

Supplementary Material of A Matrix Chernoff Bound for Markov Chains and Its Application to Co-occurrence Matrices

A Convergence Rate of Co-occurrence Matrices

A.1 Proof of Claim 1

Claim 1 (Properties of \mathbf{Q}). *If \mathbf{P} is a regular Markov chain, then \mathbf{Q} satisfies:*

1. \mathbf{Q} is a regular Markov chain with stationary distribution $\sigma_{(u_0, \dots, u_T)} = \pi_{u_0} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T}$;
2. The sequence (X_1, \dots, X_{L-T}) is a random walk on \mathbf{Q} starting from a distribution ρ such that $\rho_{(u_0, \dots, u_T)} = \phi_{u_0} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T}$, and $\|\rho\|_\sigma = \|\phi\|_\pi$.
3. $\forall \delta > 0$, the δ -mixing time of \mathbf{P} and \mathbf{Q} satisfies $\tau(\mathbf{Q}) < \tau(\mathbf{P}) + T$;
4. $\exists \mathbf{P}$ with $\lambda(\mathbf{P}) < 1$ s.t. the induced \mathbf{Q} has $\lambda(\mathbf{Q}) = 1$, i.e. \mathbf{Q} may have zero spectral gap.

Proof. We prove the four parts of this Claim one by one.

Part 1 To prove \mathbf{Q} is regular, it is sufficient to show that $\exists N_1, \forall n_1 > N_1, (v_0, \dots, v_T)$ can reach (u_0, \dots, u_T) at n_1 steps. We know \mathbf{P} is a regular Markov chain, so there exists $N_2 \geq T$ s.t., for any $n_2 \geq N_2, v_T$ can reach u_0 at exact n_2 step, i.e., there is a n_2 -step walk s.t. $(v_T, w_1, \dots, w_{n_2-1}, u_0)$ on \mathbf{P} . This induces an n_2 -step walk from (v_0, \dots, v_T) to $(w_{n_2-T+1}, \dots, w_{n_2-1}, u_0)$. Take further T step, we can reach (u_0, \dots, u_T) , so we construct a $n_1 = n_2 + T$ step walk from (v_0, \dots, v_T) to (u_0, \dots, u_T) . Since this is true for any $n_2 \geq N_2$, we then claim that any state can be reached from any other state in any number of steps greater than or equal to a number $N_1 = N_2 + T$. Next to verify σ such that $\sigma_{(u_0, \dots, u_T)} = \pi_{u_0} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T}$ is the stationary distribution of Markov chain \mathbf{Q} ,

$$\begin{aligned}
 & \sum_{(u_0, \dots, u_T) \in \mathcal{S}} \sigma_{(u_0, \dots, u_T)} \mathbf{Q}_{(u_0, \dots, u_T), (w_0, \dots, w_T)} \\
 &= \sum_{u_0: (u_0, w_0, \dots, w_{T-1}) \in \mathcal{S}} \pi_{u_0} \mathbf{P}_{u_0, w_0} \mathbf{P}_{w_0, w_1}, \dots, \mathbf{P}_{w_{T-2}, w_{T-1}} \mathbf{P}_{w_{T-1}, w_T} \\
 &= \left(\sum_{u_0} \pi_{u_0} \mathbf{P}_{u_0, w_0} \right) \mathbf{P}_{w_0, w_1}, \dots, \mathbf{P}_{w_{T-2}, w_{T-1}} \mathbf{P}_{w_{T-1}, w_T} \\
 &= \pi_{w_0} \mathbf{P}_{w_0, w_1}, \dots, \mathbf{P}_{w_{T-2}, w_{T-1}} \mathbf{P}_{w_{T-1}, w_T} = \sigma_{w_0, \dots, w_T}.
 \end{aligned}$$

Part 2 Recall (v_1, \dots, v_L) is a random walk on \mathbf{P} starting from distribution ϕ , so the probability we observe $X_1 = (v_1, \dots, v_{T+1})$ is $\phi_{v_1} \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_T, v_{T+1}} = \rho_{(v_1, \dots, v_{T+1})}$, i.e., X_1 is sampled from the distribution ρ . Then we study the transition probability from $X_i = (v_i, \dots, v_{i+T})$ to $X_{i+1} = (v_{i+1}, \dots, v_{i+T+1})$, which is $\mathbf{P}_{v_{i+T}, v_{i+T+1}} = \mathbf{Q}_{X_i, X_{i+1}}$. Consequently, we can claim (X_i, \dots, X_{L-T}) is a random walk on \mathbf{Q} . Moreover,

$$\begin{aligned}
 \|\rho\|_\sigma^2 &= \sum_{(u_0, \dots, u_T) \in \mathcal{S}} \frac{\rho_{(u_0, \dots, u_T)}^2}{\sigma_{(u_0, \dots, u_T)}} = \sum_{(u_0, \dots, u_T) \in \mathcal{S}} \frac{(\phi_{u_0} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T})^2}{\pi_{u_0} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T}} \\
 &= \sum_{u_0} \frac{\phi_{u_0}^2}{\pi_{u_0}} \sum_{(u_0, u_1, \dots, u_T) \in \mathcal{S}} \mathbf{P}_{u_0, u_1} \cdots \mathbf{P}_{u_{T-1}, u_T} = \sum_{u_0} \frac{\phi_{u_0}^2}{\pi_{u_0}} = \|\phi\|_\pi^2,
 \end{aligned}$$


which implies $\|\rho\|_\sigma = \|\phi\|_\pi$.

Part 3 For any distribution \mathbf{y} on \mathcal{S} , define $\mathbf{x} \in \mathbb{R}^n$ such that $x_i = \sum_{(v_1, \dots, v_{T-1}, i) \in \mathcal{S}} y_{v_1, \dots, v_{T-1}, i}$. Easy to see \mathbf{x} is a probability vector, since \mathbf{x} is the marginal probability of \mathbf{y} . For convenience, we

assume for a moment the $\mathbf{x}, \mathbf{y}, \boldsymbol{\sigma}, \boldsymbol{\pi}$ are row vectors. We can see that:

$$\begin{aligned}
\|\mathbf{y}\mathbf{Q}^{\tau(\mathbf{P})+T-1} - \boldsymbol{\sigma}\|_{TV} &= \frac{1}{2} \|\mathbf{y}\mathbf{Q}^{\tau(\mathbf{P})+T-1} - \boldsymbol{\sigma}\|_1 \\
&= \frac{1}{2} \sum_{(v_1, \dots, v_T) \in \mathcal{S}} \left| \left(\mathbf{y}\mathbf{Q}^{\tau(\mathbf{P})+T-1} - \boldsymbol{\sigma} \right)_{v_1, \dots, v_T} \right| \\
&= \frac{1}{2} \sum_{(v_1, \dots, v_T) \in \mathcal{S}} \left| \left(\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} \right)_{v_1} \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_{T-1}, v_T} - \pi_{v_1} \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_{T-1}, v_T} \right| \\
&= \frac{1}{2} \sum_{(v_1, \dots, v_T) \in \mathcal{S}} \left| \left(\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} \right)_{v_1} - \pi_{v_1} \right| \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_{T-1}, v_T} \\
&= \frac{1}{2} \sum_{v_1} \left| \left(\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} \right)_{v_1} - \pi_{v_1} \right| \sum_{(v_1, \dots, v_T) \in \mathcal{S}} \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_{T-1}, v_T} \\
&= \frac{1}{2} \sum_{v_1} \left| \left(\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} \right)_{v_1} - \pi_{v_1} \right| = \frac{1}{2} \|\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} - \boldsymbol{\pi}\|_1 = \|\mathbf{x}\mathbf{P}^{\tau(\mathbf{P})} - \boldsymbol{\pi}\|_{TV} \leq \delta.
\end{aligned}$$

which indicates $\tau(\mathbf{Q}) \leq \tau(\mathbf{P}) + T - 1 < \tau(\mathbf{P}) + T$.

Part 4 This is an example showing that $\lambda(\mathbf{Q})$ cannot be bounded by $\lambda(\mathbf{P})$ — even though \mathbf{P} has $\lambda(\mathbf{P}) < 1$, the induced \mathbf{Q} may have $\lambda(\mathbf{Q}) = 1$. We consider random walk on the unweighted undirected graph  and $T = 1$. The transition probability matrix \mathbf{P} is:

$$\mathbf{P} = \begin{bmatrix} 0 & 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \end{bmatrix}$$

with stationary distribution $\boldsymbol{\pi} = [0.3 \ 0.2 \ 0.3 \ 0.2]^\top$ and $\lambda(\mathbf{P}) = \frac{2}{3}$. When $T = 1$, the induced Markov chain \mathbf{Q} has stationary distribution $\sigma_{u,v} = \pi_u \mathbf{P}_{u,v} = \frac{d_u}{2m} \frac{1}{d_u} = \frac{1}{2m}$ where $m = 5$ is the number of edges in the graph. Construct $\mathbf{y} \in \mathbb{R}^{|\mathcal{S}|}$ such that

$$\mathbf{y}_{(u,v)} = \begin{cases} 1 & (u,v) = (0,1), \\ -1 & (u,v) = (0,3), \\ 0 & \text{otherwise.} \end{cases}$$

The constructed vector \mathbf{y} has norm

$$\|\mathbf{y}\|_\sigma = \sqrt{\langle \mathbf{y}, \mathbf{y} \rangle_\sigma} = \sqrt{\sum_{(u,v) \in \mathcal{S}} \frac{\mathbf{y}_{(u,v)} \mathbf{y}_{(u,v)}}{\sigma_{(u,v)}}} = \sqrt{\frac{\mathbf{y}_{(0,1)} \mathbf{y}_{(0,1)}}{\sigma_{(0,1)}} + \frac{\mathbf{y}_{(0,3)} \mathbf{y}_{(0,3)}}{\sigma_{(0,3)}}} = 2\sqrt{m}.$$

And it is easy to check $\mathbf{y} \perp \boldsymbol{\sigma}$, since $\langle \mathbf{y}, \boldsymbol{\sigma} \rangle_\sigma = \sum_{(u,v) \in \mathcal{S}} \frac{\sigma_{(u,v)} \mathbf{y}_{(u,v)}}{\sigma_{(u,v)}} = \mathbf{y}_{(0,1)} + \mathbf{y}_{(0,3)} = 0$. Let $\mathbf{x} = (\mathbf{y}^* \mathbf{Q})^*$, we have for $(u,v) \in \mathcal{S}$:

$$\mathbf{x}_{(u,v)} = \begin{cases} 1 & (u,v) = (1,2), \\ -1 & (u,v) = (3,2), \\ 0 & \text{otherwise.} \end{cases}$$

