

# Random Matrix Methods for Machine Learning

Romain Couillet

University Grenoble Alpes, France

`romain.couillet@gipsa-lab.grenoble-inp.fr`

Zhenyu Liao

Huazhong University of Science and Technology, China

`zhenyu_liao@hust.edu.cn`<sup>1</sup>

March 14, 2023

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# Erratum

**Section 3.1.1 “GLRT asymptotics” around Equation (3.2).** As a consequence, in order to set a maximum false alarm rate (or false positive, or Type I error) of  $r > 0$  in the limit of large  $n, p$ , one must choose a threshold  $f(\alpha)$  for  $T_p$  such that

$$\mathbb{P}(T_p \geq f(\alpha)) = r,$$

that is, such that

$$\mu_{\text{TW}_1}([A_p, +\infty)) = r, \quad A_p = (f(\alpha) - (1 + \sqrt{c})^2)(1 + \sqrt{c})^{-\frac{4}{3}} c^{\frac{1}{6}} n^{\frac{2}{3}} \quad (3.2)$$

with  $\mu_{\text{TW}_1}$  the Tracy-Widom measure in Theorem 2.15.

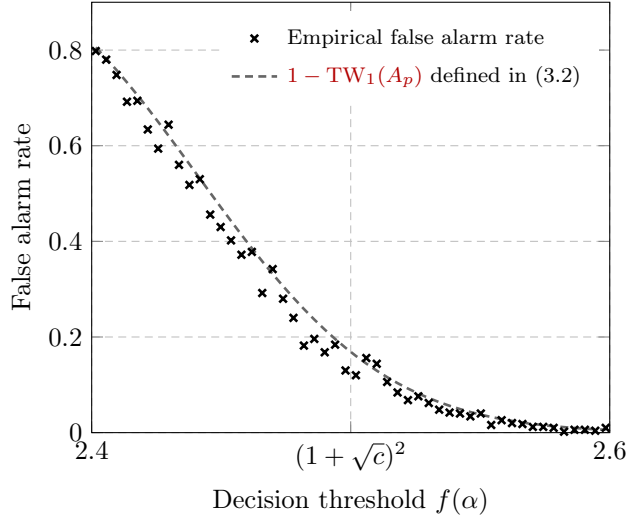


Figure 1: Comparison between empirical false alarm rates and  $1 - \text{TW}_1(A_p)$  for  $A_p$  of the form in (3.2), as a function of the threshold  $f(\alpha) \in [(1 + \sqrt{c})^2 - 5n^{-2/3}, (1 + \sqrt{c})^2 + 5n^{-2/3}]$ , for  $p = 256$ ,  $n = 1024$  and  $\sigma = 1$ . Results obtained from 500 runs. Link to code: Matlab and Python.

**Section 5.1.1 “Regression with random neural network” after Equation (5.12).** The fact that this denominator scales like  $\|\gamma\bar{\mathbf{Q}}\|$  as  $\gamma \rightarrow 0$  explains the major difference between the training and test error behavior in Figure 5.5. Due to the  $\gamma^2$  prefactor in  $\bar{E}_{\text{train}}$ , the training error is guaranteed to be finite (even possibly to vanish) as  $\gamma \rightarrow 0$ . But for the test error, since  $\gamma\bar{\mathbf{Q}} \rightarrow 0$  as  $N$  approaches  $n$  from each side, if the numerator term  $\frac{1}{\hat{n}} \text{tr} \bar{\mathbf{K}}_{\hat{\mathbf{X}}\hat{\mathbf{X}}} - \frac{1}{\hat{n}} \text{tr}(\mathbf{I}_n + \gamma\bar{\mathbf{Q}})(\bar{\mathbf{K}}_{\mathbf{X}\hat{\mathbf{X}}} \bar{\mathbf{K}}_{\mathbf{X}\hat{\mathbf{X}}}^T \bar{\mathbf{Q}})$  does not scale like  $\gamma\bar{\mathbf{Q}}$ , then  $\bar{E}_{\text{test}}$  diverges to infinity at  $N = n$ . A first counterexample is of course when  $\hat{\mathbf{X}} = \mathbf{X}$ , for which the numerator term of  $\bar{E}_{\text{test}}$  is now

$$\frac{1}{\hat{n}} \text{tr} \bar{\mathbf{K}}_{\hat{\mathbf{X}}\hat{\mathbf{X}}} - \frac{1}{\hat{n}} \text{tr}(\mathbf{I}_n + \gamma\bar{\mathbf{Q}})(\bar{\mathbf{K}}_{\mathbf{X}\hat{\mathbf{X}}} \bar{\mathbf{K}}_{\mathbf{X}\hat{\mathbf{X}}}^T \bar{\mathbf{Q}}) = \frac{\gamma^2}{n} \text{tr} \bar{\mathbf{Q}} \bar{\mathbf{K}} \bar{\mathbf{Q}}$$