any \( t \in \mathbb{N} \), \( \mathbb{V}[F_t | \mathcal{F}_{t-1}] = O(\lambda_1 w_{t-1,1}^3) \) and \( \mathbb{V}[Q_t | \mathcal{F}_{t-1}] = O(\lambda_1 w_{t-1,1}^2) \).

**Proof of Lemma E.3.**

- (Bounded difference) Let us start with bounding \( |F_t| = |w_{t-1,1} (A_t + B_t + C_t)| \). A straightforward application of Cauchy-Schwarz inequality would give \( |B_t|, |C_t| = O(1) \) almost surely. The bound for \( |A_t| \) is slightly trickier as follows.
\[
|A_t| \leq \sum_{i=1}^{n} |x_{t,i} w_{t-1,i}| \cdot \sum_{j \neq i} |x_{t,j} w_{t-1,j}|
= \mathcal{O} \left( \sum_{i=1}^{n} w_{t-1,i} \right)^2 \mathcal{O}(1)
= \mathcal{O}(1)
\]

almost surely.

As for the other two quantities, follow from their definitions we have \( Q_t = O(w_{t-1,1}) \) and \( E_t \geq 0 \) almost surely.
• (Conditional expectation) Since $\mathbb{E}[x_{t,i}w_{t,j} \mid F_{t-1}] = \lambda_i \cdot 1_{i=j}$ for any $i, j \in [n]$, we immediately have $\mathbb{E}[F_t \mid F_{t-1}] = 0$ and $\mathbb{E}[Q_t \mid F_{t-1}] = O(\lambda_1 w_{t-1,1}^2)$.

• (Conditional variance) First rewrite

$$A_t = -2\sum_{i=2}^{n} x_{t,i}x_{t,j} w_{t-1,i} w_{t-1,j} - \left(\sum_{i=2}^{n} x_{t,i} w_{t-1,i}\right)^2 + \sum_{i=2}^{n} x_{t,i}^2 w_{t-1,i}^2.$$ 

Consider the first term of $A_t$,

$$\mathbb{E}\left[ \sum_{i,j=2}^{n} x_{t,i}^2 x_{t,j} w_{t-1,i}^2 w_{t-1,j} \mid F_{t-1} \right] = \mathbb{E}\left[ x_{t,1}^2 w_{t-1,1}^2 \cdot \left(\sum_{i=2}^{n} x_{t,i} w_{t-1,i}\right)^2 \mid F_{t-1} \right]$$

(\because \text{Cauchy-Schwarz}) \leq \mathbb{E}\left[ x_{t,1}^2 w_{t-1,1}^2 \cdot \left(\sum_{i=2}^{n} x_{t,i}^2 \sum_{i=2}^{n} w_{t-1,i}^2 \right) \mid F_{t-1} \right]

\leq \mathbb{E}\left[ O\left(x_{t,1}^2 w_{t-1,1}^2 \right) \mid F_{t-1} \right]

\leq O(\lambda_1 w_{t-1,1}^2).

The conditional variance of last two terms of $A_t$ and the $B_t, C_t$ terms can be bounded similarly by noticing that $\mathbb{E}[x_{t,i}^2] \leq \lambda_i$. So $\text{Var}[F_t \mid F_{t-1}] \leq O(\lambda_1 w_{t-1,1}^2)$. On the other hand, the conditional variance of $Q_t$ is $O(\lambda_1 w_{t-1,1}^2)$ by checking the definition.

\[ \square \]

**E.2 Linearization in Phase 2**

In this subsection, we prove Lemma 7.2 using Lemma E.4 and Lemma E.5.

**Lemma E.4** (Linearization in Phase 2). For any $t \in \mathbb{N}$, we have

$$w'_{t,1} = H \cdot w_{t-1,1} + \eta F_t + \eta P_t + \eta^2 Q_t$$

almost surely, where

- $A_t = -\sum_{i\neq j} x_{t,i}x_{t,j} w_{t-1,i} w_{t-1,j}$,
- $B_t = \sum_{i=3}^{n} (x_{t,2}^2 - x_{t,i}^2 - (\lambda_2 - \lambda_i)) w_{t-1,i}^2$,
- $C_t = (1 - w_{t-1,1}^2) (x_{t,1}^2 - x_{t,2}^2 - (\lambda_1 - \lambda_2))$,
- $D_t = \sum_{i=2}^{n} x_{t,1}x_{t,i} w_{t-1,i}$,
- $E_t = (\lambda_1 - \lambda_2)(1 - w_{t-1,1})(w_{t-1,1}^2 + w_{t-1,1} - \frac{3}{4})$,
- $P_t = w_{t-1,1} E_t + G_t$, and
- $H = \exp(-3\eta(\lambda_1 - \lambda_2)/4)$.