This vector has norm:

$$\|\mathbf{x}\|_\sigma = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle_\sigma} = \sqrt{\sum_{(u,v) \in \mathcal{S}} \frac{\mathbf{x}_{(u,v)} \mathbf{x}_{(u,v)}}{\sigma_{(u,v)}}} = \sqrt{\frac{\mathbf{y}_{(1,2)} \mathbf{y}_{(1,2)}}{\sigma_{(1,2)}} + \frac{\mathbf{y}_{(3,2)} \mathbf{y}_{(3,2)}}{\sigma_{(3,2)}}} = 2\sqrt{m}$$

Thus we have $\frac{\|(\mathbf{y}^* \mathbf{Q})^*\|_\sigma}{\|\mathbf{y}\|_\sigma} = 1$. Taking maximum over all possible \mathbf{y} gives $\lambda(\mathbf{Q}) \geq 1$. Also note that fact that $\lambda(\mathbf{Q}) \leq 1$, so $\lambda(\mathbf{Q}) = 1$. \square

A.2 Proof of Claim 2

Claim 2 (Properties of f). *The function f in Equation 2 satisfies (1) $\sum_{X \in \mathcal{S}} \sigma_X f(X) = 0$; (2) $f(X)$ is symmetric and $\|f(X)\|_2 \leq 1, \forall X \in \mathcal{S}$.*

Proof. Note that Equation 2 is indeed a random value minus its expectation, so naturally Equation 2 has zero mean, i.e., $\sum_{X \in \mathcal{S}} \sigma_X f(X) = 0$. Moreover, $\|f(X)\|_2 \leq 1$ because

$$\begin{aligned} \|f(X)\|_2 &\leq \frac{1}{2} \left(\sum_{r=1}^T \frac{|\alpha_r|}{2} \left(\|e_{v_0} e_{v_r}^\top\|_2 + \|e_{v_r} e_{v_0}^\top\|_2 \right) + \sum_{r=1}^T \frac{|\alpha_r|}{2} \left(\|\mathbf{\Pi}\|_2 \|\mathbf{P}\|_2^r + \|\mathbf{P}^\top\|_2^r \|\mathbf{\Pi}\|_2 \right) \right) \\ &\leq \frac{1}{2} \left(\sum_{r=1}^T |\alpha_r| + \sum_{r=1}^T |\alpha_r| \right) = 1. \end{aligned}$$

where the first step follows triangle inequality and submultiplicativity of 2-norm, and the third step follows by (1) $\|e_i e_j^\top\|_2 = 1$; (2) $\|\mathbf{\Pi}\|_2 = \|\text{diag}(\boldsymbol{\pi})\|_2 \leq 1$ for distribution $\boldsymbol{\pi}$; (3) $\|\mathbf{P}\|_2 = \|\mathbf{P}^\top\|_2 = 1$. \square

A.3 Proof of Corollary 1

Corollary 1 (Co-occurrence Matrices of HMMs). *For a HMM with observable states $y_t \in \mathcal{Y}$ and hidden states $x_t \in \mathcal{X}$, let $P(y_t|x_t)$ be the emission probability and $P(x_{t+1}|x_t)$ be the hidden state transition probability. Given an L -step trajectory observations from the HMM, (y_1, \dots, y_L) , one needs a trajectory of length $L = O(\tau(\log |\mathcal{Y}| + \log \tau)/\epsilon^2)$ to achieve a co-occurrence matrix within error bound ϵ with high probability, where τ is the mixing time of the Markov chain on hidden states.*

Proof. A HMM can be model by a Markov chain \mathbf{P} on $\mathcal{Y} \times \mathcal{X}$ such that $P(y_{t+1}, x_{t+1}|y_t, x_t) = P(y_{t+1}|x_{t+1})P(x_{t+1}|x_t)$. For the co-occurrence matrix of observable states, applying a similar proof like our Theorem 2 shows that one needs a trajectory of length $O(\tau(\mathbf{P})(\log |\mathcal{Y}| + \log \tau(\mathbf{P}))/\epsilon^2)$ to achieve error bound ϵ with high probability. Moreover, the mixing time $\tau(\mathbf{P})$ is bounded by the mixing time of the Markov chain on the hidden state space (i.e., $P(x_{t+1}|x_t)$). \square

B Matrix Chernoff Bounds for Markov Chains

B.1 Preliminaries

Kronecker Products If \mathbf{A} is an $M_1 \times N_1$ matrix and \mathbf{B} is a $M_2 \times N_2$ matrix, then the Kronecker product $\mathbf{A} \otimes \mathbf{B}$ is the $M_2 M_1 \times N_1 N_2$ block matrix such that

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} \mathbf{A}_{1,1} \mathbf{B} & \cdots & \mathbf{A}_{1,N_1} \mathbf{B} \\ \vdots & \ddots & \vdots \\ \mathbf{A}_{M_1,1} \mathbf{B} & \cdots & \mathbf{A}_{M_1,N_1} \mathbf{B} \end{bmatrix}.$$

Kronecker product has the mixed-product property. If $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}$ are matrices of such size that one can form the matrix products \mathbf{AC} and \mathbf{BD} , then $(\mathbf{A} \otimes \mathbf{B})(\mathbf{C} \otimes \mathbf{D}) = (\mathbf{AC}) \otimes (\mathbf{BD})$.

Vectorization For a matrix $\mathbf{X} \in \mathbb{C}^{d \times d}$, $\text{vec}(\mathbf{X}) \in \mathbb{C}^{d^2}$ denote the vectorization of the matrix \mathbf{X} , s.t. $\text{vec}(\mathbf{X}) = \sum_{i \in [d]} \sum_{j \in [d]} \mathbf{X}_{i,j} e_i \otimes e_j$, which is the stack of rows of \mathbf{X} . And there is a relationship between matrix multiplication and Kronecker product s.t. $\text{vec}(\mathbf{AXB}) = (\mathbf{A} \otimes \mathbf{B}^\top) \text{vec}(\mathbf{X})$.

Matrices and Norms For a matrix $\mathbf{A} \in \mathbb{C}^{N \times N}$, we use \mathbf{A}^\top to denote matrix transpose, use $\overline{\mathbf{A}}$ to denote entry-wise matrix conjugation, use \mathbf{A}^* to denote matrix conjugate transpose ($\mathbf{A}^* = \overline{\mathbf{A}^\top} = \overline{\mathbf{A}}^\top$). The vector 2-norm is defined to be $\|\mathbf{x}\|_2 = \sqrt{\mathbf{x}^* \mathbf{x}}$, and the matrix 2-norm is defined to be $\|\mathbf{A}\|_2 = \max_{\mathbf{x} \in \mathbb{C}^N, \mathbf{x} \neq 0} \frac{\|\mathbf{Ax}\|_2}{\|\mathbf{x}\|_2}$.

We then recall the definition of inner-product under $\boldsymbol{\pi}$ -kernel in Section 2. The inner-product under $\boldsymbol{\pi}$ -kernel for \mathbb{C}^N is $\langle \mathbf{x}, \mathbf{y} \rangle_\boldsymbol{\pi} = \mathbf{y}^* \mathbf{\Pi}^{-1} \mathbf{x}$ where $\mathbf{\Pi} = \text{diag}(\boldsymbol{\pi})$, and its induced $\boldsymbol{\pi}$ -norm $\|\mathbf{x}\|_\boldsymbol{\pi} = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle_\boldsymbol{\pi}}$. The above definition allow us to define a inner product under $\boldsymbol{\pi}$ -kernel on \mathbb{C}^{Nd^2} :

Definition 1. Define inner product on \mathbb{C}^{Nd^2} under $\boldsymbol{\pi}$ -kernel to be $\langle \mathbf{x}, \mathbf{y} \rangle_\boldsymbol{\pi} = \mathbf{y}^* (\mathbf{\Pi}^{-1} \otimes \mathbf{I}_{d^2}) \mathbf{x}$.

Remark 1. For $\mathbf{x}, \mathbf{y} \in \mathbb{C}^N$ and $\mathbf{p}, \mathbf{q} \in \mathbb{C}^{d^2}$, then inner product (under $\boldsymbol{\pi}$ -kernel) between $\mathbf{x} \otimes \mathbf{p}$ and $\mathbf{y} \otimes \mathbf{q}$ can be simplified as

$$\langle \mathbf{x} \otimes \mathbf{p}, \mathbf{y} \otimes \mathbf{q} \rangle_\boldsymbol{\pi} = (\mathbf{y} \otimes \mathbf{q})^* (\mathbf{\Pi}^{-1} \otimes \mathbf{I}_{d^2}) (\mathbf{x} \otimes \mathbf{p}) = (\mathbf{y}^* \mathbf{\Pi}^{-1} \mathbf{x}) \otimes (\mathbf{q}^* \mathbf{p}) = \langle \mathbf{x}, \mathbf{y} \rangle_\boldsymbol{\pi} \langle \mathbf{p}, \mathbf{q} \rangle.$$

Remark 2. The induced π -norm is $\|\mathbf{x}\|_\pi = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle_\pi}$. When $\mathbf{x} = \mathbf{y} \otimes \mathbf{w}$, the π -norm can be simplified to be: $\|\mathbf{x}\|_\pi = \sqrt{\langle \mathbf{y} \otimes \mathbf{w}, \mathbf{y} \otimes \mathbf{w} \rangle_\pi} = \sqrt{\langle \mathbf{y}, \mathbf{y} \rangle_\pi \langle \mathbf{w}, \mathbf{w} \rangle} = \|\mathbf{y}\|_\pi \|\mathbf{w}\|_2$.

Matrix Exponential The matrix exponential of a matrix $\mathbf{A} \in \mathbb{C}^{d \times d}$ is defined by Taylor expansion $\exp(\mathbf{A}) = \sum_{j=0}^{+\infty} \frac{\mathbf{A}^j}{j!}$. And we will use the fact that $\exp(\mathbf{A}) \otimes \exp(\mathbf{B}) = \exp(\mathbf{A} \otimes \mathbf{I} + \mathbf{I} \otimes \mathbf{B})$.

Golden-Thompson Inequality We need the following multi-matrix Golden-Thompson inequality from Garg et al. [10].

