

Paper Review: Neural Tangent Kernel

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Paper Information.

- Arthur Jacot, Franck Gabriel, and Clément Hongler. Neural Tangent Kernel. In Neural Information Processing Systems, 2018.

1 Introduction

2 Neural Networks

- We consider fully-connected ANNs with layers numbered from 0 (input) to L (output).
- n_l : number of neurons in layer l .
- $\sigma : \mathbb{R} \rightarrow \mathbb{R}$: Lipschitz, twice differentiable nonlinearity function, with bounded second derivative.
- θ : weights $W^{(l)} \in \mathbb{R}^{n_l \times n_{l+1}}$ and bias vectors $b^{(l)} \in \mathbb{R}^{n_{l+1}}$. Initialized as i.i.d. Gaussians $\mathcal{N}(0, 1)$.
- $P = \sum_{l=0}^{L-1} (n_l + 1)n_{l+1}$: number of parameters.
- $\mathcal{F} = \{f : \mathbb{R}^{n_0} \rightarrow \mathbb{R}^{n_L}\}$: space of functions.
- $F^{(L)} : \mathbb{R}^P \rightarrow \mathcal{F}$: ANN realization function, mapping parameters to the functions $f_\theta \in \mathcal{F}$.
- $p^{in} = \sum_{i=1}^N \delta_{x_i}$: input distribution.
- $\langle f, g \rangle_{p^{in}} = \mathbb{E}_{x \sim p^{in}} [f(x)^\top g(x)]$: bilinear form defined on p^{in} .
- $\|f\|_{p^{in}} = \langle f, f \rangle_{p^{in}}^{1/2}$: seminorm defined on p^{in} .
- Define the functions

$$\begin{aligned}\alpha^{(0)}(x; \theta) &= x, \\ \tilde{\alpha}^{(l+1)}(x; \theta) &= \frac{1}{\sqrt{n_l}} W^{(l)} \alpha^{(l)}(x; \theta) + \beta b^{(l)}, \\ \alpha^{(l)}(x; \theta) &= \sigma(\tilde{\alpha}^{(l)}(x; \theta)), \\ f_\theta(x) &= \tilde{\alpha}^{(L)}(x; \theta).\end{aligned}$$

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3 Kernel Gradient

- $C : \mathcal{F} \rightarrow \mathbb{R}$: functional cost.
- $K : \mathbb{R}^{n_0 \times n_0} \rightarrow \mathbb{R}^{n_L \times n_L}$: multi-dimensional kernel which satisfies $K(x, x') = K(x', x)^\top$.
- $\langle f, g \rangle_K = \mathbb{E}_{x, x' \sim p^{in}} [f(x)^\top K(x, x') g(x')] :$ inner product w.r.t. kernel K .
- The kernel K is positive definite w.r.t. $\|\cdot\|_{p^{in}}$ if $\|f\|_{p^{in}} > 0 \implies \|f\|_K > 0$.
- $\mathcal{F}^* = \{\mu = \langle d, \cdot \rangle_{p^{in}} : d \in \mathcal{F}\} :$ the dual space of \mathcal{F} .
- $\Phi_K : \mathcal{F}^* \rightarrow \mathcal{F}$ is defined such that

$$\Phi_K : \langle d, \cdot \rangle_{p^{in}} \mapsto \frac{1}{N} \sum_{i=1}^N K(\cdot, x_i) d(x_i).$$

Φ_K can be interpreted as a map which interpolates d using the kernel K .

- $\partial_f^{in} C|_{f_0} = \langle d|_{f_0}, \cdot \rangle_{p^{in}} :$ functional derivative of C at a point $f_0 \in \mathcal{F}$.
- $\nabla_K C|_{f_0} = \Phi_K(\partial_f^{in} C|_{f_0}) :$ kernel gradient.
- In contrast to $\partial_f^{in} C$ which is only defined on the dataset, the kernel gradient generalizes to values x outside the dataset thanks to the kernel K .
- A time-dependent function $f(t)$ follows the kernel gradient descent w.r.t. K if it satisfies

$$\partial_t f(t) = -\nabla_K C|_{f(t)} = -\Phi_K(\partial_f^{in} C|_{f(t)}) = -\frac{1}{N} \sum_{i=1}^N K(\cdot, x_i) d|_{f(t)}(x_i).$$