**Proof of Lemma E.4.** For the simplicity of the proof, we do not derive the linearization from Taylor’s expansion here and only prove the correctness of the statement. See the continuous analysis in Section 3 for more intuition.

From Equation E.2 in the linearization of Phase 1 (i.e., Lemma 6.2), we have

$$w_{t,1} = w_{t-1,1} + \eta \cdot [(\lambda_1 - \lambda_2)w_{t-1,1}(1 - w_{t-1,1}^2) + w_{t-1,1}(A_t + B_t + C_t + E_t) + D_t] + \eta^2 Q_t.$$ 

Observe that $w_{t-1,1}(1 - w_{t-1,1}^2) = -(w_{t-1,1} - 1)(w_{t-1,1}^2 + w_{t-1,1})$, we have

$$= w_{t-1,1} + \eta \cdot [(\lambda_1 - \lambda_2)(w_{t-1,1} - 1)(w_{t-1,1}^2 + w_{t-1,1}) + w_{t-1,1}(A_t + B_t + C_t + E_t) + D_t] + \eta^2 Q_t.$$ 

Now, by adding and subtracting $\frac{3}{4}(\lambda_1 - \lambda_2)(w_{t-1,1} - 1)$, the equation becomes

$$= w_{t-1,1} + \eta \cdot \left[-\frac{3}{4}(\lambda_1 - \lambda_2)(w_{t-1,1} - 1) + w_{t-1,1}(A_t + B_t + C_t + E_t) + D_t + G_t \right] + \eta^2 Q_t.$$ 

Finally, the lemma is concluded by replacing $w_{t,1}$ and $w_{t-1,1}$ with $w'_{t,1} + 1$ and $w'_{t-1,1}$ respectively and apply Lemma 2.16 as we did in the proof of Lemma 6.2.
The following lemma shows the nice martingale structure of the noise terms.

**Lemma E.5** (Bounded difference and conditional variance in Phase 2). For each \( t \in \mathbb{N} \), we have the following.

- **(Bounded difference)** For any \( t \in \mathbb{N} \), \( |F_t| = O(\sqrt{w_{t-1}} + \eta) \), \( Q_t = O(1) \) almost surely. If \( w_{t-1,1} \geq 0.5 \), then \( P_t \geq -O(\eta \lambda_1) \) almost surely.

- **(Conditional expectation)** For any \( t \in \mathbb{N} \), \( \mathbb{E}[F_t \mid \mathcal{F}_{t-1}] = 0 \) and \( \mathbb{E}[Q_t \mid \mathcal{F}_{t-1}] = O(\lambda_1) \).

- **(Conditional variance)** \( \text{Var}[F_t \mid \mathcal{F}_{t-1}] \leq O(\lambda_1(w_{t-1}^2 + \eta)) \) and \( \text{Var}[Q_t \mid \mathcal{F}_{t-1}] \leq O(\lambda_1) \).

**Proof of Lemma E.5.** The proof is based on a careful manipulation of Cauchy-Schwarz inequality.

- **(Bounded difference)** Let us start with bounding \( |F_t| = |w_{t-1,1}(A_t + B_t + C_t) + D_t| \). A straightforward application of Cauchy-Schwarz inequality and **Lemma 5.1** would give \( |B_t|, |C_t|, |D_t| = O(\|w_{t-1}\|_2^2 - w_{t-1,1}^2)^{1/2} \) almost surely. The bound for \( |A_t| \) is slightly trickier as follows. First, rewrite

\[
A_t = -2 \sum_{i=2}^{n} x_{t,i}x_{t,i} w_{t-1,1} w_{t-1,i} - \left( \sum_{i=2}^{n} x_{t,i} w_{t-1,i} \right)^2 + \sum_{i=2}^{n} x_{t,i}^2 w_{t-1,i}^2. \tag{E.6}
\]

By Cauchy-Schwarz and **Lemma 5.1**, the last two terms can be bounded as follows.

\[
O(\|w_{t-1}\|_2^2 - w_{t-1,1}^2) = O(w_{t-1,1} + \eta) = O(\sqrt{w_{t-1,1} + \eta}).
\]

As for the first term, we have

\[
\sum_{i=2}^{n} x_{t,i} x_{t,i} w_{t-1,1} w_{t-1,i} \leq \left( \sum_{i=2}^{n} x_{t,i}^2 \right)^{1/2} \left( \sum_{i=2}^{n} x_{t,i}^2 w_{t-1,i}^2 \right)^{1/2} \leq O(\|w_{t-1}\|_2^2 - w_{t-1,1}^2)^{1/2}) = O(\sqrt{w_{t-1,1} + \eta})
\]

almost surely.