Theorem 4 (Multi-matrix Golden-Thompson Inequality, Theorem 1.5 in [10]). *Let $\mathbf{H}_1, \dots, \mathbf{H}_k$ be k Hermitian matrices, then for some probability distribution μ on $[-\frac{\pi}{2}, \frac{\pi}{2}]$.*

$$\log \left(\text{Tr} \left[\exp \left(\sum_{j=1}^k \mathbf{H}_j \right) \right] \right) \leq \frac{4}{\pi} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \log \left(\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} \mathbf{H}_j \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} \mathbf{H}_j \right) \right] \right) d\mu(\phi).$$

B.2 Proof of Theorem 3

Theorem 3 (A Real-Valued Version of Theorem 1). *Let \mathbf{P} be a regular Markov chain with state space $[N]$, stationary distribution π and spectral expansion λ . Let $f : [N] \rightarrow \mathbb{R}^{d \times d}$ be a function such that (1) $\forall v \in [N]$, $f(v)$ is symmetric and $\|f(v)\|_2 \leq 1$; (2) $\sum_{v \in [N]} \pi_v f(v) = \mathbf{0}$. Let (v_1, \dots, v_k) denote a k -step random walk on \mathbf{P} starting from a distribution ϕ on $[N]$. Then given $\epsilon \in (0, 1)$,*

$$\begin{aligned} \mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \geq \epsilon \right] &\leq \|\phi\|_\pi d^2 \exp(-(\epsilon^2(1-\lambda)k/72)) \\ \mathbb{P} \left[\lambda_{\min} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \leq -\epsilon \right] &\leq \|\phi\|_\pi d^2 \exp(-(\epsilon^2(1-\lambda)k/72)). \end{aligned}$$

Proof. Due to symmetry, it suffices to prove one of the statements. Let $t > 0$ be a parameter to be chosen later. Then

$$\begin{aligned} \mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \geq \epsilon \right] &= \mathbb{P} \left[\lambda_{\max} \left(\sum_{j=1}^k f(v_j) \right) \geq k\epsilon \right] \\ &\leq \mathbb{P} \left[\text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \geq \exp(tk\epsilon) \right] \\ &\leq \frac{\mathbb{E}_{v_1, \dots, v_k} \left[\text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \right]}{\exp(tk\epsilon)}. \end{aligned} \quad (3)$$

The second inequality follows Markov inequality.

Next to bound $\mathbb{E}_{v_1, \dots, v_k} \left[\text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \right]$. Using Theorem 4, we have:

$$\begin{aligned} \log \left(\text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \right) &\leq \frac{4}{\pi} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \log \left(\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right] \right) d\mu(\phi) \\ &\leq \frac{4}{\pi} \log \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right] d\mu(\phi), \end{aligned}$$

where the second step follows by concavity of log function and the fact that $\mu(\phi)$ is a probability distribution on $[-\frac{\pi}{2}, \frac{\pi}{2}]$. This implies

$$\text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \leq \left(\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right] d\mu(\phi) \right)^{\frac{4}{\pi}}.$$

Note that $\|\mathbf{x}\|_p \leq d^{1/p-1} \|\mathbf{x}\|_1$ for $p \in (0, 1)$, choosing $p = \pi/4$ we have

$$\left(\text{Tr} \left[\exp \left(\frac{\pi}{4} t \sum_{j=1}^k f(v_j) \right) \right] \right)^{\frac{4}{\pi}} \leq d^{\frac{4}{\pi}-1} \text{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right].$$

Combining the above two equations together, we have

$$\mathrm{Tr} \left[\exp \left(\frac{\pi}{4} t \sum_{j=1}^k f(v_j) \right) \right] \leq d^{1-\frac{\pi}{4}} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \mathrm{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right] d\mu(\phi). \quad (4)$$

Write $e^{i\phi} = \gamma + ib$ with $\gamma^2 + b^2 = |\gamma + ib|^2 = |e^{i\phi}|^2 = 1$:

Lemma 1 (Analogous to Lemma 4.3 in [10]). *Let \mathbf{P} be a regular Markov chain with state space $[N]$ with spectral expansion λ . Let f be a function $f : [N] \rightarrow \mathbb{R}^{d \times d}$ such that (1) $\sum_{v \in [N]} \pi_v f(v) = 0$; (2) $\|f(v)\|_2 \leq 1$ and $f(v)$ is symmetric, $v \in [N]$. Let (v_1, \dots, v_k) denote a k -step random walk on \mathbf{P} starting from a distribution ϕ on $[N]$. Then for any $t > 0, \gamma \geq 0, b > 0$ such that $t^2(\gamma^2 + b^2) \leq 1$ and $t\sqrt{\gamma^2 + b^2} \leq \frac{1-\lambda}{4\lambda}$, we have*

$$\mathbb{E} \left[\mathrm{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \right] \leq \|\phi\|_{\pi} d \exp \left(kt^2(\gamma^2 + b^2) \left(1 + \frac{8}{1-\lambda} \right) \right).$$

Assuming the above lemma, we can complete the proof of the theorem as:

$$\begin{aligned} & \mathbb{E}_{v_1, \dots, v_k} \left[\mathrm{Tr} \left[\exp \left(\frac{\pi}{4} t \sum_{j=1}^k f(v_j) \right) \right] \right] \\ & \leq d^{1-\frac{\pi}{4}} \mathbb{E}_{v_1, \dots, v_k} \left[\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \left(\mathrm{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right) \right] d\mu(\phi) \right] \\ & = d^{1-\frac{\pi}{4}} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \mathbb{E}_{v_1, \dots, v_k} \left[\mathrm{Tr} \left[\prod_{j=1}^k \exp \left(\frac{e^{i\phi}}{2} t f(v_j) \right) \prod_{j=k}^1 \exp \left(\frac{e^{-i\phi}}{2} t f(v_j) \right) \right] \right] d\mu(\phi) \quad (5) \\ & \leq d^{1-\frac{\pi}{4}} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \|\phi\|_{\pi} d \exp \left(kt^2 |e^{i\phi}|^2 \left(1 + \frac{8}{1-\lambda} \right) \right) d\mu(\phi) \\ & = \|\phi\|_{\pi} d^{2-\frac{\pi}{4}} \exp \left(kt^2 \left(1 + \frac{8}{1-\lambda} \right) \right) \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} d\mu(\phi) \\ & = \|\phi\|_{\pi} d^{2-\frac{\pi}{4}} \exp \left(kt^2 \left(1 + \frac{8}{1-\lambda} \right) \right) \end{aligned}$$

where the first step follows Equation 4, the second step follows by swapping \mathbb{E} and \int , the third step follows by Lemma 1, the fourth step follows by $|e^{i\phi}| = 1$, and the last step follows by μ is a probability distribution on $[-\frac{\pi}{2}, \frac{\pi}{2}]$ so $\int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} d\mu(\phi) = 1$

Finally, putting it all together:

$$\begin{aligned} \mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \geq \epsilon \right] & \leq \frac{\mathbb{E} \left[\mathrm{Tr} \left[\exp \left(t \sum_{j=1}^k f(v_j) \right) \right] \right]}{\exp(tk\epsilon)} \\ & = \frac{\mathbb{E} \left[\mathrm{Tr} \left[\exp \left(\frac{\pi}{4} \left(\frac{4}{\pi} t \right) \sum_{j=1}^k f(v_j) \right) \right] \right]}{\exp(tk\epsilon)} \\ & \leq \frac{\|\phi\|_{\pi} d^{2-\frac{\pi}{4}} \exp \left(k \left(\frac{4}{\pi} t \right)^2 \left(1 + \frac{8}{1-\lambda} \right) \right)}{\exp(tk\epsilon)} \\ & = \|\phi\|_{\pi} d^{2-\frac{\pi}{4}} \exp \left(\left(\frac{4}{\pi} \right)^2 k \epsilon^2 (1-\lambda)^2 \frac{1}{36^2} \frac{9}{1-\lambda} - k \frac{(1-\lambda)\epsilon}{36} \right) \\ & \leq \|\phi\|_{\pi} d^2 \exp(-k\epsilon^2(1-\lambda)/72). \end{aligned}$$

where the first step follows by Equation 3, the second step follows by Equation 5, the third step follows by choosing $t = (1-\lambda)\epsilon/36$. The only thing to check is that $t = (1-\lambda)\epsilon/36$ satisfies $t\sqrt{\gamma^2 + b^2} = t \leq \frac{1-\lambda}{4\lambda}$. Recall that $\epsilon < 1$ and $\lambda \leq 1$, we have $t = \frac{(1-\lambda)\epsilon}{36} \leq \frac{1-\lambda}{4} \leq \frac{1-\lambda}{4\lambda}$. \square

B.3 Proof of Lemma 1

Lemma 1 (Analogous to Lemma 4.3 in [10]). *Let \mathbf{P} be a regular Markov chain with state space $[N]$ with spectral expansion λ . Let f be a function $f : [N] \rightarrow \mathbb{R}^{d \times d}$ such that (1) $\sum_{v \in [N]} \pi_v f(v) = 0$; (2) $\|f(v)\|_2 \leq 1$ and $f(v)$ is symmetric, $v \in [N]$. Let (v_1, \dots, v_k) denote a k -step random walk on \mathbf{P} starting from a distribution ϕ on $[N]$. Then for any $t > 0, \gamma \geq 0, b > 0$ such that $t^2(\gamma^2 + b^2) \leq 1$ and $t\sqrt{\gamma^2 + b^2} \leq \frac{1-\lambda}{4\lambda}$, we have*

$$\mathbb{E} \left[\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \right] \leq \|\phi\|_{\pi} d \exp \left(kt^2(\gamma^2 + b^2) \left(1 + \frac{8}{1-\lambda} \right) \right).$$

Proof. Note that for $\mathbf{A}, \mathbf{B} \in \mathbb{C}^{d \times d}$, $\langle (\mathbf{A} \otimes \mathbf{B}) \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \rangle = \text{Tr} [\mathbf{A}\mathbf{B}^{\top}]$. By letting $\mathbf{A} = \prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right)$ and $\mathbf{B} = \left(\prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right)^{\top} = \prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right)$. The trace term in LHS of Lemma 1 becomes

$$\begin{aligned} & \text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \\ &= \left\langle \left(\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \otimes \prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right) \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \right\rangle. \end{aligned} \quad (6)$$