- During kernel gradient descent, the cost $C(f(t))$ evolves as

$$\begin{aligned} \partial_t C|_{f(t)} &= \partial_t C(f(t)) = \partial_f^{in} C|_{f(t)}(\partial_t f(t)) \\ &= \langle d|_{f(t)}, \partial_t f(t) \rangle_{p^{in}} \\ &= \left\langle d|_{f(t)}, -\frac{1}{N} \sum_{i=1}^N K(\cdot, x_i) d|_{f(t)}(x_i) \right\rangle_{p^{in}} \\ &= \frac{1}{N} \sum_{j=1}^N d|_{f(t)}(x_j)^\top \left(-\frac{1}{N} \sum_{i=1}^N K(x_j, x_i) d|_{f(t)}(x_i) \right) \\ &= -\frac{1}{N^2} \sum_{j=1}^N \sum_{i=1}^N d|_{f(t)}(x_j)^\top K(x_j, x_i) d|_{f(t)}(x_i) \\ &= -\mathbb{E}_{x, x' \sim p^{in}} [d|_{f(t)}(x)^\top K(x, x') d|_{f(t)}(x')] \\ &= -\|d|_{f(t)}\|_K^2. \end{aligned}$$

Convergence to a critical point of C is hence guaranteed if the kernel K is positive definite with respect to $\|\cdot\|_{p^{in}}$: the cost is then strictly decreasing except at points such that $\|d|_{f(t)}\|_{p^{in}} = 0$. If the cost is convex and bounded from below, the function $f(t)$ therefore converges to a global minimum as $t \rightarrow \infty$.

3.1 Random Functions Approximation

- A kernel K can be approximated by a choice of P random functions $f^{(p)}$ sampled independently from any distribution on \mathcal{F} whose (non-centered) covariance is given by the kernel K :

$$\mathbb{E}[f^{(p)}(x)f^{(p)}(x')^\top] = K(x, x')$$

or equivalently,

$$\mathbb{E}[f_k^{(p)}(x)f_{k'}^{(p)}(x')] = K_{kk'}(x, x').$$

- These functions define a random linear parametrization

$$F^{lin} : \mathbb{R}^P \rightarrow \mathcal{F} : \theta \mapsto f_\theta^{lin} = \frac{1}{\sqrt{P}} \sum_{p=1}^P \theta_p f^{(p)}.$$

- The partial derivatives of the parametrization are given by (e_p is the p -th standard basis vector)

$$\partial_{\theta_p} F^{lin}(\theta) = \lim_{h \rightarrow 0} \frac{F^{lin}(\theta + h e_p) - F^{lin}(\theta)}{h} = \frac{1}{\sqrt{P}} f^{(p)}.$$

- Optimizing the cost $C \circ F^{lin}$ through gradient descent, the parameters follow the ODE

$$\begin{aligned} \partial_t \theta_p(t) &= -\partial_{\theta_p} (C \circ F^{lin})(\theta(t)) = -\partial_{\theta_p} C(f_{\theta(t)}^{lin}) \\ &= -\partial_f^{in} C|_{f_{\theta(t)}^{lin}} (\partial_{\theta_p} f_{\theta(t)}^{lin}) \\ &= -\frac{1}{\sqrt{P}} \partial_f^{in} C|_{f_{\theta(t)}^{lin}} (f^{(p)}) = -\frac{1}{\sqrt{P}} \left\langle d|_{f_{\theta(t)}^{lin}}, f^{(p)} \right\rangle_{p^{in}}. \end{aligned}$$

The first equality holds since we are performing gradient descent, i.e., the instantaneous change of θ_p at time t must equal the gradient of θ_p w.r.t. the cost at time t .