As for the \( P_t \) term, first observe that \( E_t \geq 0 \) trivially from the definition and

\[
G_t = (\lambda_1 - \lambda_2)(1 - w_{t-1,1})(w_{t-1,1}^2 + w_{t-1,1} - \frac{3}{4}) \geq -(\lambda_1 - \lambda_2)O(\eta)(w_{t-1,1}^2 + w_{t-1,1} - \frac{3}{4}) = -O(\eta \lambda_1)
\]

where the inequality is due to \( \|w_t\|^2 - 1 = O(\eta) \) by **Lemma 5.1** which implies that \( 1 - w_{t-1,1} \geq -O(\eta) \) almost surely. As a result, we have

\[
P_t = G_t + w_{t-1,1} E_t \geq -O(\eta \lambda_1)
\]

almost surely.

- **(Conditional variance)** It suffices to show that \( \mathbb{E}[F_t^2 \mid \mathcal{F}_{t-1}] = O(\lambda_1(w_{t-1}^2 + \eta)^2) \) and \( \mathbb{E}[Q_t^2 \mid \mathcal{F}_{t-1}] = O(\lambda_1) \).

First, rewrite the \( A_t \) term as in **Equation E.6**. Consider the first term of \( A_t \),

\[
\mathbb{E} \left[ \sum_{i,j=2}^{n} x_{t,i}^2 x_{t,j} x_{t,i} x_{t,j} w_{t-1,1}^2 w_{t-1,i} w_{t-1,j} \mid \mathcal{F}_{t-1} \right] = \mathbb{E} \left[ x_{t,1}^2 w_{t-1,1}^2 \left( \sum_{i=2}^{n} x_{t,i} w_{t-1,i} \right)^2 \mid \mathcal{F}_{t-1} \right]
\]

(\therefore \text{Cauchy-Schwarz}) \leq \mathbb{E} \left[ x_{t,1}^2 w_{t-1,1}^2 \left( \sum_{i=2}^{n} x_{t,i}^2 \sum_{i=2}^{n} w_{t-1,i} \right) \mid \mathcal{F}_{t-1} \right]

\leq \mathbb{E} \left[ O(x_{t,1}^2 w_{t-1,1}^2 (w_{t-1}^2 + \eta)) \mid \mathcal{F}_{t-1} \right]

\leq \lambda_1(w_{t-1,1}^2 + \eta).

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Similarly, the conditional variance of the last two terms and $B_t, C_t, D_t$ are all $O(w_{t-1,1} + \eta)$ and thus $\text{Var}[F_t | F_{t-1}] = O(\lambda_1(w_{t-1,1} + \eta))$.

As for the $Q_t$ term, as $\mathbb{E}[x_{t,2} | F_{t-1}] \leq \lambda_1$, we have $\text{Var}[Q_t | F_{t-1}] = O(\lambda_1)$.

\[ \square \]

### E.3 Linearization in Appendix D

In this subsection, we provide the full proof for Lemma D.6 on the linearization and Lemma D.10 on the bounded difference, conditional expectation, and the conditional variance of the noise terms.

**Proof of Lemma D.6**

**Proof of Lemma D.6.** The proof is based on Taylor's expansion. Concretely,

\[
 f_{t,j}(w_s) = f_{t,j}(w_{s-1}) + \eta \sum_{i=1}^{n} \frac{\partial f_{t,j}}{\partial w_i}(w_{s-1}) \cdot z_{s,i} + \eta^2 \sum_{i,i'=1}^{n} \frac{\partial^2 f_{t,j}}{\partial w_i \partial w_{i'}}(w_{s-1}) \cdot z_{s,i}z_{s,i'} .
\]