By iteratively applying $(\mathbf{A} \otimes \mathbf{B})(\mathbf{C} \otimes \mathbf{D}) = (\mathbf{A}\mathbf{C}) \otimes (\mathbf{B}\mathbf{D})$, we have

$$\begin{aligned} & \prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \otimes \prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \\ &= \prod_{j=1}^k \left(\exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \otimes \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right) \triangleq \prod_{j=1}^k \mathbf{M}_{v_j}, \end{aligned}$$

where we define

$$\mathbf{M}_{v_j} \triangleq \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \otimes \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right). \quad (7)$$

Plug it to the trace term, we have

$$\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] = \left\langle \left(\prod_{j=1}^k \mathbf{M}_{v_j} \right) \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \right\rangle.$$

Next, taking expectation on Equation 6 gives

$$\begin{aligned} & \mathbb{E}_{v_1, \dots, v_k} \left[\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \right] \\ &= \mathbb{E}_{v_1, \dots, v_k} \left[\left\langle \left(\prod_{j=1}^k \mathbf{M}_{v_j} \right) \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \right\rangle \right] \\ &= \left\langle \mathbb{E}_{v_1, \dots, v_k} \left[\prod_{j=1}^k \mathbf{M}_{v_j} \right] \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \right\rangle. \end{aligned} \quad (8)$$

We turn to study $\mathbb{E}_{v_1, \dots, v_k} \left[\prod_{j=1}^k \mathbf{M}_{v_j} \right]$, which is characterized by the following lemma:

Lemma 2. *Let $\mathbf{E} \triangleq \text{diag}(\mathbf{M}_1, \mathbf{M}_2, \dots, \mathbf{M}_N) \in \mathbb{C}^{Nd^2 \times Nd^2}$ and $\tilde{\mathbf{P}} \triangleq \mathbf{P} \otimes \mathbf{I}_{d^2} \in \mathbb{R}^{Nd^2 \times Nd^2}$. For a random walk (v_1, \dots, v_k) such that v_1 is sampled from an arbitrary probability distribution ϕ on $[N]$, $\mathbb{E}_{v_1, \dots, v_k} \left[\prod_{j=1}^k \mathbf{M}_{v_j} \right] = (\phi \otimes \mathbf{I}_{d^2})^{\top} \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \mathbf{I}_{d^2})$, where $\mathbf{1}$ is the all-ones vector.*

Proof. (of Lemma 2) We always treat $\mathbf{E}\tilde{\mathbf{P}}$ as a block matrix, s.t.,

$$\mathbf{E}\tilde{\mathbf{P}} = \begin{bmatrix} \mathbf{M}_1 & & \\ & \ddots & \\ & & \mathbf{M}_N \end{bmatrix} \begin{bmatrix} \mathbf{P}_{1,1} \mathbf{I}_{d^2} & \cdots & \mathbf{P}_{1,N} \mathbf{I}_{d^2} \\ \vdots & \ddots & \vdots \\ \mathbf{P}_{N,1} \mathbf{I}_{d^2} & \cdots & \mathbf{P}_{N,N} \mathbf{I}_{d^2} \end{bmatrix} = \begin{bmatrix} \mathbf{P}_{1,1} \mathbf{M}_1 & \cdots & \mathbf{P}_{1,N} \mathbf{M}_1 \\ \vdots & \ddots & \vdots \\ \mathbf{P}_{N,1} \mathbf{M}_N & \cdots & \mathbf{P}_{N,N} \mathbf{M}_N \end{bmatrix}.$$

I.e., the (u, v) -th block of $\mathbf{E}\tilde{\mathbf{P}}$, denoted by $(\mathbf{E}\tilde{\mathbf{P}})_{u,v}$, is $\mathbf{P}_{u,v}\mathbf{M}_u$.

$$\begin{aligned}
\mathbb{E}_{v_1, \dots, v_k} \left[\prod_{j=1}^k \mathbf{M}_{v_j} \right] &= \sum_{v_1, \dots, v_k} \phi_{v_1} \mathbf{P}_{v_1, v_2} \cdots \mathbf{P}_{v_{k-1}, v_k} \prod_{j=1}^k \mathbf{M}_{v_j} \\
&= \sum_{v_1} \phi_{v_1} \sum_{v_2} (\mathbf{P}_{v_1, v_2} \mathbf{M}_{v_1}) \cdots \sum_{v_k} (\mathbf{P}_{v_{k-1}, v_k} \mathbf{M}_{v_{k-1}}) \mathbf{M}_{v_k} \\
&= \sum_{v_1} \phi_{v_1} \sum_{v_2} (\mathbf{E}\tilde{\mathbf{P}})_{v_1, v_2} \sum_{v_3} (\mathbf{E}\tilde{\mathbf{P}})_{v_2, v_3} \cdots \sum_{v_k} (\mathbf{E}\tilde{\mathbf{P}}\mathbf{E})_{v_{k-1}, v_k} \\
&= \sum_{v_1} \phi_{v_1} \sum_{v_k} \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right)_{v_1, v_k} = (\phi \otimes \mathbf{I}_{d^2})^\top \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \mathbf{I}_{d^2})
\end{aligned}$$

□

Given Lemma 2, Equation 8 becomes:

$$\begin{aligned}
&\mathbb{E}_{v_1, \dots, v_k} \left[\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \right] \\
&= \left\langle \mathbb{E}_{v_1, \dots, v_k} \left[\prod_{j=1}^k \mathbf{M}_{v_j} \right] \text{vec}(\mathbf{I}_d), \text{vec}(\mathbf{I}_d) \right\rangle \\
&= \left\langle (\phi \otimes \mathbf{I}_{d^2})^\top \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \mathbf{I}_{d^2}), \text{vec}(\mathbf{I}_d) \right\rangle \\
&= \left\langle \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \mathbf{I}_{d^2}) \text{vec}(\mathbf{I}_d), (\phi \otimes \mathbf{I}_{d^2}) \text{vec}(\mathbf{I}_d) \right\rangle \\
&= \left\langle \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \text{vec}(\mathbf{I}_d)), \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d) \right\rangle
\end{aligned}$$

The third equality is due to $\langle x, \mathbf{A}y \rangle = \langle \mathbf{A}^*x, y \rangle$. The fourth equality is by setting $\mathbf{C} = 1$ (scalar) in $(\mathbf{A} \otimes \mathbf{B})(\mathbf{C} \otimes \mathbf{D}) = (\mathbf{A}\mathbf{C}) \otimes (\mathbf{B}\mathbf{D})$. Then

$$\begin{aligned}
&\mathbb{E}_{v_1, \dots, v_k} \left[\text{Tr} \left[\prod_{j=1}^k \exp \left(\frac{tf(v_j)(\gamma + ib)}{2} \right) \prod_{j=k}^1 \exp \left(\frac{tf(v_j)(\gamma - ib)}{2} \right) \right] \right] \\
&= \left\langle \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \text{vec}(\mathbf{I}_d)), \phi \otimes \text{vec}(\mathbf{I}_d) \right\rangle \\
&= (\phi \otimes \text{vec}(\mathbf{I}_d))^* \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) (\mathbf{1} \otimes \text{vec}(\mathbf{I}_d)) \\
&= (\phi \otimes \text{vec}(\mathbf{I}_d))^* \left((\mathbf{E}\tilde{\mathbf{P}})^{k-1} \mathbf{E} \right) \left((\mathbf{P}\boldsymbol{\Pi}^{-1}\boldsymbol{\pi}) \otimes (\mathbf{I}_{d^2}\mathbf{I}_{d^2} \text{vec}(\mathbf{I}_d)) \right) \\
&= (\phi \otimes \text{vec}(\mathbf{I}_d))^* \left(\mathbf{E}\tilde{\mathbf{P}} \right)^k (\boldsymbol{\Pi}^{-1} \otimes \mathbf{I}_{d^2}) (\boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d)) \triangleq \langle \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d), \mathbf{z}_k \rangle_{\boldsymbol{\pi}},
\end{aligned}$$

where we define $\mathbf{z}_0 = \phi \otimes \text{vec}(\mathbf{I}_d)$ and $\mathbf{z}_k = \left(\mathbf{z}_0^* \left(\mathbf{E}\tilde{\mathbf{P}} \right)^k \right)^* = \left(\mathbf{z}_{k-1}^* \mathbf{E}\tilde{\mathbf{P}} \right)^*$. Moreover, by

Remark 2, we have $\|\boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d)\|_{\boldsymbol{\pi}} = \|\boldsymbol{\pi}\|_{\boldsymbol{\pi}} \|\text{vec}(\mathbf{I}_d)\|_2 = \sqrt{d}$ and $\|\mathbf{z}_0\|_{\boldsymbol{\pi}} = \|\phi \otimes \text{vec}(\mathbf{I}_d)\|_{\boldsymbol{\pi}} = \|\phi\|_{\boldsymbol{\pi}} \|\text{vec}(\mathbf{I}_d)\|_2 = \|\phi\|_{\boldsymbol{\pi}} \sqrt{d}$

Definition 2. Define linear subspace $\mathcal{U} = \left\{ \boldsymbol{\pi} \otimes \mathbf{w}, \mathbf{w} \in \mathbb{C}^{d^2} \right\}$.

Remark 3. $\{\boldsymbol{\pi} \otimes \mathbf{e}_i, i \in [d^2]\}$ is an orthonormal basis of \mathcal{U} . This is because $\langle \boldsymbol{\pi} \otimes \mathbf{e}_i, \boldsymbol{\pi} \otimes \mathbf{e}_j \rangle_{\boldsymbol{\pi}} = \langle \boldsymbol{\pi}, \boldsymbol{\pi} \rangle_{\boldsymbol{\pi}} \langle \mathbf{e}_i, \mathbf{e}_j \rangle = \delta_{ij}$ by Remark 1, where δ_{ij} is the Kronecker delta.