- As a result, the function $f_{\theta(t)}^{lin}$ evolves according to

$$\begin{aligned} \partial_t f_{\theta(t)}^{lin} &= \partial_t \left(\frac{1}{\sqrt{P}} \sum_{p=1}^P \theta_p(t) f^{(p)} \right) = \frac{1}{\sqrt{P}} \sum_{p=1}^P \partial_t \theta_p(t) f^{(p)} \\ &= -\frac{1}{P} \sum_{p=1}^P \left\langle d|_{f_{\theta(t)}^{lin}}, f^{(p)} \right\rangle_{p^{in}} f^{(p)} \\ &= -\frac{1}{P} \sum_{p=1}^P \frac{1}{N} \sum_{i=1}^N d|_{f_{\theta(t)}^{lin}}(x_i)^\top f^{(p)}(x_i) f^{(p)}(\cdot) \\ &= -\frac{1}{P} \sum_{p=1}^P \frac{1}{N} \sum_{i=1}^N (f^{(p)} \otimes f^{(p)})(\cdot, x_i) d|_{f_{\theta(t)}^{lin}}(x_i) \\ &= -\frac{1}{N} \sum_{i=1}^N \left(\frac{1}{P} \sum_{p=1}^P f^{(p)} \otimes f^{(p)} \right) (\cdot, x_i) d|_{f_{\theta(t)}^{lin}}(x_i) \\ &= -\Phi_{\tilde{K}}(\partial_f^{in} C|_{f_{\theta(t)}^{lin}}) \\ &= -\nabla_{\tilde{K}} C|_{f_{\theta(t)}^{lin}} \end{aligned}$$

where

$$\tilde{K} = \sum_{p=1}^P \partial_{\theta_p} F^{lin}(\theta) \otimes \partial_{\theta_p} F^{lin}(\theta) = \frac{1}{P} \sum_{p=1}^P f^{(p)} \otimes f^{(p)}.$$

- This is a random n_L -dimensional kernel with values

$$\tilde{K}_{ii'}(x, x') = \frac{1}{P} \sum_{p=1}^P f_i^{(p)}(x) f_{i'}^{(p)}(x').$$

- Performing gradient descent on the cost $C \circ F^{lin}$ is therefore equivalent to performing kernel gradient descent with the tangent kernel \tilde{K} in the function space.
- With $P \rightarrow \infty$, by the law of large numbers, the random kernel \tilde{K} tends to the fixed kernel K .

$$\lim_{P \rightarrow \infty} \tilde{K}_{ii'}(x, x') = \lim_{P \rightarrow \infty} \frac{1}{P} \sum_{p=1}^P f_i^{(p)}(x) f_{i'}^{(p)}(x') = \mathbb{E}[f_i^{(p)}(x) f_{i'}^{(p)}(x')] = K_{ii'}(x, x').$$

Hence, this method approximates kernel gradient descent with respect to the limiting kernel K .

4 Neural Tangent Kernel

- During training, the network function f_θ evolves along the negative kernel gradient

$$\partial_t f_{\theta(t)} = -\nabla_{\Theta^{(L)}} C|_{f_{\theta(t)}}$$

with respect to the neural tangent kernel (NTK)

$$\Theta^{(L)}(\theta) = \sum_{p=1}^P \partial_{\theta_p} F^{(L)}(\theta) \otimes \partial_{\theta_p} F^{(L)}(\theta).$$

This can be derived by following the steps in Section 3.1 with $F^{(L)}$ in place of F^{lin} .

- However, in contrast to F^{lin} , the realization function $F^{(L)}$ of ANNs is not linear.
- As a consequence, the derivatives $\partial_{\theta_p} F^{(L)}(\theta)$ and the NTK depend on the parameters θ .

4.1 Initialization

- The first key result is that in the limit $n_1, \dots, n_{L-1} \rightarrow \infty$, the NTK converges in probability to a deterministic limiting kernel.

4.2 Training

- The second key result is that the NTK stays asymptotically constant during training.
- In general, the parameters can be updated according to a training direction $d_t \in \mathcal{F}$.

$$\partial_t \theta_p(t) = \left\langle \partial_{\theta_p} F^{(L)}(\theta(t)), d_t \right\rangle_{p^{in}}$$