Note that $\frac{\partial f_{t,j}(w)}{\partial w_i} = -f_{t,j}(w)/w_1$ and $\frac{\partial^2 f_{t,j}(w)}{\partial w_i \partial w_{i'}} = 1_{i \leq j} \cdot x_{t,i}/w_1$ for $i = 2, \ldots, n$. Denote the $\eta^2$ term as $\eta^2 C_{t,s,j}$, we have

\[
 = f_{t,j}(w_{s-1}) - \eta f_{t,j}(w_{s-1}) \cdot z_{s,1} + \sum_{i=2}^{j} x_{s,i}z_{s,i} + \eta^2 C_{t,s,j}.
\]

Next, recall that $\mathbb{E}[z_{s,i} | F_{s-1}] = (\lambda_i - w_{s-1}^T \text{diag}(\lambda) w_{s-1,i}) \cdot w_{s-1,i}$. Denote $B_{t,s,j} = \sum_{i=1}^{n} \partial w_i f_{t,j}(w_{s-1}) \cdot (z_{s,i} - \mathbb{E}[z_{s,i} | F_{t-1}])$. By adding and subtracting the expectations, the equation becomes

\[
 = f_{t,j}(w_{s-1}) - \eta \lambda_1 f_{t,j}(w_{s-1}) + \eta \sum_{i=2}^{j} \lambda_i x_{s,i}w_{s-1,i} - \eta \lambda_1 f_{t,j}(w_{s-1}) + \eta B_{t,s,j} + \eta^2 C_{t,s,j}
\]

Observe that the two terms in the parenthesis becomes 0 after cancelling out with each other. Finally, by adding and subtracting $\eta \lambda_i f_{t,i}(w_{s-1})$ for each $i = 2, 3, \ldots, j$, we have

\[
 = (1 - \eta(\lambda_1 - \lambda_j)) \cdot f_{t,j}(w_{s-1}) + \eta \sum_{i=2}^{j} (\lambda_i - \lambda_{i+1}) f_{t,i}(w_{s-1}) + \eta B_{t,s,j} + \eta^2 C_{t,s,j}.
\]

Finally, denote $A_{t,s,j} = \sum_{i=2}^{j-1} (\lambda_i - \lambda_{i+1}) f_{t,i}(w_{s-1})$, we have

\[
 = (1 - \eta(\lambda_1 - \lambda_j)) \cdot f_{t,j}(w_{s-1}) + \eta A_{t,s,j} + \eta B_{t,s,j} + \eta^2 C_{t,s,j}.
\]

\[ \square \]

**Proof of Lemma D.10** It is not difficult to see that $f_{t,j}(w_s)$ can be nicely bounded by $O(\Lambda)$ as follows, though the bound is not good enough.

**Lemma E.7.** For any $t \in [T], s \in [t], j \in [n],$ and $c \in [0,1]$, we have,

\[
|f_{t,j}(w_{(s\wedge \tau_c)-1} + c\eta z_s)| = O(\Lambda)
\]

almost surely.
The reason why we consider \(c \eta z_s\) is that it shows up later in \(C_{t,s,j}\) due to the mean value theorem used in the linearization. Note that ideally we want \(|f_{t,j}(w_s)| \leq \Lambda\). To get the bound, we need to apply the ODE trick which requires the concentration of \(B_{t,s,j}\) and \(C_{t,s,j}\). Recall that this is exactly what we have done in Section D.3.

First, we expand the differential terms in \(B_{t,s,j}, C_{t,s,j}\) and rewrite them as follows.

**Lemma E.8** (Rewrite \(B_{t,s,j}\) and \(C_{t,s,j}\)). For any \(t \in [T]\), \(s \in [t-1]\), and \(j \in [n]\), we have

\[
B_{t,s,j} = f_{t,j}(w_{s-1}) \cdot (-x_{s,1}^2 - f_{s,n}(w_{s-1})x_{s,1} + \lambda_1) + \sum_{i=2}^{j} f_{s,n}(w_{s-1})x_{t,i}x_{s,i} + \sum_{i=2}^{j} (\lambda_i - \lambda_{i+1})f_{t,i}(w_{s-1})
\]

and

\[
C_{t,s,j} = \frac{2f_{t,j}(w_{s-1} + c \eta z_s)z_{s,1}^2 - \sum_{i=2}^{j} x_{t,i}z_{s,i}z_{s,1}}{w_{s-1,1}^2 [1 + c \eta (x_{s,1} + f_{s,n}(w_{s-1}))(x_{s,1} - y_s w_{s-1,1})]^2}.
\] (E.9)

Now, the bounded difference, conditional expectation, and the conditional variance of \(B_{t,s,j}\) and \(C_{t,s,j}\) can be easily proved with the help of Lemma E.8.