Remark 4. Given $\mathbf{x} = \mathbf{y} \otimes \mathbf{w}$. The projection of \mathbf{x} on to \mathcal{U} is $\mathbf{x}^{\parallel} = (\mathbf{1}^* \mathbf{y})(\boldsymbol{\pi} \otimes \mathbf{w})$. This is because

$$\mathbf{x}^{\parallel} = \sum_{i=1}^{d^2} \langle \mathbf{y} \otimes \mathbf{w}, \boldsymbol{\pi} \otimes \mathbf{e}_i \rangle_{\boldsymbol{\pi}} (\boldsymbol{\pi} \otimes \mathbf{e}_i) = \sum_{i=1}^{d^2} \langle \mathbf{y}, \boldsymbol{\pi} \rangle_{\boldsymbol{\pi}} \langle \mathbf{w}, \mathbf{e}_i \rangle (\boldsymbol{\pi} \otimes \mathbf{e}_i) = (\mathbf{1}^* \mathbf{y})(\boldsymbol{\pi} \otimes \mathbf{w}).$$

We want to bound

$$\begin{aligned}
\langle \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d), \mathbf{z}_k \rangle_{\boldsymbol{\pi}} &= \left\langle \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d), \mathbf{z}_k^{\perp} + \mathbf{z}_k^{\parallel} \right\rangle_{\boldsymbol{\pi}} = \left\langle \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d), \mathbf{z}_k^{\parallel} \right\rangle_{\boldsymbol{\pi}} \\
&\leq \|\boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d)\|_{\boldsymbol{\pi}} \left\| \mathbf{z}_k^{\parallel} \right\|_{\boldsymbol{\pi}} = \sqrt{d} \left\| \mathbf{z}_k^{\parallel} \right\|_{\boldsymbol{\pi}}.
\end{aligned}$$

As z_k can be expressed as recursively applying operator E and \tilde{P} on z_0 , we turn to analyze the effects of E and \tilde{P} operators.

Definition 3. The spectral expansion of \tilde{P} is defined as $\lambda(\tilde{P}) \triangleq \max_{\mathbf{x} \perp \mathcal{U}, \mathbf{x} \neq 0} \frac{\|(\mathbf{x}^* \tilde{P})^*\|_{\pi}}{\|\mathbf{x}\|_{\pi}}$

Lemma 3. $\lambda(P) = \lambda(\tilde{P})$.

Proof. First show $\lambda(\tilde{P}) \geq \lambda(P)$. Suppose the maximizer of $\lambda(P) \triangleq \max_{\mathbf{y} \perp \pi, \mathbf{y} \neq 0} \frac{\|(\mathbf{y}^* P)^*\|_{\pi}}{\|\mathbf{y}\|_{\pi}}$ is $\mathbf{y} \in \mathbb{C}^n$, i.e., $\|(\mathbf{y}^* P)^*\|_{\pi} = \lambda(P) \|\mathbf{y}\|_{\pi}$. Construct $\mathbf{x} = \mathbf{y} \otimes \mathbf{o}$ for arbitrary non-zero $\mathbf{o} \in \mathbb{C}^{d^2}$. Easy to check that $\mathbf{x} \perp \mathcal{U}$, because $\langle \mathbf{x}, \pi \otimes \mathbf{w} \rangle_{\pi} = \langle \mathbf{y}, \pi \rangle_{\pi} \langle \mathbf{o}, \mathbf{w} \rangle = 0$, where the last equality is due to $\mathbf{y} \perp \pi$. Then we can bound $\|(\mathbf{x}^* \tilde{P})^*\|_{\pi}$ such that

$$\begin{aligned} \|(\mathbf{x}^* \tilde{P})^*\|_{\pi} &= \|\tilde{P}^* \mathbf{x}\|_{\pi} = \|(P^* \otimes I_{d^2})(\mathbf{y} \otimes \mathbf{o})\|_{\pi} = \|(P^* \mathbf{y}) \otimes \mathbf{o}\|_{\pi} \\ &= \|(\mathbf{y}^* P)^*\|_{\pi} \|\mathbf{o}\|_2 = \lambda(P) \|\mathbf{y}\|_{\pi} \|\mathbf{o}\|_2 = \lambda(P) \|\mathbf{x}\|_{\pi}, \end{aligned}$$

which indicate for $\mathbf{x} = \mathbf{y} \otimes \mathbf{o}$, $\frac{\|(\mathbf{x}^* \tilde{P})^*\|_{\pi}}{\|\mathbf{x}\|_{\pi}} = \lambda(P)$. Taking maximum over all \mathbf{x} gives $\lambda(\tilde{P}) \geq \lambda(P)$.

Next to show $\lambda(P) \geq \lambda(\tilde{P})$. For $\forall \mathbf{x} \in \mathbb{C}^{Nd^2}$ such that $\mathbf{x} \perp \mathcal{U}$ and $\mathbf{x} \neq 0$, we can decompose it to be

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{Nd^2} \end{bmatrix} = \begin{bmatrix} x_1 \\ x_{d^2+1} \\ \vdots \\ x_{(N-1)d^2+1} \end{bmatrix} \otimes \mathbf{e}_1 + \begin{bmatrix} x_2 \\ x_{d^2+2} \\ \vdots \\ x_{(N-1)d^2+2} \end{bmatrix} \otimes \mathbf{e}_2 + \cdots + \begin{bmatrix} x_{d^2} \\ x_{2d^2} \\ \vdots \\ x_{Nd^2} \end{bmatrix} \otimes \mathbf{e}_{d^2} \triangleq \sum_{i=1}^{d^2} \mathbf{x}_i \otimes \mathbf{e}_i,$$

where we define $\mathbf{x}_i \triangleq [x_i \ \cdots \ x_{(N-1)d^2+i}]^{\top}$ for $i \in [d^2]$. We can observe that $\mathbf{x}_i \perp \pi$, $i \in [d^2]$, because for $\forall j \in [d^2]$, we have

$$0 = \langle \mathbf{x}, \pi \otimes \mathbf{e}_j \rangle_{\pi} = \left\langle \sum_{i=1}^{d^2} \mathbf{x}_i \otimes \mathbf{e}_i, \pi \otimes \mathbf{e}_j \right\rangle_{\pi} = \sum_{i=1}^{d^2} \langle \mathbf{x}_i \otimes \mathbf{e}_i, \pi \otimes \mathbf{e}_j \rangle_{\pi} = \sum_{i=1}^{d^2} \langle \mathbf{x}_i, \pi \rangle_{\pi} \langle \mathbf{e}_i, \mathbf{e}_j \rangle = \langle \mathbf{x}_j, \pi \rangle_{\pi},$$

which indicates $\mathbf{x}_j \perp \pi$, $j \in [d^2]$. Furthermore, we can also observe that $\mathbf{x}_i \otimes \mathbf{e}_i$, $i \in [d^2]$ is pairwise orthogonal. This is because for $\forall i, j \in [d^2]$, $\langle \mathbf{x}_i \otimes \mathbf{e}_i, \mathbf{x}_j \otimes \mathbf{e}_j \rangle_{\pi} = \langle \mathbf{x}_i, \mathbf{x}_j \rangle_{\pi} \langle \mathbf{e}_i, \mathbf{e}_j \rangle = \delta_{ij}$, which suggests us to use Pythagorean theorem such that $\|\mathbf{x}\|_{\pi}^2 = \sum_{i=1}^{d^2} \|\mathbf{x}_i \otimes \mathbf{e}_i\|_{\pi}^2 = \sum_{i=1}^{d^2} \|\mathbf{x}_i\|_{\pi} \|\mathbf{e}_i\|_2^2$.

We can use similar way to decompose and analyze $(\mathbf{x}^* \tilde{P})^*$:

$$(\mathbf{x}^* \tilde{P})^* = \tilde{P}^* \mathbf{x} = \sum_{i=1}^{d^2} (P^* \otimes I_{d^2})(\mathbf{x}_i \otimes \mathbf{e}_i) = \sum_{i=1}^{d^2} (P^* \mathbf{x}_i) \otimes \mathbf{e}_i.$$

where we can observe that $(P^* \mathbf{x}_i) \otimes \mathbf{e}_i$, $i \in [d^2]$ is pairwise orthogonal. This is because for $\forall i, j \in [d^2]$, we have $\langle (P^* \mathbf{x}_i) \otimes \mathbf{e}_i, (P^* \mathbf{x}_j) \otimes \mathbf{e}_j \rangle_{\pi} = \langle P^* \mathbf{x}_i, P^* \mathbf{x}_j \rangle_{\pi} \langle \mathbf{e}_i, \mathbf{e}_j \rangle = \delta_{ij}$. Again, applying Pythagorean theorem gives:

$$\begin{aligned} \|(\mathbf{x}^* \tilde{P})^*\|_{\pi}^2 &= \sum_{i=1}^{d^2} \|(P^* \mathbf{x}_i) \otimes \mathbf{e}_i\|_{\pi}^2 = \sum_{i=1}^{d^2} \|(\mathbf{x}_i^* P)^*\|_{\pi}^2 \|\mathbf{e}_i\|_2^2 \\ &\leq \sum_{i=1}^{d^2} \lambda(P)^2 \|\mathbf{x}_i\|_{\pi}^2 \|\mathbf{e}_i\|_2^2 = \lambda(P)^2 \left(\sum_{i=1}^{d^2} \|\mathbf{x}_i\|_{\pi}^2 \|\mathbf{e}_i\|_2^2 \right) = \lambda(P)^2 \|\mathbf{x}\|_{\pi}^2, \end{aligned}$$

which indicate that for $\forall \mathbf{x}$ such that $\mathbf{x} \perp \mathcal{U}$ and $\mathbf{x} \neq 0$, we have $\frac{\|(\mathbf{x}^* \tilde{P})^*\|_{\pi}}{\|\mathbf{x}\|_{\pi}} \leq \lambda(P)$, or equivalently $\lambda(\tilde{P}) \leq \lambda(P)$.

Overall, we have shown both $\lambda(\tilde{P}) \geq \lambda(P)$ and $\lambda(\tilde{P}) \leq \lambda(P)$. We conclude $\lambda(\tilde{P}) = \lambda(P)$. \square

Lemma 4. (The effect of \tilde{P} operator) This lemma is a generalization of lemma 3.3 in [6].

1. $\forall \mathbf{y} \in \mathcal{U}$, then $(\mathbf{y}^* \tilde{P})^* = \mathbf{y}$.
2. $\forall \mathbf{y} \perp \mathcal{U}$, then $(\mathbf{y}^* \tilde{P})^* \perp \mathcal{U}$, and $\left\| (\mathbf{y}^* \tilde{P})^* \right\|_{\pi} \leq \lambda \|\mathbf{y}\|_{\pi}$.

