

## Appendix

### A. Proof of Proposition 1

We divide the proof into two parts: approximation error and effective dimension.

*Part I: Approximation error.* Let  $g^* : \mathcal{X} \rightarrow R$  be the target function. By assumption, there exist latent maps:

$$\mathbf{z}^* = g_0(\mathbf{x}), \quad \mathbf{x}_b^* = g_1(\mathbf{z}^*), \quad \mathbf{h}^* = g_2(\mathbf{z}^*), \quad \boldsymbol{\phi}^* = g_3(\mathbf{h}^*),$$

such that

$$\sup_{\mathbf{x} \in \mathcal{X}} |g^*(\mathbf{x}) - Q_L(\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*)| \leq \epsilon_q(U, L), \quad (\text{A.1})$$

which is exactly Eq. (9) in the main text.

Now let  $f_\omega \in \mathcal{F}_\omega^{(r)}$  be a TensorDual-VQC model with TT-rank at most  $r$ , producing the outputs as follows:

$$\mathbf{z} = f_\theta^{(0)}(\mathbf{x}), \quad (\widehat{\mathbf{x}}, \mathbf{h}) = (f_\theta^{(1)}(\mathbf{z}), f_\theta^{(2)}(\mathbf{z})), \quad \boldsymbol{\phi} = f_\psi(\mathbf{h}),$$

and

$$f_\omega(\mathbf{x}) = Q_L(\widehat{\mathbf{x}}, \boldsymbol{\phi}).$$

By the shared low-rank approximation assumption, the joint mapping  $\mathbf{x} \mapsto (\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*)$  admits an approximate TT representation of rank  $r$ , so there exists a model in  $\mathcal{F}_\omega^{(r)}$  such that

$$\|(\widehat{\mathbf{x}}, \boldsymbol{\phi}) - (\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*)\|_2 \leq C_f r^{-\alpha} \quad (\text{A.2})$$

uniformly over  $\mathbf{x} \in \mathcal{X}$ . This corresponds to Eq. (11) in the main text.

Further, by the joint Lipschitz property of  $Q_L$  in  $(\widehat{\mathbf{x}}, \boldsymbol{\phi})$ ,

$$|Q_L(\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*) - Q_L(\widehat{\mathbf{x}}, \boldsymbol{\phi})| \leq L_Q \|(\widehat{\mathbf{x}}, \boldsymbol{\phi}) - (\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*)\|_2, \quad (\text{A.3})$$

which is Eq. (12).

We now decompose the approximation error:

$$\begin{aligned} |g^*(\mathbf{x}) - f_\omega(\mathbf{x})| &= |g^*(\mathbf{x}) - Q_L(\widehat{\mathbf{x}}, \boldsymbol{\phi})| \\ &\leq |g^*(\mathbf{x}) - Q_L(\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*)| + |Q_L(\widehat{\mathbf{x}}^*, \boldsymbol{\phi}^*) - Q_L(\widehat{\mathbf{x}}, \boldsymbol{\phi})|. \end{aligned} \quad (\text{A.4})$$

Applying (A.1), (A.3), and then (A.2), we obtain

$$|g^*(\mathbf{x}) - f_\omega(\mathbf{x})| \leq \epsilon_q(U, L) + L_Q C r^{-\alpha}. \quad (\text{A.5})$$

Taking the supremum over  $\mathbf{x} \in \mathcal{X}$  gives

$$\|f_\omega - g^*\|_\infty \leq \epsilon_q(U, L) + L_Q C r^{-\alpha}. \quad (\text{A.6})$$

Since  $L_Q$  and  $C$  are constants independent of  $r$ , this yields

$$\inf_{f_\omega \in \mathcal{F}_\omega^{(r)}} \|f_\omega - g^*\|_\infty \leq \mathcal{O}(r^{-\alpha}) + \epsilon_q(U, L), \quad (\text{A.7})$$

which completes the proof.

*B. Proof of Proposition 3*

We exploit the fact that  $\mathcal{K}_\theta$  and  $\mathcal{K}_\psi$  are positive semidefinite (PSD) Gram matrices.