**Proof of Lemma D.10.** The bounded difference immediately follows from Lemma E.8 while the conditional expectation and the conditional variance require some small extra cares.

- **(Bounded difference)** For the \(B_{t,s \wedge \xi \wedge \tau_{t,j}}\) term, from Lemma E.7, we have

\[
|f_{t,j}(w_{(s \wedge \tau_{t})-1})|, |f_{s,n}(w_{(s \wedge \tau_{t})-1})| = O(\Lambda)
\]

almost surely. Thus, by Lemma E.8, we have

\[
|B_{t,s \wedge \xi \wedge \tau_{t,j}}| \leq (\Lambda^2) + \Lambda \cdot O \left( \sum_{i=2}^{j} x_{t,i}x_{s,i} + \sum_{i=2}^{j} (\lambda_i - \lambda_{i+1}) \right).
\]

By Cauchy-Schwarz inequality and telescoping sum, the parenthesis can be bounded by \(O(1)\) and thus we have \(|B_{t,s \wedge \xi \wedge \tau_{t,j}}| = O(\Lambda^2)\) almost surely.

As for \(C_{t,s,j}\), from Lemma E.7 and Cauchy-Schwarz inequality, we can bound the numerator in Equation E.9 by \(O(y_s^2 \Lambda)\) almost surely where the \(y_s^2\) terms are borrowed from the \(z\) terms. To see the denominator cannot be too small, first by the choice of \(\eta, \Lambda\), and Lemma E.7, we have

\[
c \eta (x_{s,1} + f_{s,n}(w_{(s \wedge \tau_{t})-1})) = O(\lambda_1)
\] (E.10)

almost surely. Thus, the bracket in the denominator of Equation E.9 would be \(\Omega(1)\). Next, as \(|f_{t,n}(w_{(s \wedge \tau_{t})-1})| = O(\Lambda)\) almost surely by Lemma E.7, we have

\[
|C_{t,s \wedge \xi \wedge \tau_{t,j}}| = O \left( \frac{y_s^2 \Lambda}{w_{(s \wedge \tau_{t})-1,1}} \right) = O \left( f_t(w_{(s \wedge \tau_{t})-1})^2 \Lambda \right) = O(\Lambda^3).
\]

- **(Conditional expectation)** Recall the original definition of \(B_{t,s,j}\) in Lemma D.6, it is naturally a martingale. Thus, its stopped process \(\{B_{t,s \wedge \xi \wedge \tau_{t,j}}\}\) is also a martingale and the conditional expectation of the stopped process is zero.
As for the $C_{t,s \wedge \xi \wedge \tau, j}$ term, let us start with rewriting the numerator of Equation E.9 by replacing $z_{s,i}$ with $y_s(x_{s,i} - y_s w_{s-1,i})$ as follows.

$$2y^2_s f_{l,j}(w_{s-1} + c_n z_s)(x_{s,1} - y_s w_{s-1,1})^2 - \sum_{i=2}^{j} y^2_s x_{t,i}(x_{s,i} - y_s w_{s-1,i})(x_{s,1} - y_s w_{s-1,1})$$

$$= 2y^2_s f_{l,j}(w_{s-1} + c_n z_s)(x_{s,1} - y_s w_{s-1,1})^2 - \sum_{i=2}^{j} y^2_s x_{t,i} x_{s,1} + \sum_{i=2}^{j} y^2_s x_{t,i} w_{s-1,i}(x_{s,1} - y_s w_{s-1,1}).$$

Let $D = [1 + c_n(x_{s,\wedge \xi \wedge \tau, 1} + f_{s,\wedge \xi \wedge \tau, n}(w_{(s,\wedge \xi \wedge \tau)_1} - y_s w_{(s,\wedge \xi \wedge \tau)_1} - 1))]2$ be the bracket term in the denominator of Equation E.9, from the previous discussion we know that $|D| = \Theta(1)$ almost surely. Now, Consider the first term combining with the denominator, we have

$$\mathbb{E} \left[ \frac{2y^2_s f_{l,j}(w_{(s,\wedge \xi \wedge \tau)_1} - 1) + c_n z_s(x_{s,\wedge \xi \wedge \tau, 1} - y_s w_{(s,\wedge \xi \wedge \tau)_1} - 1,1)}{w^2_{(s,\wedge \xi \wedge \tau)_1} - 1,1} | \mathcal{F}_{s-1} \right] = O(\lambda_1 A^3).$$