Proof. First prove the Part 1 of lemma 4. $\forall \mathbf{y} = \boldsymbol{\pi} \otimes \mathbf{w} \in \mathcal{U}$:

$$\mathbf{y}^* \tilde{P} = (\boldsymbol{\pi}^* \otimes \mathbf{w}^*) (\mathbf{P} \otimes \mathbf{I}_{d^2}) = (\boldsymbol{\pi}^* \mathbf{P}) \otimes (\mathbf{w}^* \mathbf{I}_{d^2}) = \boldsymbol{\pi}^* \otimes \mathbf{w}^* = \mathbf{y}^*,$$

where third equality is because $\boldsymbol{\pi}$ is the stationary distribution. Next to prove Part 2 of lemma 4. Given $\mathbf{y} \perp \mathcal{U}$, want to show $(\mathbf{y}^* \tilde{P})^* \perp \boldsymbol{\pi} \otimes \mathbf{w}$, for every $\mathbf{w} \in \mathbb{C}^{d^2}$. It is true because

$$\begin{aligned} \left\langle \boldsymbol{\pi} \otimes \mathbf{w}, (\mathbf{y}^* \tilde{P})^* \right\rangle_{\pi} &= \mathbf{y}^* \tilde{P} (\boldsymbol{\Pi}^{-1} \otimes \mathbf{I}_{d^2}) (\boldsymbol{\pi} \otimes \mathbf{w}) = \mathbf{y}^* ((\mathbf{P} \boldsymbol{\Pi}^{-1} \boldsymbol{\pi}) \otimes \mathbf{w}) = \mathbf{y}^* ((\boldsymbol{\Pi}^{-1} \boldsymbol{\pi}) \otimes \mathbf{w}) \\ &= \mathbf{y}^* (\boldsymbol{\Pi}^{-1} \otimes \mathbf{I}_{d^2}) (\boldsymbol{\pi} \otimes \mathbf{w}) = \langle \boldsymbol{\pi} \otimes \mathbf{w}, \mathbf{y} \rangle_{\pi} = 0. \end{aligned}$$

The third equality is due to $\mathbf{P} \boldsymbol{\Pi}^{-1} \boldsymbol{\pi} = \mathbf{P} \mathbf{1} = \mathbf{1} = \boldsymbol{\Pi}^{-1} \boldsymbol{\pi}$. Moreover, $\left\| (\mathbf{y}^* \tilde{P})^* \right\|_{\pi} \leq \lambda \|\mathbf{y}\|_{\pi}$ is simply a re-statement of definition 3. \square

Remark 5. Lemma 4 implies that $\forall \mathbf{y} \in \mathbb{C}^{nd^2}$

1. $\left\| (\mathbf{y}^* \tilde{P})^* \right\| = \left\| (\mathbf{y}^{\parallel*} \tilde{P})^* \right\| + \left\| (\mathbf{y}^{\perp*} \tilde{P})^* \right\| = \mathbf{y}^{\parallel} + \mathbf{0} = \mathbf{y}^{\parallel}$
2. $\left\| (\mathbf{y}^* \tilde{P})^* \right\|^{\perp} = \left\| (\mathbf{y}^{\parallel*} \tilde{P})^* \right\|^{\perp} + \left\| (\mathbf{y}^{\perp*} \tilde{P})^* \right\|^{\perp} = \mathbf{0} + (\mathbf{y}^{\perp*} \tilde{P})^* = (\mathbf{y}^{\perp*} \tilde{P})^*$.

Lemma 5. (The effect of E operator) Given three parameters $\lambda \in [0, 1]$, $\ell \geq 0$ and $t > 0$. Let \mathbf{P} be a regular Markov chain on state space $[N]$, with stationary distribution $\boldsymbol{\pi}$ and spectral expansion λ . Suppose each state $i \in [N]$ is assigned a matrix $\mathbf{H}_i \in \mathbb{C}^{d^2 \times d^2}$ s.t. $\|\mathbf{H}_i\|_2 \leq \ell$ and $\sum_{i \in [N]} \pi_i \mathbf{H}_i = \mathbf{0}$. Let $\tilde{P} = \mathbf{P} \otimes \mathbf{I}_{d^2}$ and E denotes the $Nd^2 \times Nd^2$ block matrix where the i -th diagonal block is the matrix $\exp(t\mathbf{H}_i)$, i.e., $E = \text{diag}(\exp(t\mathbf{H}_1), \dots, \exp(t\mathbf{H}_N))$. Then for any $\forall \mathbf{z} \in \mathbb{C}^{Nd^2}$, we have:

1. $\left\| \left((\mathbf{z}^{\parallel*} E \tilde{P})^* \right) \right\|_{\pi} \leq \alpha_1 \|\mathbf{z}^{\parallel}\|_{\pi}$, where $\alpha_1 = \exp(t\ell) - t\ell$.
2. $\left\| \left((\mathbf{z}^{\parallel*} E \tilde{P})^* \right) \right\|_{\pi}^{\perp} \leq \alpha_2 \|\mathbf{z}^{\parallel}\|_{\pi}$, where $\alpha_2 = \lambda(\exp(t\ell) - 1)$.
3. $\left\| \left((\mathbf{z}^{\perp*} E \tilde{P})^* \right) \right\|_{\pi} \leq \alpha_3 \|\mathbf{z}^{\perp}\|_{\pi}$, where $\alpha_3 = \exp(t\ell) - 1$.
4. $\left\| \left((\mathbf{z}^{\perp*} E \tilde{P})^* \right) \right\|_{\pi}^{\perp} \leq \alpha_4 \|\mathbf{z}^{\perp}\|_{\pi}$, where $\alpha_4 = \lambda \exp(t\ell)$.

Proof. (of Lemma 5) We first show that, for $\mathbf{z} = \mathbf{y} \otimes \mathbf{w}$,

$$\begin{aligned} (\mathbf{z}^* E)^* = E^* \mathbf{z} &= \begin{bmatrix} \exp(t\mathbf{H}_1^*) & & \\ & \ddots & \\ & & \exp(t\mathbf{H}_N^*) \end{bmatrix} \begin{bmatrix} y_1 \mathbf{w} \\ \vdots \\ y_N \mathbf{w} \end{bmatrix} = \begin{bmatrix} y_1 \exp(t\mathbf{H}_1^*) \mathbf{w} \\ \vdots \\ y_N \exp(t\mathbf{H}_N^*) \mathbf{w} \end{bmatrix} \\ &= \begin{bmatrix} y_1 \exp(t\mathbf{H}_1^*) \mathbf{w} \\ \vdots \\ 0 \end{bmatrix} + \dots + \begin{bmatrix} 0 \\ \vdots \\ y_N \exp(t\mathbf{H}_N^*) \mathbf{w} \end{bmatrix} = \sum_{i=1}^N y_i (\mathbf{e}_i \otimes (\exp(t\mathbf{H}_i^*) \mathbf{w})). \end{aligned}$$

Due to the linearity of projection,

$$\left((z^* E)^* \right)^\parallel = \sum_{i=1}^N y_i (e_i \otimes (\exp(tH_i^*) w))^\parallel = \sum_{i=1}^N y_i (\mathbf{1}^* e_i) (\pi \otimes (\exp(tH_i^*) w)) = \pi \otimes \left(\sum_{i=1}^N y_i \exp(tH_i^*) w \right), \quad (9)$$

where the second inequality follows by Remark 4.

Proof of Lemma 5, Part 1 Firstly We can bound $\left\| \sum_{i=1}^N \pi_i \exp(tH_i^*) \right\|_2$ by

$$\begin{aligned} \left\| \sum_{i=1}^N \pi_i \exp(tH_i^*) \right\|_2 &= \left\| \sum_{i=1}^N \pi_i \exp(tH_i) \right\|_2 = \left\| \sum_{i=1}^N \pi_i \sum_{k=0}^{+\infty} \frac{t^k H_i^k}{k!} \right\|_2 = \left\| \mathbf{I} + \sum_{i=1}^N \pi_i \sum_{j=2}^{+\infty} \frac{t^j H_i^j}{j!} \right\|_2 \\ &\leq 1 + \sum_{i=1}^N \pi_i \sum_{j=2}^{+\infty} \frac{t^j \|H_i\|_2^j}{j!} \leq 1 + \sum_{i=1}^N \pi_i \sum_{j=2}^{+\infty} \frac{(t\ell)^j}{j!} = \exp(t\ell) - t\ell, \end{aligned}$$

where the first step follows by $\|A\|_2 = \|A^*\|_2$, the second step follows by matrix exponential, the third step follows by $\sum_{i \in [N]} \pi_i H_i = 0$, and the fourth step follows by triangle inequality. Given the above bound, for any z^\parallel which can be written as $z^\parallel = \pi \otimes w$ for some $w \in \mathbb{C}^{d^2}$, we have

$$\begin{aligned} \left\| \left((z^* E \tilde{P})^* \right)^\parallel \right\|_\pi &= \left\| \left((z^* E)^* \right)^\parallel \right\|_\pi = \left\| \pi \otimes \left(\sum_{i=1}^N \pi_i \exp(tH_i^*) w \right) \right\|_\pi = \|\pi\|_\pi \left\| \sum_{i=1}^N \pi_i \exp(tH_i^*) w \right\|_2 \\ &\leq \|\pi\|_\pi \left\| \sum_{i=1}^N \pi_i \exp(tH_i^*) \right\|_2 \|w\|_2 = \left\| \sum_{i=1}^N \pi_i \exp(tH_i^*) \right\|_2 \|z^\parallel\|_\pi \\ &\leq (\exp(t\ell) - t\ell) \|z^\parallel\|_\pi, \end{aligned}$$

where step one follows by Part 1 of Remark 5 and step two follows by Equation 9.