*Step 1: Kernel decomposition.* From the definition of the empirical NTK,

$$\mathcal{K}_{\text{td}} = \mathbf{G}_\theta \mathbf{G}_\theta^\top + \mathbf{G}_\psi \mathbf{G}_\psi^\top = \mathcal{K}_\theta + \mathcal{K}_\psi, \quad (\text{B.1})$$

where both  $\mathcal{K}_\theta$  and  $\mathcal{K}_\psi$  are symmetric PSD matrices.

*Step 2: Nullspace characterization.* Let  $\mathbf{x} \in \mathbb{R}^N$  (where  $N$  is the number of training samples). Then

$$\mathbf{x} \in \ker(\mathcal{K}_{\text{td}}) \iff \mathbf{x}^\top \mathcal{K}_{\text{td}} \mathbf{x} = 0. \quad (\text{B.2})$$

Using the decomposition,

$$\mathbf{x}^\top \mathcal{K}_{\text{td}} \mathbf{x} = \mathbf{x}^\top \mathcal{K}_\theta \mathbf{x} + \mathbf{x}^\top \mathcal{K}_\psi \mathbf{x}.$$

Since both  $\mathcal{K}_\theta$  and  $\mathcal{K}_\psi$  are PSD,

$$\mathbf{x}^\top \mathcal{K}_\theta \mathbf{x} \geq 0, \quad \mathbf{x}^\top \mathcal{K}_\psi \mathbf{x} \geq 0.$$

Thus,

$$\mathbf{x}^\top \mathcal{K}_{\text{td}} \mathbf{x} = 0 \implies \mathbf{x}^\top \mathcal{K}_\theta \mathbf{x} = 0 \quad \text{and} \quad \mathbf{x}^\top \mathcal{K}_\psi \mathbf{x} = 0. \quad (\text{B.3})$$

For PSD matrices,  $\mathbf{x}^\top \mathcal{K} \mathbf{x} = 0$  implies  $\mathcal{K} \mathbf{x} = 0$ . Therefore,

$$\mathbf{x} \in \ker(\mathcal{K}_\theta) \cap \ker(\mathcal{K}_\psi). \quad (\text{B.4})$$

Conversely, if  $\mathbf{x} \in \ker(\mathcal{K}_\theta) \cap \ker(\mathcal{K}_\psi)$ , then clearly  $\mathcal{K}_{\text{td}} \mathbf{x} = 0$ . Hence,

$$\ker(\mathcal{K}_{\text{td}}) = \ker(\mathcal{K}_\theta) \cap \ker(\mathcal{K}_\psi). \quad (\text{B.5})$$

*Step 3: Rank inequality.* Taking dimensions,

$$\dim \ker(\mathcal{K}_{\text{td}}) = \dim (\ker(\mathcal{K}_\theta) \cap \ker(\mathcal{K}_\psi)) \leq \min\{\dim \ker(\mathcal{K}_\theta), \dim \ker(\mathcal{K}_\psi)\}.$$

Applying the rank–nullity theorem,

$$\text{rank}(\mathcal{K}) = N - \dim \ker(\mathcal{K}),$$

we obtain

$$\text{rank}(\mathcal{K}_{\text{td}}) = N - \dim \ker(\mathcal{K}_{\text{td}}) \geq N - \min\{\dim \ker(\mathcal{K}_\theta), \dim \ker(\mathcal{K}_\psi)\}. \quad (\text{B.6})$$

Thus,

$$\text{rank}(\mathcal{K}_{\text{td}}) \geq \max\{\text{rank}(\mathcal{K}_\theta), \text{rank}(\mathcal{K}_\psi)\}, \quad (\text{B.7})$$

which proves the claimed inequality.

*C. Proof of Variance Scaling under Isotropic Perturbations*

*Step 1: Bound the parameter-induced output fluctuation.* Define

$$\delta_{\boldsymbol{\omega}}(\mathbf{x}) := f_{\boldsymbol{\omega}+\Delta\boldsymbol{\omega}}(\mathbf{x}) - f_{\boldsymbol{\omega}}(\mathbf{x}).$$

By the local Lipschitz property,

$$|\delta_{\boldsymbol{\omega}}(\mathbf{x})| \leq L_{\boldsymbol{\omega}} \|\Delta\boldsymbol{\omega}\|_2.$$

Squaring both sides gives:

$$|\delta_{\boldsymbol{\omega}}(\mathbf{x})|^2 \leq L_{\boldsymbol{\omega}}^2 \|\Delta\boldsymbol{\omega}\|_2^2.$$