Note that the first equality holds because the quantity in the expectation is always non-negative. Next, consider the second term as follows.

$$\mathbb{E} \left[ \sum_{i=2}^{j} y^2_s x_{t,i} x_{s,\wedge \xi \wedge \tau, 1} x_{s,\wedge \xi \wedge \tau, 1} | \mathcal{F}_{s-1} \right] \leq \mathbb{E} \left[ \sum_{i=2}^{j} y^2_s x_{t,i} (x^2_{s,\wedge \xi \wedge \tau, i} + x^2_{s,\wedge \xi \wedge \tau, i}) | \mathcal{F}_{s-1} \right] \leq O(\lambda^2 \cdot \mathbb{E}[x^2_{s,\wedge \xi \wedge \tau, i} + x^2_{s,\wedge \xi \wedge \tau, i}] = O(\lambda_1 A^2).$$

The third term can be upper bounded as follows.

$$\mathbb{E} \left[ \sum_{i=2}^{j} y^2_s x_{t,i} w_{s,\wedge \xi \wedge \tau, 1} w_{s,\wedge \xi \wedge \tau, 1} | \mathcal{F}_{s-1} \right] = O(\lambda \cdot \mathbb{E}[y^2_s x_{s,\wedge \xi \wedge \tau} | \mathcal{F}_{s-1}]) = O(\lambda_1 A).$$

The last term can be upper bounded as follows.

$$\mathbb{E} \left[ \sum_{i=2}^{j} y^2_s x_{t,i} w_{s,\wedge \xi \wedge \tau, 1} w_{s,\wedge \xi \wedge \tau, 1} | \mathcal{F}_{s-1} \right] = O(\lambda^2 \cdot \mathbb{E}[y^2_s x_{s,\wedge \xi \wedge \tau} | \mathcal{F}_{s-1}] = O(\lambda_1 A^2).$$

We conclude that $|\mathbb{E}[C_{t,s,\wedge \xi \wedge \tau, j} | \mathcal{F}_{s-1}]| = O(\lambda^3)$.  

- (Conditional variance) The conditional variance of $B_{t,s,\wedge \xi \wedge \tau, j}$ and $C_{t,s,\wedge \xi \wedge \tau, j}$ can be upper bounded using the same argument as we did in the calculation of conditional expectation. Thus, we omit the details here for simplicity.

**Proof of Lemma E.8** Let us complete this subsection with the proof for the lemma that rewrites $B_{t,s,j}$ and $C_{t,s,j}$.

**Proof of Lemma E.8.** Recall that

$$B_{t,s,j} = \sum_{i=1}^{n} \frac{\partial f_{l,j}}{\partial w_{i}}(w_{s-1}) \cdot (z_{s,i} - \mathbb{E}[z_{s,i} | \mathcal{F}_{s-1}])$$

and

$$C_{t,s,j} = \sum_{i,i'=1}^{n} \frac{\partial^2 f_{l,j}}{\partial w_{i} \partial w_{i'}}(w_{s-1}) \cdot z_{s,i} z_{s,i'}$$

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For simplicity, in the following we denote $\mathbb{E}_{t-1}[:]=\mathbb{E}_t[:|\mathcal{F}_{t-1}]$. Observe that

$$\frac{\partial f_{t,j}(w)}{\partial w_i} = \begin{cases} \frac{-f_{t,j}(w)}{w_i}, & \text{if } i = 1 \\ \frac{x_{s,i}}{w_i}, & \text{if } i = 2, 3, \ldots, j \end{cases}$$

and

$$\frac{\partial^2 f_{t,j}(w)}{\partial w_i \partial w_{i'}} = \begin{cases} \frac{2f_{t,j}(w)}{w_i}, & \text{if } i = i' = 1 \\ \frac{-x_{s,i'}}{w_i}, & \text{if } i = 1 \text{ and } i' = 2, 3, \ldots, j \\ \frac{-x_{s,i}}{w_i}, & \text{if } i = 2, 3, \ldots, j \text{ and } i' = 1 \\ 0, & \text{else}. \end{cases}$$

Let us start with rewriting $B_{t,s,j}$ as follows.