- In the case of gradient descent,

$$\begin{aligned}
\partial_t \theta_p(t) &= -\partial_{\theta_p}(C \circ F^{(L)})(\theta(t)) = -\partial_{\theta_p} C(f_{\theta(t)}) \\
&= -\partial_f^{in} C|_{f_{\theta(t)}}(\partial_{\theta_p} f_{\theta(t)}) \\
&= \langle \partial_{\theta_p} f_{\theta(t)}, -d|_{f_{\theta(t)}} \rangle_{p^{in}} \\
&= \langle \partial_{\theta_p} F^{(L)}(\theta(t)), -d|_{f_{\theta(t)}} \rangle_{p^{in}}
\end{aligned}$$

and so

$$d_t = -d|_{f_{\theta(t)}}.$$

A Appendix

- We study the limit of the NTK as $n_1, \dots, n_{L-1} \rightarrow \infty$ sequentially. That is, we first take $n_1 \rightarrow \infty$, then $n_2 \rightarrow \infty$, and so on. This leads to much simpler proofs, but our results could in principle be strengthened to the more general setting when $\min(n_1, \dots, n_{L-1}) \rightarrow \infty$.
- A natural choice of convergence to study the NTK is w.r.t. the operator norm on kernels

$$\|K\|_{op} = \max_{\|f\|_{p^{in}} \leq 1} \|f\|_K = \max_{\|f\|_{p^{in}} \leq 1} \sqrt{\mathbb{E}_{x, x' \sim p^{in}} [f(x)^\top K(x, x') f(x')]}.$$

- Define

$$\mathbf{f} := (f(x_1), \dots, f(x_N)) \in \mathbb{R}^{Nn_L}, \quad \mathbf{K} := (K_{kk'}(x_i, x_j))_{k, k' < n_L, i, j < N} \in \mathbb{R}^{Nn_L \times Nn_L}.$$

We then have

$$\|f\|_{p^{in}}^2 = \langle f, f \rangle_{p^{in}} = \mathbb{E}_{x \sim p^{in}} [\|f(x)\|_2^2] = \frac{1}{N} \sum_{i=1}^N \|f(x_i)\|_2^2 = \frac{1}{N} \|(f(x_1), \dots, f(x_N))\|^2 = \frac{1}{N} \|\mathbf{f}\|_2^2.$$

Also, note that

$$\mathbb{E}_{x, x'} [f(x)^\top K(x, x') f(x')] = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N f(x_i)^\top K(x_i, x_j) f(x_j) = \frac{1}{N^2} \mathbf{f}^\top \mathbf{K} \mathbf{f}$$

and so

$$\|K\|_{op} = \frac{1}{N} \max_{\|\mathbf{f}\|_2 \leq \sqrt{N}} \sqrt{\mathbf{f}^\top \mathbf{K} \mathbf{f}} = \frac{1}{\sqrt{N}} \max_{\|\mathbf{f}\|_2 \leq 1} \sqrt{\mathbf{f}^\top \mathbf{K} \mathbf{f}}$$

Hence, $\|K\|_{op}$ is equal to the (scaled) leading eigenvalue of the $Nn_L \times Nn_L$ Gram matrix \mathbf{K} .

A.1 Asymptotics at Initialization

Proposition 1. *For a network of depth L at initialization, with a Lipschitz nonlinearity σ , and in the limit as $n_1, \dots, n_{L-1} \rightarrow \infty$ sequentially, the output functions $f_{\theta,k}$, for $k = 1, \dots, n_L$, tend (in law) to i.i.d. centered Gaussian processes of covariance $\Sigma^{(L)}$, where $\Sigma^{(L)}$ is defined recursively by*

$$\begin{aligned}\Sigma^{(1)}(x, x') &= \frac{1}{n_0} x^\top x' + \beta^2, \\ \Sigma^{(L+1)}(x, x') &= \mathbb{E}_{f \sim \mathcal{N}(0, \Sigma^{(L)})} [\sigma(f(x)) \sigma(f(x'))] + \beta^2\end{aligned}$$

where $\mathcal{N}(0, \Sigma^{(L)})$ denotes the centered Gaussian process with covariance function $\Sigma^{(L)}$.