Taking expectations yields:

$$\mathbb{E}[|\delta_{\boldsymbol{\omega}}(\mathbf{x})|^2] \leq L_{\boldsymbol{\omega}}^2 \mathbb{E}[\|\Delta\boldsymbol{\omega}\|_2^2]. \quad (\text{C.1})$$

Since for any random variable  $Z$ ,

$$\text{Var}[Z] \leq \mathbb{E}[Z^2],$$

we obtain

$$\text{Var}[\delta_{\boldsymbol{\omega}}(\mathbf{x})] \leq \mathbb{E}[|\delta_{\boldsymbol{\omega}}(\mathbf{x})|^2] \leq L_{\boldsymbol{\omega}}^2 \mathbb{E}[\|\Delta\boldsymbol{\omega}\|_2^2]. \quad (\text{C.2})$$

Using the isotropic perturbation assumption,

$$\mathbb{E}[\|\Delta\boldsymbol{\omega}\|_2^2] \leq C_{\boldsymbol{\omega}}^2 d_{\text{eff}} \varepsilon^2,$$

we conclude

$$\text{Var}[\delta_{\boldsymbol{\omega}}(\mathbf{x})] \leq L_{\boldsymbol{\omega}}^2 C_{\boldsymbol{\omega}}^2 d_{\text{eff}} \varepsilon^2. \quad (\text{C.3})$$

This is the desired variance scaling for the parameter-perturbation part. In big- $\mathcal{O}$  form,

$$\text{Var}[\delta_{\boldsymbol{\omega}}(\mathbf{x})] = \mathcal{O}(d_{\text{eff}} \varepsilon^2). \quad (\text{C.4})$$

*Step 2: Add the measurement-noise contribution.*

$$\tilde{f}_{\boldsymbol{\omega}}(\mathbf{x}) = f_{\boldsymbol{\omega}}(\mathbf{x}) + \delta_{\boldsymbol{\omega}}(\mathbf{x}) + \xi(\mathbf{x}).$$

Since  $f_{\boldsymbol{\omega}}(\mathbf{x})$  is deterministic for fixed  $\mathbf{x}$  and  $\boldsymbol{\omega}$ ,

$$\text{Var}[\tilde{f}_{\boldsymbol{\omega}}(\mathbf{x})] = \text{Var}[\delta_{\boldsymbol{\omega}}(\mathbf{x}) + \xi(\mathbf{x})].$$

If  $\delta_{\boldsymbol{\omega}}(\mathbf{x})$  and  $\xi(\mathbf{x})$  are independent, then

$$\text{Var}[\tilde{f}_{\boldsymbol{\omega}}(\mathbf{x})] = \text{Var}[\delta_{\boldsymbol{\omega}}(\mathbf{x})] + \text{Var}[\xi(\mathbf{x})].$$

Using (C.3) and  $\text{Var}[\xi(\mathbf{x})] \leq \sigma^2$ , we obtain

$$\text{Var}[\tilde{f}_{\boldsymbol{\omega}}(\mathbf{x})] \leq L_{\boldsymbol{\omega}}^2 C_{\boldsymbol{\omega}}^2 d_{\text{eff}} \varepsilon^2 + \sigma^2. \quad (\text{C.5})$$

Hence,

$$\text{Var}[\tilde{f}_{\boldsymbol{\omega}}(\mathbf{x})] = \mathcal{O}(d_{\text{eff}} \varepsilon^2) + \mathcal{O}(\sigma^2), \quad (\text{C.6})$$

which is exactly the scaling stated in the robustness section. This proves the variance scaling under isotropic perturbations.

*D. Proof of The Generalization Bound (Eq. (33))*

Fix a sample set  $S = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ . The empirical Rademacher complexity is

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) := \mathbb{E}_\sigma \left[ \sup_{\mathbf{u} \in \mathcal{U}} \frac{1}{N} \sum_{i=1}^N \sigma_i f_{\mathbf{u}}(\mathbf{x}_i) \right], \quad (\text{D.1})$$

where  $\sigma_1, \dots, \sigma_N$  are i.i.d. Rademacher variables.