Proof of Lemma 5, Part 2 For $\forall z \in \mathbb{C}^{Nd^2}$, we can write it as block matrix such that:

$$z = \begin{bmatrix} z_1 \\ \vdots \\ z_N \end{bmatrix} = \begin{bmatrix} z_1 \\ \vdots \\ 0 \end{bmatrix} + \cdots + \begin{bmatrix} 0 \\ \vdots \\ z_N \end{bmatrix} = \sum_{i=1}^N e_i \otimes z_i,$$

where each $z_i \in \mathbb{C}^{d^2}$. Please note that above decomposition is pairwise orthogonal. Applying Pythagorean theorem gives $\|z\|_\pi^2 = \sum_{i=1}^N \|e_i \otimes z_i\|_\pi^2 = \sum_{i=1}^N \|e_i\|_\pi^2 \|z_i\|_2^2$. Similarly, we can decompose $(E^* - I_{Nd^2})z$ such that

$$\begin{aligned} (E^* - I_{Nd^2})z &= \begin{bmatrix} \exp(tH_1^*) - I_{d^2} & & \\ & \ddots & \\ & & \exp(tH_N^*) - I_{d^2} \end{bmatrix} \begin{bmatrix} z_1 \\ \vdots \\ z_N \end{bmatrix} = \begin{bmatrix} (\exp(tH_1^*) - I_{d^2})z_1 \\ \vdots \\ (\exp(tH_N^*) - I_{d^2})z_N \end{bmatrix} \\ &= \begin{bmatrix} (\exp(tH_1^*) - I_{d^2})z_1 \\ \vdots \\ 0 \end{bmatrix} + \cdots + \begin{bmatrix} 0 \\ \vdots \\ (\exp(tH_N^*) - I_{d^2})z_N \end{bmatrix} \quad (10) \\ &= \sum_{i=1}^N e_i \otimes ((\exp(tH_i^*) - I_{d^2})z_i). \end{aligned}$$

Note that above decomposition is pairwise orthogonal, too. Applying Pythagorean theorem gives

$$\begin{aligned} \|(E^* - I_{Nd^2})z\|_\pi^2 &= \sum_{i=1}^N \|e_i \otimes ((\exp(tH_i^*) - I_{d^2})z_i)\|_\pi^2 = \sum_{i=1}^N \|e_i\|_\pi^2 \|(\exp(tH_i^*) - I_{d^2})z_i\|_2^2 \\ &\leq \sum_{i=1}^N \|e_i\|_\pi^2 \|\exp(tH_i^*) - I_{d^2}\|_2^2 \|z_i\|_2^2 \leq \max_{i \in [N]} \|\exp(tH_i^*) - I_{d^2}\|_2^2 \sum_{i=1}^N \|e_i\|_\pi^2 \|z_i\|_2^2 \\ &= \max_{i \in [N]} \|\exp(tH_i^*) - I_{d^2}\|_2^2 \|z\|_\pi^2 = \max_{i \in [N]} \|\exp(tH_i) - I_{d^2}\|_2^2 \|z\|_\pi^2, \end{aligned}$$

which indicates

$$\begin{aligned} \|(\mathbf{E}^* - \mathbf{I}_{Nd^2})\mathbf{z}\|_\pi &= \max_{i \in [N]} \|\exp(t\mathbf{H}_i) - \mathbf{I}_{d^2}\|_2 \|\mathbf{z}\|_\pi = \max_{i \in [N]} \left\| \sum_{j=1}^{+\infty} \frac{t^j \mathbf{H}_i^j}{j!} \right\|_2 \|\mathbf{z}\|_\pi \\ &\leq \left(\sum_{j=1}^{+\infty} \frac{t^j \ell^j}{j!} \right) \|\mathbf{z}\|_\pi = (\exp(t\ell) - 1) \|\mathbf{z}\|_\pi. \end{aligned}$$

Now we can formally prove Part 2 of Lemma 5 by:

$$\begin{aligned} \left\| \left((\mathbf{z}^\parallel * \mathbf{E}\tilde{\mathbf{P}})^* \right)^\perp \right\|_\pi &= \left\| \left((\mathbf{E}^* \mathbf{z}^\parallel)^{\perp *} \tilde{\mathbf{P}} \right)^* \right\|_\pi \leq \lambda \left\| (\mathbf{E}^* \mathbf{z}^\parallel)^\perp \right\|_\pi = \lambda \left\| (\mathbf{E}^* \mathbf{z}^\parallel - \mathbf{z}^\parallel + \mathbf{z}^\parallel)^\perp \right\|_\pi \\ &= \lambda \left\| (\mathbf{E}^* - \mathbf{I}_{Nd^2}) \mathbf{z}^\parallel \right\|_\pi \leq \lambda \left\| (\mathbf{E}^* - \mathbf{I}_{Nd^2}) \mathbf{z} \right\|_\pi \leq \lambda (\exp(t\ell) - 1) \|\mathbf{z}\|_\pi. \end{aligned}$$

The first step follows by Part 2 of Remark 5, the second step follows by Part 1 on Lemma 4 and the forth step is due to $(\mathbf{z}^\parallel)^\perp = \mathbf{0}$.

Proof of Lemma 5, Part 3 Note that

$$\begin{aligned} \left\| \left((\mathbf{z}^\perp * \mathbf{E}\tilde{\mathbf{P}})^* \right)^\parallel \right\|_\pi &= \left\| (\mathbf{E}^* \mathbf{z}^\perp)^\parallel \right\|_\pi = \left\| (\mathbf{E}^* \mathbf{z}^\perp - \mathbf{z}^\perp + \mathbf{z}^\perp)^\parallel \right\|_\pi = \left\| (\mathbf{E}^* - \mathbf{I}_{Nd^2}) \mathbf{z}^\perp \right\|_\pi \\ &\leq \left\| (\mathbf{E}^* - \mathbf{I}_{Nd^2}) \mathbf{z}^\perp \right\|_\pi \leq (\exp(t\ell) - 1) \|\mathbf{z}^\perp\|_\pi, \end{aligned}$$

where the first step follows by Part 1 of Remark 5, the third step follows by $(\mathbf{z}^\perp)^\parallel = \mathbf{0}$, and the last step follows by Part 2 of Lemma 4.

Proof of Lemma 5, Part 4 Simiar to Equation 10, for $\forall \mathbf{z} \in \mathbb{C}^{Nd^2}$, we can decompose $\mathbf{E}^* \mathbf{z}$ as $\mathbf{E}^* \mathbf{z} = \sum_{i=1}^N \mathbf{e}_i \otimes (\exp(t\mathbf{H}_i^*) \mathbf{z}_i)$. This decomposition is pairwise orthogonal, too. Applying Pythagorean theorem gives

$$\begin{aligned} \|\mathbf{E}^* \mathbf{z}\|_\pi^2 &= \sum_{i=1}^N \|\mathbf{e}_i \otimes (\exp(t\mathbf{H}_i^*) \mathbf{z}_i)\|_\pi^2 = \sum_{i=1}^N \|\mathbf{e}_i\|_\pi^2 \|\exp(t\mathbf{H}_i^*) \mathbf{z}_i\|_2^2 \leq \sum_{i=1}^N \|\mathbf{e}_i\|_\pi^2 \|\exp(t\mathbf{H}_i^*)\|_2^2 \|\mathbf{z}_i\|_2^2 \\ &\leq \max_{i \in [N]} \|\exp(t\mathbf{H}_i^*)\|_2^2 \sum_{i=1}^N \|\mathbf{e}_i\|_\pi^2 \|\mathbf{z}_i\|_2^2 \leq \max_{i \in [N]} \exp(\|\mathbf{H}_i\|_2) \|\mathbf{z}\|_\pi^2 \leq \exp(t\ell) \|\mathbf{z}\|_\pi^2 \end{aligned}$$

which indicates $\|\mathbf{E}^* \mathbf{z}\|_\pi \leq \exp(t\ell) \|\mathbf{z}\|_\pi$. Now we can prove Part 4 of Lemma 5: Note that

$$\left\| \left((\mathbf{z}^\perp * \mathbf{E}\tilde{\mathbf{P}})^* \right)^\perp \right\|_\pi = \left\| \left((\mathbf{E}^* \mathbf{z}^\perp)^{\perp *} \tilde{\mathbf{P}} \right)^* \right\|_\pi \leq \lambda \left\| (\mathbf{E}^* \mathbf{z}^\perp)^\perp \right\|_\pi \leq \lambda \|\mathbf{E}^* \mathbf{z}^\perp\|_\pi \leq \lambda \exp(t\ell) \|\mathbf{z}^\perp\|_\pi. \quad \square$$

Recursive Analysis We now use Lemma 5 to analyze the evolution of \mathbf{z}_i^\parallel and \mathbf{z}_i^\perp . Let $\mathbf{H}_v \triangleq \frac{f(v)(\gamma+ib)}{2} \otimes \mathbf{I}_{d^2} + \mathbf{I}_{d^2} \otimes \frac{f(v)(\gamma-ib)}{2}$ in Lemma 5. We can see verify the following three facts: (1) $\exp(t\mathbf{H}_v) = \mathbf{M}_v$; (2) $\|\mathbf{H}_v\|_2$ is bounded (3) $\sum_{v \in [N]} \pi_v \mathbf{H}_v = \mathbf{0}$.

Firstly, easy to see that

$$\begin{aligned} \exp(t\mathbf{H}_v) &= \exp\left(\frac{tf(v)(\gamma+ib)}{2} \otimes \mathbf{I}_{d^2} + \mathbf{I}_{d^2} \otimes \frac{tf(v)(\gamma-ib)}{2}\right) \\ &= \exp\left(\frac{tf(v)(\gamma+ib)}{2}\right) \otimes \exp\left(\frac{tf(v)(\gamma-ib)}{2}\right) = \mathbf{M}_v, \end{aligned}$$

where the first step follows by definition of \mathbf{H}_i and the second step follows by the fact that $\exp(\mathbf{A} \otimes \mathbf{I}_d + \mathbf{I}_d \otimes \mathbf{B}) = \exp(\mathbf{A}) \otimes \exp(\mathbf{B})$, and the last step follows by Equation 7.

Secondly, we can bound $\|\mathbf{H}_v\|_2$ by:

$$\begin{aligned} \|\mathbf{H}_v\|_2 &\leq \left\| \frac{f(v)(\gamma+ib)}{2} \otimes \mathbf{I}_{d^2} \right\|_2 + \left\| \mathbf{I}_{d^2} \otimes \frac{f(v)(\gamma-ib)}{2} \right\|_2 \\ &= \left\| \frac{f(v)(\gamma+ib)}{2} \right\|_2 \|\mathbf{I}_{d^2}\|_2 + \|\mathbf{I}_{d^2}\|_2 \left\| \frac{f(v)(\gamma-ib)}{2} \right\|_2 \leq \sqrt{\gamma^2 + b^2}, \end{aligned}$$

where the first step follows by triangle inequality, the second step follows by the fact that $\|\mathbf{A} \otimes \mathbf{B}\|_2 = \|\mathbf{A}\|_2 \|\mathbf{B}\|_2$, the third step follows by $\|\mathbf{I}_d\|_2 = 1$ and $\|f(v)\|_2 \leq 1$. We set $\ell = \sqrt{\gamma^2 + b^2}$ to satisfy the assumption in Lemma 5 that $\|\mathbf{H}_v\|_2 \leq \ell$. According to the conditions in Lemma 1, we know that $t\ell \leq 1$ and $t\ell \leq \frac{1-\lambda}{4\lambda}$.