Proof. We prove the result by induction. When $L = 1$, there are no hidden layers and f_θ is a random affine function of the form

$$f_\theta(x) = \frac{1}{\sqrt{n_0}} W^{(0)} x + \beta b^{(0)}.$$

For any index i , we thus have

$$\mathbb{E}[f_{\theta,i}(x)] = \mathbb{E} \left[\frac{1}{\sqrt{n_0}} \sum_{j=1}^{n_0} W_{i,j}^{(0)} x_j + \beta b_i^{(0)} \right] = \frac{1}{\sqrt{n_0}} \sum_{j=1}^{n_0} \mathbb{E}[W_{i,j}^{(0)}] x_j + \beta \mathbb{E}[b_i^{(0)}] = 0$$

because the parameters are initialized from $\mathcal{N}(0, 1)$. It follows that

$$\begin{aligned}\Sigma^{(1)}(x, x') &= \mathbb{E}[f_{\theta,i}(x) f_{\theta,i}(x')] - \mathbb{E}[f_{\theta,i}(x)] \mathbb{E}[f_{\theta,i}(x')] \\ &= \mathbb{E}[f_{\theta,i}(x) f_{\theta,i}(x')] \\ &= \frac{1}{n_0} \sum_{j=1}^{n_0} \sum_{j'=1}^{n_0} \mathbb{E}[W_{i,j}^{(0)} W_{i,j'}^{(0)}] x_j x_{j'} + \frac{\beta}{\sqrt{n_0}} \sum_{j=1}^{n_0} \mathbb{E}[W_{i,j}^{(0)} \beta_i^{(0)}] (x_j + x_{j'}) + \beta^2 \mathbb{E}[(b_i^{(0)})^2] \\ &= \frac{1}{n_0} x^\top x' + \beta^2\end{aligned}$$

which proves $f_{\theta,i} \sim \mathcal{N}(0, \Sigma^{(1)})$. This concludes the base case.

The key to the induction step is to consider an $(L+1)$ -network as the following composition. An L -network $\mathbb{R}^{n_0} \rightarrow \mathbb{R}^{n_L}$ mapping the input to the pre-activations $\tilde{\alpha}_i^{(L)}$, followed by an elementwise application of the nonlinearity σ and then a random affine map $\mathbb{R}^{n_L} \rightarrow \mathbb{R}^{n_{L+1}}$. The induction hypothesis gives in the limit as sequentially $n_1, \dots, n_{L-1} \rightarrow \infty$, the preactivations $\tilde{\alpha}_i^{(L)}$ tend to i.i.d. Gaussian processes with covariance $\Sigma^{(L)}$. Then, conditioned on $\tilde{\alpha}_i^{(L)} \sim \mathcal{N}(0, \Sigma^{(L)})$, the outputs

$$f_{\theta,i}(x) = \frac{1}{\sqrt{n_L}} \sum_{j=1}^{n_L} W_{i,j}^{(L)} \sigma(\tilde{\alpha}^{(L)}(x; \theta)) + \beta b_i^{(L)}$$

are i.i.d. centered Gaussians with covariance

$$\tilde{\Sigma}^{(L+1)}(x, x') = \mathbb{E}[f_{\theta,i}(x) f_{\theta,i}(x')] = \frac{1}{n_L} \sigma(\tilde{\alpha}^{(L)}(x; \theta))^\top \sigma(\tilde{\alpha}^{(L)}(x'; \theta)) + \beta^2.$$

In other words, conditioned on $\tilde{\alpha}_i^{(L)} \sim \mathcal{N}(0, \Sigma^{(L)})$, $f_{\theta,i} \sim \mathcal{N}(0, \tilde{\Sigma}^{(L+1)})$. The proof for this is identical to the proof for the base case. Specifically, repeat the proof for the base case with $\sigma(\tilde{\alpha}^{(L)}(x; \theta))$ in place of x . By

the law of large numbers, as $n_L \rightarrow \infty$, this covariance tends in probability to the expectation

$$\begin{aligned}
\Sigma^{(L+1)}(x, x') &:= \lim_{n_L \rightarrow \infty} \tilde{\Sigma}^{L+1}(x, x') \\
&= \lim_{n_L \rightarrow \infty} \frac{1}{n_L} \sigma(\tilde{\alpha}^{(L)}(x; \theta))^\top \sigma(\tilde{\alpha}^{(L)}(x'; \theta)) + \beta^2 \\
&= \lim_{n_L \rightarrow \infty} \frac{1}{n_L} \sum_{i=1}^{n_L} \sigma(\tilde{\alpha}_i^{(L)}(x; \theta)) \sigma(\tilde{\alpha}_i^{(L)}(x'; \theta)) + \beta^2 \\
&= \mathbb{E}_{f \sim \mathcal{N}(0, \Sigma^{(L)})} [\sigma(f(x)) \sigma(f(x'))] + \beta^2
\end{aligned}$$

because $\tilde{\alpha}_i^{(L)}$ are i.i.d. samples from $\mathcal{N}(0, \Sigma^{(L)})$. In particular, the covariance is deterministic and hence independent of $\alpha^{(L)}$. As a consequence, the conditioned and unconditioned distributions of $f_{\theta, i}$ are equal in the limit. They are i.i.d. centered Gaussian processes of covariance $\Sigma^{(L+1)}$. This concludes the induction step and so the proposition is proved. \square