$$B_{t,s,j} = -\frac{f_{t,j}(w_{s-1}) \cdot (z_{s,1} - \mathbb{E}_{s-1}[z_{s,1}])}{w_{s-1,1}} + \sum_{i=2}^j \frac{x_{t,i} \cdot (z_{s,i} - \mathbb{E}_{s-1}[z_{s,i}])}{w_{s-1,1}}.$$ (1)

Recall that $z_{s,i} = y_s(x_{s,i} - y_s w_{s-1,i})$ and $\mathbb{E}_{s-1}[z_{s,i}] = (\lambda_i - w_{s-1,1} \text{diag}(\lambda) w_{s-1}) \cdot w_{s-1,i}$. The equation then becomes

$$= -\frac{f_{t,j}(w_{s-1})y_s x_{s,1}}{w_{s-1,1}} + (y_s^2 + \lambda_1 - w_{s-1,1} \text{diag}(\lambda) w_{s-1}) \cdot f_{t,j}(w_{s-1})$$

$$+ \sum_{i=2}^j y_s x_{t,i} x_{s,i} - (y_s^2 + \lambda_1 - w_{s-1,1} \text{diag}(\lambda) w_{s-1}) \cdot x_{t,i} w_{s-1,i} \frac{w_{s-1,1}}{w_{s-1,1}}.$$ (2)

Recall that $y_s = \sum_{i=1}^n x_{s,i} w_{s-1,i} = x_{s,1} w_{s-1,1} + f_{s,n}(w_{s-1}) w_{s-1,1}$. The equation becomes

$$= f_{t,j}(w_{s-1}) \cdot (-x_{s,1}^2 - f_{s,n}(w_{s-1}) x_{s,1} + \lambda_1) + \sum_{i=2}^j f_{s,n}(w_{s-1}) x_{t,i} x_{s,i} + \sum_{i=2}^j (\lambda_i - \lambda_{i+1}) f_{t,i}(w_{s-1}).$$ (3)

Note that $B_{t,s,j}$ only depends on $f_{t',j'}(w_{s-1})$ for any $t' \in [t]$ and $j' \in [n]$. Next, let us rewrite $C_{t,s,j}$ by expanding the second order derivative as follows.

$$C_{t,s,j} = \frac{2f_{t,j}(w_{s-1}) z_{s,1}^2}{w_{s-1,1}} - \sum_{i=2}^j \frac{x_{t,i} z_{s,i} z_{s,1}}{w_{s-1,1}}.$$ (4)

By mean value theorem, we can replace $w_{s-1}$ with $w_{s-1} + c \eta z_s$ for some $c \in [0, 1]$ and by definition, we can replace the $z_s$ in the denominator with $y_s(x_s - y_s w_{s-1})$. The equation becomes

$$= \frac{2f_{t,j}(w_{s-1} + c \eta z_s) z_{s,1}^2 - \sum_{i=2}^j x_{t,i} z_{s,i} z_{s,1}}{(w_{s-1,1} + c \eta y_s(x_{s,1} - y_s w_{s-1,1}))^2}.$$ (5)

Next, replace $y_s$ with $x_{s,1} w_{s-1,1} + f_{s,n}(w_{s-1}) w_{s-1,1}$ as we did before and get

$$= \frac{2f_{t,j}(w_{s-1} + c \eta z_s) z_{s,1}^2 - \sum_{i=2}^j x_{t,i} z_{s,i} z_{s,1}}{w_{s-1,1}^2 [1 + c \eta (x_{s,1} + f_{s,n}(w_{s-1}))(x_{s,1} - y_s w_{s-1,1})]^2}.$$ (6)

Note that now $C_{t,s,j}$ is under control in the sense that the numerator is bounded by $O(\Lambda)$ and the denominator is $\Omega(w_{s-1,1}^2)$ under the stopping time condition.

\[\square\]

**F Proof of Theorem 4.2**

Let us first state a corollary of Lemma 7.4 as follows.
Corollary F.1. For any $\epsilon, \delta', \eta \in (0, 0.5)$ such that $\eta = O\left(\frac{\epsilon(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{\lambda_1}{\lambda_2}}\right)$, let $t_3 \in \mathbb{N}$ be

$$t_3 = \frac{4}{3} \cdot \frac{1}{\eta(\lambda_1 - \lambda_2)} + \Theta\left(\frac{1}{\eta(\lambda_1 - \lambda_2) \log \frac{1}{\epsilon}}\right).$$

