

# Abstract

### Context:

• Study of large **Gram** matrices for **concentrated** data.

## Motivation:

- **Observation:** RMT predicts ML performances in high-dimension under Gaussian assumptions on data.
- **BUT Real data** are **unlikely close** to **Gaussian** vectors.
- Gaussian vectors fall within a larger, more useful, class of random vectors.

## **Results:**

- GAN data [1] fall within the class of concentrated vectors.
- Only first and second order statistics of concentrated data matter to describe the behavior of **Gram** matrices.

# **Concentrated Vectors**

**Definition 1.** Given a normed space  $(E, \|\cdot\|_E)$  and  $q \in \mathbb{R}$ , a random vector  $X \in E$  is *q*-exponentially concentrated if for any 1-Lipschitz function  $\mathcal{F} : \mathbb{R}^p \to \mathbb{R}$ , there exists C, c > 0 s.t.

 $\forall t > 0, \ \mathbb{P}\left\{ |\mathcal{F}(X) - \mathbb{E}\mathcal{F}(X)| \ge t \right\} \le C e^{-c t^q} \xrightarrow{\text{denoted}} X \in \mathcal{O}(e^{-\cdot^q}) \text{ in } (E, \|\cdot\|_E)$ 

(P1)  $X \sim \mathcal{N}(0, I_p)$  is 2-exponentially concentrated [2].

(P2) If  $X \in \mathcal{O}(e^{-\cdot^q})$  and  $\mathcal{G}$  is  $\ell$ -Lipschitz, then  $\mathcal{G}(X) \in \mathcal{O}(e^{-(\cdot/\ell)^q})$ .

## "Concentrated vectors are stable through Lipschitz maps."

# **Model & Assumptions**



$$X = \left[\underbrace{x_1, \dots, x_{n_1}}_{\in \mathcal{O}(e^{-.q_1})}, \underbrace{x_{n_1+1}, \dots, x_{n_2}}_{\in \mathcal{O}(e^{-.q_2})}, \dots, \underbrace{x_{n-n_k+1}, \dots, x_n}_{\in \mathcal{O}(e^{-.q_k})}\right] \in$$

## Model statistics:

$$\mu_{\ell} = \mathbb{E}_{x_i \in \mathcal{C}_{\ell}}[x_i], \quad C_{\ell} = \mathbb{E}_{x_i \in \mathcal{C}_{\ell}}[x_i x_i^{\mathsf{T}}]$$

## (A2) Growth rate assumptions: As $p \to \infty$ ,

- 1.  $p/n \rightarrow c \in (0, \infty)$ .
- 2. The number of classers k is bounded.
- 3. For any  $\ell \in [k]$ ,  $\|\mu_{\ell}\| = \mathcal{O}(\sqrt{p})$ .

## Gram matrix and its resolvent:

$$G = \frac{1}{p} X^{\mathsf{T}} X, \ Q(z) = (G + z I_n)^{-1}$$
$$m_L(z) = \frac{1}{n} \operatorname{tr}(Q(-z)), \ UU^{\mathsf{T}} = \frac{1}{2\pi i} \oint_{\gamma} Q(-z) dz$$

# Why do Random Matrices Explain Learning? An Argument of Universality Offered by GANs

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# Why Concentrated Vectors?



 $\mathbb{R}^{p imes n}$ 









Lipschitz operation





## **Representation Network**



Lipschitz operation

# **Deterministic Equivalent for** Q(z)

**Theorem** Under the assumptions (A1) and (A2). We have  $Q(z) \in \mathcal{O}(e^{-(\sqrt{p} \cdot)^q})$  in  $(\mathbb{R}^{n \times n}, \|\cdot\|)$ . Furthermore,

$$\left\|\mathbb{E}[Q(z)] - \tilde{Q}(z)\right\| = \mathcal{O}\left(\sqrt{\frac{\log p}{p}}\right) \text{ where } \tilde{Q}(z) = \frac{1}{z}\Lambda(z) + \frac{1}{p\,z}J\Omega(z)J^{\mathsf{T}}$$

with 
$$\Lambda(z) = \left\{\frac{1_{n_{\ell}}}{1+\delta_{\ell}(z)}\right\}_{\ell=1}^{k}$$
 and  $\Omega(z) = \{\mu_{\ell}^{\mathsf{T}}\tilde{R}(z)\mu_{\ell}\}_{\ell=1}^{k}$ 

$$\tilde{R}(z) = \left(\frac{1}{k} \sum_{\ell=1}^{k} \frac{C_{\ell}}{1 + \delta_{\ell}(z)} + \right)$$

with  $\delta(z) = [\delta_1(z), \dots, \delta_k(z)]$  is the unique fixed point of the system of equations

$$\delta_{\ell}(z) = \frac{1}{p} \operatorname{tr} \left( \frac{C_{\ell}}{k} \left( \frac{1}{k} \sum_{j=1}^{k} \frac{C_{j}}{1 + \delta_{j}(z)} + zI_{p} \right) \right)$$

Key Observation: Only first and second order statistics matter!



**Concentrated Vectors** 

$$zI_p \biggr)^-$$

for each 
$$\ell \in [k]$$
.

# **Application to GAN-Generated Images**





 Generalize to other ML tasks (Classification, Regression and TL). Understand and improve GANs by adding statistic constraints.

[1] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, "Generative adversarial nets", in NIPS 2014.

[2] Terence Tao, "Topics in random matrix theory, volume 132". American Mathematical Society Providence, RI, 2012.

[3] Andrew Brock, Jeff Donahue, and Karen Simonyan, "Large scale GAN training for high fidelity image synthesis", in ICLR 2019.



## **Perspectives**

# References

Figure 1. Images generated by the BigGAN model [3].