Theorem 1. *For a network of depth L at initialization, with a Lipschitz nonlinearity σ , and in the limit as the layers width $n_1, \dots, n_{L-1} \rightarrow \infty$ sequentially, the NTK $\Theta^{(L)}$ converges in probability to a deterministic limiting kernel*

$$\Theta^{(L)} \rightarrow \Theta_\infty^{(L)} \otimes Id_{n_L}.$$

The scalar kernel $\Theta_\infty^{(L)} : \mathbb{R}^{n_0} \times \mathbb{R}^{n_0} \rightarrow \mathbb{R}$ is defined recursively by

$$\begin{aligned}
\Theta_\infty^{(1)}(x, x') &= \Sigma^{(1)}(x, x') \\
\Theta_\infty^{(L+1)}(x, x') &= \Theta_\infty^{(L)}(x, x') \dot{\Sigma}^{(L+1)}(x, x') + \Sigma^{(L+1)}(x, x'),
\end{aligned}$$

where

$$\dot{\Sigma}^{(L+1)}(x, x') = \mathbb{E}_{f \sim \mathcal{N}(0, \Sigma^{(L)})} [\dot{\sigma}(f(x)) \dot{\sigma}(f(x'))],$$

where $\dot{\sigma}$ denotes the derivative of σ .

A.2 Asymptotics During Training

Given a training direction $t \mapsto d_t \in \mathcal{F}$, a neural network is trained in the following manner: the parameters θ_p are initialized as i.i.d. $\mathcal{N}(0, 1)$ and follow the differential equation

$$\partial_t \theta_p(t) = \left\langle \partial_{\theta_p} F^{(L)}(\theta(t)), d_t \right\rangle_{p^{in}}.$$

Theorem 2. *Assume that σ is a Lipschitz twice differentiable nonlinearity function, with bounded second derivative. For any T such that the integral $\int_0^T \|d_t\|_{p^{in}} dt$ stays stochastically bounded, as $n_1, \dots, n_{L-1} \rightarrow \infty$ sequentially, we have, uniformly for $t \in [0, T]$,*

$$\Theta^{(L)}(t) \rightarrow \Theta_\infty^{(L)} \otimes Id_{n_L}.$$

As a consequence, in this limit, the dynamics of f_θ is described by the differential equation

$$\partial_t f_{\theta(t)} = \Phi_{\Theta_\infty^{(L)} \otimes Id_{n_L}} \left(\langle d_t, \cdot \rangle_{p^{in}} \right).$$

Proof. Let $\tilde{\theta}$ be the parameters of the smaller network, and let $\theta_p \in \tilde{\theta}$. Then

$$\begin{aligned} \partial_{\theta_p} F^{(L+1)}(\theta) &= \partial_{\theta_p} \left(\frac{1}{\sqrt{n_L}} W^{(L)} \sigma(F^{(L)}(\tilde{\theta})) + \beta b^{(L)} \right) \\ &= \frac{1}{\sqrt{n_L}} W^{(L)} \dot{\sigma}(F^{(L)}(\tilde{\theta})) \partial_{\theta_p} F^{(L)}(\tilde{\theta}) \end{aligned}$$

and so

$$\begin{aligned} \partial_t \theta_p(t) &= \left\langle \partial_{\theta_p} F^{(L)}(\theta(t)), d_t \right\rangle_{p^{in}} \\ &= \left\langle \frac{1}{\sqrt{n_L}} W^{(L)}(t) \dot{\sigma}(F^{(L)}(\tilde{\theta}(t))) \partial_{\theta_p} F^{(L)}(\tilde{\theta}(t)), d_t \right\rangle_{p^{in}} \\ &= \left\langle \partial_{\theta_p} F^{(L)}(\tilde{\theta}(t)), \dot{\sigma}(F^{(L)}(\tilde{\theta}(t))) \left(\frac{1}{\sqrt{n_L}} W^{(L)}(t) \right)^\top d_t \right\rangle \end{aligned}$$

which implies that the smaller network follows the training direction

$$d'_t = \dot{\sigma}(F^{(L)}(\tilde{\theta}(t))) \left(\frac{1}{\sqrt{n_L}} W^{(L)}(t) \right)^\top d_t.$$