Define the empirical  $L_2$ -norm metric on the function class by

$$d_S(f_{\mathbf{u}}, f_{\mathbf{v}}) := \left( \frac{1}{N} \sum_{i=1}^N (f_{\mathbf{u}}(\mathbf{x}_i) - f_{\mathbf{v}}(\mathbf{x}_i))^2 \right)^{1/2}. \quad (\text{D.2})$$

By the assumed Lipschitz dependence on the effective coordinates,

$$d_S(f_{\mathbf{u}}, f_{\mathbf{v}}) \leq \left( \frac{1}{N} \sum_{i=1}^N L_{\mathbf{u}}^2 \|\mathbf{u} - \mathbf{v}\|_2^2 \right)^{1/2} = L_{\mathbf{u}} \|\mathbf{u} - \mathbf{v}\|_2.$$

So the map  $\mathbf{u} \mapsto f_{\mathbf{u}}$  is  $L_{\mathbf{u}}$ -Lipschitz from  $(\mathcal{U}, \|\cdot\|_2)$  into  $(\mathcal{F}_\omega^{(r)}, d_S)$ . Because  $\mathcal{U} \subseteq B_2(A) \subset \mathbb{R}^M$ , an  $\varepsilon/L_{\mathbf{u}}$ -cover of  $B_2(A)$  in Euclidean norm induces an  $\varepsilon$ -cover of  $\mathcal{F}_\omega^{(r)}$  in  $d_S$ . Hence, the empirical covering number satisfies:

$$\mathcal{N}(\varepsilon, \mathcal{F}_\omega^{(r)}, d_S) \leq \mathcal{N}\left(\frac{\varepsilon}{L_{\mathbf{u}}}, B_2(A), \|\cdot\|_2\right) \leq \left(1 + \frac{2AL_{\mathbf{u}}}{\varepsilon}\right)^M,$$

where  $M = d_{\text{eff}}$ . Therefore,

$$\log \mathcal{N}(\varepsilon, \mathcal{F}_\omega^{(r)}, d_S) \leq M \log\left(1 + \frac{2AL_{\mathbf{u}}}{\varepsilon}\right). \quad (\text{D.3})$$

Next, applying Dudley's entropy integral for empirical Rademacher complexity:

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) \leq \frac{4\alpha}{\sqrt{N}} + \frac{12}{\sqrt{N}} \int_\alpha^{\text{diam}(\mathcal{F}_\omega^{(r)}, d_S)} \sqrt{\log \mathcal{N}(\varepsilon, \mathcal{F}_\omega^{(r)}, d_S)} d\varepsilon,$$

for any  $\alpha > 0$ . Since  $d_S(f_{\mathbf{u}}, f_{\mathbf{v}}) \leq L_{\mathbf{u}} \|\mathbf{u} - \mathbf{v}\|_2$  and  $\mathcal{U} \subseteq B_2(A)$ ,

$$\text{diam}(\mathcal{F}_\omega^{(r)}, d_S) \leq 2AL_{\mathbf{u}}.$$

Substituting the covering-number bound gives

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) \leq \frac{4\alpha}{\sqrt{N}} + \frac{12\sqrt{M}}{\sqrt{N}} \int_\alpha^{2AL_{\mathbf{u}}} \sqrt{\log\left(1 + \frac{2AL_{\mathbf{u}}}{\varepsilon}\right)} d\varepsilon. \quad (\text{D.4})$$

Taking the limit  $\alpha \downarrow 0$ , and using the change of variables

$$t = \frac{\varepsilon}{2AL_{\mathbf{u}}},$$

we obtain

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) \leq \frac{24AL_u\sqrt{M}}{\sqrt{N}} \int_0^1 \sqrt{\log(1 + 1/t)} dt. \quad (\text{D.5})$$

The integral is finite and bounded by a universal constant, so it can be absorbed into a constant  $C$ . Therefore,

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) \leq CAL_u \sqrt{\frac{M}{N}} = CAL_u \sqrt{\frac{d_{\text{eff}}}{N}}. \quad (\text{D.6})$$

Using the manuscript's intrinsic-dimension scaling

$$d_{\text{eff}} = \mathcal{O}(rKd),$$

we conclude

$$\widehat{\mathfrak{R}}_S(\mathcal{F}_\omega^{(r)}) = \mathcal{O}\left(\sqrt{\frac{rKd}{N}}\right), \quad (\text{D.7})$$

which proves the claimed scaling.