Finally, we show that $\sum_{v \in [N]} \pi_v \mathbf{H}_v = 0$, because

$$\begin{aligned} \sum_{v \in [N]} \pi_v \mathbf{H}_v &= \sum_{v \in [N]} \left(\frac{f(v)(\gamma + ib)}{2} \otimes \mathbf{I}_{d^2} + \mathbf{I}_{d^2} \otimes \frac{f(v)(\gamma - ib)}{2} \right) \\ &= \frac{\gamma + ib}{2} \left(\sum_{v \in [N]} \pi_v f(v) \right) \otimes \mathbf{I}_d + \frac{\gamma - ib}{2} \mathbf{I}_d \otimes \left(\sum_{v \in [N]} \pi_v f(v) \right) = 0, \end{aligned}$$

where the last step follows by $\sum_{v \in [N]} \pi_v f(v) = 0$.

Claim 4. $\|z_i^\perp\|_\pi \leq \frac{\alpha_2}{1-\alpha_4} \max_{0 \leq j < i} \|z_j^\parallel\|_\pi$.

Proof. Using Part 2 and Part 4 of Lemma 5, we have

$$\begin{aligned} \|z_i^\perp\|_\pi &= \left\| \left((z_{i-1}^* \mathbf{E} \tilde{\mathbf{P}})^* \right)^\perp \right\|_\pi \\ &\leq \left\| \left((z_{i-1}^\parallel \mathbf{E} \tilde{\mathbf{P}})^* \right)^\perp \right\|_\pi + \left\| \left((z_{i-1}^\perp \mathbf{E} \tilde{\mathbf{P}})^* \right)^\perp \right\|_\pi \\ &\leq \alpha_2 \|z_{i-1}^\parallel\|_\pi + \alpha_4 \|z_{i-1}^\perp\|_\pi \\ &\leq (\alpha_2 + \alpha_2 \alpha_4 + \alpha_2 \alpha_4^2 + \dots) \max_{0 \leq j < i} \|z_j^\parallel\|_\pi \\ &\leq \frac{\alpha_2}{1-\alpha_4} \max_{0 \leq j < i} \|z_j^\parallel\|_\pi \end{aligned}$$

□

Claim 5. $\|z_i^\parallel\|_\pi \leq \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1-\alpha_4} \right) \max_{0 \leq j < i} \|z_j^\parallel\|_\pi$.

Proof. Using Part 1 and Part 3 of Lemma 5 as well as Claim 4, we have

$$\begin{aligned} \|z_i^\parallel\|_\pi &= \left\| \left((z_{i-1}^* \mathbf{E} \tilde{\mathbf{P}})^* \right)^\parallel \right\|_\pi \\ &\leq \left\| \left((z_{i-1}^\parallel \mathbf{E} \tilde{\mathbf{P}})^* \right)^\parallel \right\|_\pi + \left\| \left((z_{i-1}^\perp \mathbf{E} \tilde{\mathbf{P}})^* \right)^\parallel \right\|_\pi \\ &\leq \alpha_1 \|z_{i-1}^\parallel\|_\pi + \alpha_3 \|z_{i-1}^\perp\|_\pi \\ &\leq \alpha_1 \|z_{i-1}^\parallel\|_\pi + \alpha_3 \frac{\alpha_2}{1-\alpha_4} \max_{0 \leq j < i-1} \|z_j^\parallel\|_\pi \\ &\leq \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1-\alpha_4} \right) \max_{0 \leq j < i} \|z_j^\parallel\|_\pi. \end{aligned}$$

□

Combining Claim 4 and Claim 5 gives

$$\begin{aligned} \|z_k^\parallel\|_\pi &\leq \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1-\alpha_4} \right) \max_{0 \leq j < k} \|z_j^\parallel\|_\pi \\ (\text{because } \alpha_1 + \alpha_2 \alpha_3 / (1-\alpha_4) &\geq \alpha_1 \geq 1) &\leq \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1-\alpha_4} \right)^k \|z_0^\parallel\|_\pi \\ &= \|\phi\|_\pi \sqrt{d} \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1-\alpha_4} \right)^k, \end{aligned}$$

which implies

$$\langle \boldsymbol{\pi} \otimes \text{vec}(\mathbf{I}_d), \mathbf{z}_k \rangle_{\boldsymbol{\pi}} \leq \|\boldsymbol{\phi}\|_{\boldsymbol{\pi}} d \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1 - \alpha_4} \right)^k.$$

Finally, we bound $\left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1 - \alpha_4} \right)^k$. The same as [10], we can bound $\alpha_1, \alpha_2 \alpha_3, \alpha_4$ by:

$$\alpha_1 = \exp(t\ell) - t\ell \leq 1 + t^2 \ell^2 = 1 + t^2(\gamma^2 + b^2),$$

and

$$\alpha_2 \alpha_3 = \lambda(\exp(t\ell) - 1)^2 \leq \lambda(2t\ell)^2 = 4\lambda t^2(\gamma^2 + b^2)$$

where the second step is because $\exp(x) \leq 1 + 2x, \forall x \in [0, 1]$ and $t\ell < 1$,

$$\alpha_4 = \lambda \exp(t\ell) \leq \lambda(1 + 2t\ell) \leq \frac{1}{2} + \frac{1}{2}\lambda$$

where the second step is because $t\ell < 1$, and the third step follows by $t\ell \leq \frac{1-\lambda}{4\lambda}$.

Overall, we have

$$\begin{aligned} \left(\alpha_1 + \frac{\alpha_2 \alpha_3}{1 - \alpha_4} \right)^k &\leq \left(1 + t^2(\gamma^2 + b^2) + \frac{4\lambda t^2(\gamma^2 + b^2)}{\frac{1}{2} - \frac{1}{2}\lambda} \right)^k \\ &\leq \exp \left(kt^2(\gamma^2 + b^2) \left(1 + \frac{8}{1 - \lambda} \right) \right). \end{aligned}$$

This completes our proof of Lemma 1. \square

B.4 Proof of Theorem 1

Theorem 1 (Markov Chain Matrix Chernoff Bound). *Let \mathbf{P} be a regular Markov chain with state space $[N]$, stationary distribution $\boldsymbol{\pi}$ and spectral expansion λ . Let $f : [N] \rightarrow \mathbb{C}^{d \times d}$ be a function such that (1) $\forall v \in [N]$, $f(v)$ is Hermitian and $\|f(v)\|_2 \leq 1$; (2) $\sum_{v \in [N]} \pi_v f(v) = 0$. Let (v_1, \dots, v_k) denote a k -step random walk on \mathbf{P} starting from a distribution $\boldsymbol{\phi}$. Given $\epsilon \in (0, 1)$,*

$$\begin{aligned} \mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \geq \epsilon \right] &\leq 4 \|\boldsymbol{\phi}\|_{\boldsymbol{\pi}} d^2 \exp(-(\epsilon^2(1 - \lambda)k/72)) \\ \mathbb{P} \left[\lambda_{\min} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \leq -\epsilon \right] &\leq 4 \|\boldsymbol{\phi}\|_{\boldsymbol{\pi}} d^2 \exp(-(\epsilon^2(1 - \lambda)k/72)). \end{aligned}$$

Proof. (of Theorem 1) Our strategy is to adopt complexification technique [8]. For any $d \times d$ complex Hermitian matrix \mathbf{X} , we may write $\mathbf{X} = \mathbf{Y} + i\mathbf{Z}$, where \mathbf{Y} and $i\mathbf{Z}$ are the real and imaginary parts of \mathbf{X} , respectively. Moreover, the Hermitian property of \mathbf{X} (i.e., $\mathbf{X}^* = \mathbf{X}$) implies that (1) \mathbf{Y} is real and symmetric (i.e., $\mathbf{Y}^\top = \mathbf{Y}$); (2) \mathbf{Z} is real and skew symmetric (i.e., $\mathbf{Z} = -\mathbf{Z}^\top$). The eigenvalues of \mathbf{X} can be found via a $2d \times 2d$ real symmetric matrix $\mathbf{H} \triangleq \begin{bmatrix} \mathbf{Y} & \mathbf{Z} \\ -\mathbf{Z} & \mathbf{Y} \end{bmatrix}$, where the symmetry of \mathbf{H} follows by the symmetry of \mathbf{Y} and skew-symmetry of \mathbf{Z} . Note the fact that, if the eigenvalues (real) of \mathbf{X} are $\lambda_1, \lambda_2, \dots, \lambda_d$, then those of \mathbf{H} are $\lambda_1, \lambda_1, \lambda_2, \lambda_2, \dots, \lambda_d, \lambda_d$. I.e., \mathbf{X} and \mathbf{H} have the same eigenvalues, but with different multiplicity.

Using the above technique, we can formally prove Theorem 1. For any complex matrix function $f : [N] \rightarrow \mathbb{C}^{d \times d}$ in Theorem 1, we can separate its real and imaginary parts by $f = f_1 + i f_2$. Then we construct a real-valued matrix function $g : [N] \rightarrow \mathbb{R}^{2d \times 2d}$ s.t. $\forall v \in [N], g(v) = \begin{bmatrix} f_1(v) & f_2(v) \\ -f_2(v) & f_1(v) \end{bmatrix}$. According to the complexification technique, we know that (1) $\forall v \in [N], g(v)$ is real symmetric and $\|g(v)\|_2 = \|f(v)\|_2 \leq 1$; (2) $\sum_{v \in [N]} \pi_v g(v) = 0$. Then

$$\mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k f(v_j) \right) \geq \epsilon \right] = \mathbb{P} \left[\lambda_{\max} \left(\frac{1}{k} \sum_{j=1}^k g(v_j) \right) \geq \epsilon \right] \leq 4 \|\boldsymbol{\phi}\|_{\boldsymbol{\pi}} d^2 \exp(-(\epsilon^2(1 - \lambda)k/72)),$$

where the first step follows by the fact that $\frac{1}{k} \sum_{j=1}^k f(v_j)$ and $\frac{1}{k} \sum_{j=1}^k g(v_j)$ have the same eigenvalues (with different multiplicity), and the second step follows by Theorem 3.⁵ The bound on λ_{\min} also follows similarly. \square

⁵The additional factor 4 is because the constructed $g(v)$ has shape $2d \times 2d$.