Since σ is a c -Lipschitz function, $|\dot{\sigma}| \leq c$ and so

$$\begin{aligned} \|d'_t\|_{p^{in}} &\leq |\dot{\sigma}(F^{(L)}(\tilde{\theta}(t)))| \left\| \frac{1}{\sqrt{n_L}} W^{(L)}(t) \right\|_{op} \|d_t\|_{p^{in}} \\ &\leq c \left\| \frac{1}{\sqrt{n_L}} W^{(L)}(t) \right\|_{op} \|d_t\|_{p^{in}}. \end{aligned}$$

From the law of large numbers,

$$\left\| \frac{1}{\sqrt{n_L}} W_i^{(L)}(0) \right\|_2^2 = \frac{1}{n_L} \sum_{j=1}^{n_L} W_{ij}^2(0) \rightarrow \mathbb{E}[W_{ij}^2(0)] = 1$$

since $W_{ij}(0)$ are i.i.d. samples from $\mathcal{N}(0, 1)$. Hence, $\|\frac{1}{\sqrt{n_L}} W^{(L)}(0)\|_{op}$ is bounded.

Observe that by the triangle inequality,

$$\partial_t \|f(t)\| = \lim_{h \rightarrow 0} \frac{\|f(t+h)\| - \|f(t)\|}{h} \leq \lim_{h \rightarrow 0} \frac{\|f(t+h) - f(t)\|}{h} = \|\partial_t f(t)\|$$

and so $\partial_t \|\cdot\| \leq \|\partial_t \cdot\|$. It follows that

$$\begin{aligned} \partial_t \left\| W_i^{(L)}(t) - W_i^{(L)}(0) \right\|_2 &\leq \left\| \partial_t \left(W_i^{(L)}(t) - W_i^{(L)}(0) \right) \right\|_2 \\ &= \left\| \partial_t W_i^{(L)}(t) \right\|_2 \\ &\leq \frac{1}{\sqrt{n_L}} \|\alpha_i^{(L)}(t)\|_{p^{in}} \|d_t\|_{p^{in}}. \end{aligned}$$

$$\partial_t \left(c \left\| \tilde{\alpha}_i^{(L)}(t) - \tilde{\alpha}_i^{(L)}(0) \right\|_{p^{in}} + \left\| W_i^{(L)}(t) - W_i^{(L)}(0) \right\|_2 \right) = \partial_t (A(t) - A(0)) = \partial_t A(t) = O\left(\frac{1}{\sqrt{n_L}}\right).$$

$$\partial_{W_{ij}^{(L)}} f_{\theta(t), j'}(x) \otimes \partial_{W_{ij}^{(L)}} f_{\theta(t), j''}(x') = \frac{1}{n_L} \alpha_i^{(L)}(x; \theta(t))^2 \delta_{jj'} \delta_{jj''}$$

and so

$$\partial_t \left(\partial_{W_{ij}^{(L)}} f_{\theta(t), j'}(x) \otimes \partial_{W_{ij}^{(L)}} f_{\theta(t), j''}(x') \right) = \frac{2}{n_L} \partial_t \alpha_i^{(L)}(x; \theta(t)) \delta_{jj'} \delta_{jj''}$$

and since $|\partial_t \alpha_i^{(L)}| = O(\frac{1}{\sqrt{n_L}})$, we see that the summands vary at the rate $n_L^{-3/2}$. Since the dimension of $W^{(L)}$ is $n_L \times n_{L+1}$ (recall that n_{L+1} is fixed), the sum induces a variation of the NTK of rate $\frac{1}{\sqrt{n_L}}$. \square

A.3 A Priori Control During Training

A.4 Positive-Definiteness of $\Theta_{\infty}^{(L)}$