Suppose there exists some $t_0 \in \mathbb{N}$ such that $w_{t_0,1} \geq 1 - \frac{\epsilon}{2}$. Then,

$$H^{t_3} = \exp\left(-\frac{3}{4}\eta(\lambda_1 - \lambda_2)t_3\right) \leq \frac{1}{10}$$

and

$$\Pr\left[\min_{1 \leq t \leq t_3} \sum_{i=t_0+1}^{t_0+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{t_i-t_0}} < -\frac{\epsilon}{2}\right] < \delta'.$$

Proof of Corollary F.1. This is an immediately corollary of Lemma 7.4 by setting $\epsilon' = \epsilon$, $k = \log \log(1/\epsilon)$, and $\gamma = \epsilon$. \hfill \square

Proof of Theorem 4.2. The first statement of the theorem is an immediate corollary of Lemma 7.4 by setting $\delta' = \delta/10s^2$.

Claim F.2. For any $s \in \mathbb{N}$, denote $t_0 = (s - 1)t_3$ we have

$$\Pr\left[\min_{1 \leq t \leq t_3} w_{t_0+t,1} < 1 - \epsilon \bigg| w_{t_0+t,1} < 1 - \frac{\epsilon}{2} \bigg| w_{t_0,1} \geq 1 - \frac{\epsilon}{2}\right] < \frac{\delta}{10s^2}.$$

Proof of Claim F.2. For any $s \in \mathbb{N}$, let $t_0 = (s - 1)t_3$ and condition on the event $\{w_{t_0,1} \geq 1 - \epsilon/2\}$. Next, invoke Corollary F.1 with $\delta' = \frac{\delta}{10s^2}$. Check that $10 \log \frac{w_{t_0}}{a} \geq 10 \log \frac{\epsilon}{2} \geq \log \frac{10s^2}{\epsilon} = \log \frac{1}{\delta}$. Thus,

$$\eta_{t_0+t} = O\left(\frac{\epsilon(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{\lambda_1}{\lambda_2}}\right) = O\left(\frac{\epsilon(\lambda_1 - \lambda_2)}{\lambda_1 \log \frac{w_{t_0}}{a}}\right)$$

for all $1 \leq t \leq t_3$. Then, by Lemma 7.4 we have

$$\Pr\left[\min_{1 \leq t \leq t_3} \sum_{i=t_0+1}^{t_0+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{t_i-t_0}} < -\frac{\epsilon}{2} \bigg| w_{t_0,1} \geq 1 - \frac{\epsilon}{2}\right] < \frac{\delta}{10s^2}$$

and $H^{t_3} \leq \frac{1}{10s^2}$. For any $1 \leq t \leq t_3$, recall that $w'_{t_0+t,1} = w_{t_0+t,1} - 1$. Now, apply the ODE trick in Phase 2 (i.e., Corollary 7.3), we have

$$w'_{t_0+t,1} \geq H^{t_3} \cdot \left(w_{t_0,1} + \sum_{i=t_0+1}^{t_0+t} \frac{\eta F_i + \eta P_i + \eta^2 Q_i}{H^{t_i-t_0}}\right).$$

Conditioning on the event $\{w_{t_0,1} \geq 1 - \epsilon/2\}$, with probability at least $1 - \frac{\delta}{10s^2}$, the inequality becomes

$$\geq H^{t_3} \cdot \left(-\frac{\epsilon}{2} - \frac{\epsilon}{2}\right) \geq \left\{\begin{array}{ll}
-\frac{\epsilon}{2}, & 1 \leq t < t_3 \\
-\frac{\epsilon}{2}, & t = t_3.
\end{array}\right.$$

This completes the proof of the claim. \hfill \square

By the chain rule for conditional probability, Claim F.2 gives

$$\Pr \left[\exists t \geq 0, \ w_{t,1} < 1 - \epsilon\right] \leq \sum_{s=0}^{\infty} \Pr \left[\min_{(s-1)t_3+1 \leq t \leq st_3} w_{t,1} < 1 - \epsilon \bigg| w_{s-t_3,1} < 1 - \frac{\epsilon}{2} \bigg| w_{(s-1)t_3} \geq 1 - \frac{\epsilon}{2}\right] \leq \sum_{s=0}^{\infty} \frac{\delta}{10s^2} \leq \delta.$$

This completes the proof of Theorem 4.2. \hfill \square
References


