

1 Reviewer 1: *In its current form, the scaling regimes for the statistical phase transition and the AMP phase transition do*
2 *not match, and thus the statistical-to-algorithm gap is not proved.*

3 We prove that the stat. trans. happens for $\lambda_n = \Theta(|\ln \rho_n|/\rho_n)$, with $\rho_n = \Omega(n^{-\beta})$, β small enough (in the paper Thm
4 1 states $\rho_n = \Theta(n^{-\beta})$: this can be relaxed and we only require the weaker condition $\rho_n = \Omega(n^{-\beta})$ as seen from Thm
5 3; which will be corrected). We also check the algo. trans. happens for $\lambda_n = \Theta(1/\rho_n^2)$ for $\rho_n = \Omega((\ln n)^{-\alpha})$ for any
6 $\alpha \geq 0$ (same relaxation $\Theta \rightarrow \Omega$). The fact that the scaling regimes for λ_n of the stat. and algo. transitions are different
7 is intrinsic to the problem, and actually does prove the presense of a diverging (as $\rho_n \rightarrow 0$) statistical-to-algorithm gap.
8 After these amendments, since Thm 1 and Corollary 1 hold for $\rho_n = \Omega(n^{-\beta})$ and thus for $\rho_n = \Omega((\ln n)^{-\alpha})$, then
9 both trans. (and thus the stat.-to-algo. gap) are proven for $\rho_n = \Omega((\ln n)^{-\alpha})$. All that will be clarified, thank you!

10 *It is desirable to mention whether the condition $\beta < 1/6$ is simply a technical one or not.*

11 This restriction on the sparsity is probably a consequence of the sub-optimality of our analysis. We will mention it.

12 *In Thm 1 the limit of the MI is given as the infimum of the potential function. It would be better written in terms of the*
13 *singular function given in line 213, since the authors focus the Bernoulli and Rademacher-Bernoulli cases.*

14 Thm 1 applies more generically than for Ber and Rad-Ber signals. It applies to signals verifying the hyp. in the setting
15 (line 61). It is true that the all-or-nothing is then studied, starting from Thm 1, only for Ber and Rad-Ber signals, but
16 nevertheless Thm 1 applies more generically as it precisely bounds the deviation of the Mut. Info. from a simple
17 single-letter formula for any finite size n , and for a much wider class of signals. Moreover the singular function of line
18 213 is equal to the infimum of the potential function only in the limit $n \rightarrow \infty, \rho_n \rightarrow 0$ while, again, Thm 1 is a finite
19 size bound that contains more than just the asymptotic limit. We hope this clarifies our choice of presentation.

20 *It is rather unusual that a theorem is given in the appendix.*

21 You are probably talking about appendix A in which we simply give an even more general form of Thm 1 that includes
22 not only the specific scaling regime (2) where the all-or-nothing statistical transition happens, but also a wider class of
23 scaling regimes, see (15). As the formulation of this more general theorem is long and not directly used in the main part
24 we made the choice to defer it to an appendix for people interested in more general bounds.

25 Reviewer 4: *The topic is quite far from the interests of most Neurips attendees.*

26 The present submission is part of a recent line of work mostly concerned with information theoretic results (note that we
27 bring about, in addition of information-theoretic results, strong rigorous algorithmic bounds). But we believe that it is
28 only a matter of time before the ML community realize the relevance of studying such scaling regimes. Let us cite just
29 as an example among others the recent work of Goldt et al <https://arxiv.org/pdf/1909.11500.pdf> that clearly
30 indicates that in the high-sparsity regime, which translates in their setting into a low intrinsic dimension of the data,
31 learning performance strongly increases, see their Fig. 5. Moreover our work concerns sparse PCA, a key ML problem.

32 *The term "true sparsity" as used on page 2 is very confusing and should be avoided. The authors are simply talking*
33 *about sparsity in the sublinear regime. Please stick to the standard terminology.*

34 This terminology is used to contrast with recent literature that also studies a sparse limit, but in the linear regime, with a
35 sparsity tending to 0 only after the large size limit has been taken. We will add a few words to clarify why we wish to
36 use this terminology.

37 *The details of the sublinear regime do not appear until page 4. As a reader, I was frustrated with the lack of information*
38 *about the behavior of $n\rho_n$ as n tends to infinity. All we are told is that it does not grow to infinity.*

39 We will add details earlier in the paper, thanks for the suggestion.

40 *As described around (2) and (3), the authors prove that phase transitions exist for particular sequences of λ_n and ρ_n .*
41 *The reader is left wonder about what happens with other sequences. I would think that it is possible to prove that no*
42 *phase transition exists for some sequences, which suggest that a table could be made to catalog when phase transitions*
43 *exist, when they don't exist, and when the behavior is unknown.*

44 That is a good point. But this question is out of the scope of the paper, as it is not clear yet to us what is the criterion /
45 property that generically underlies the presence or not of the all-or-nothing. This question is clearly to be considered for
46 future work, thanks for that.

47 *I am confused by the statement in line 188: "as long as $\rho_n \rightarrow \infty$ ". In the previous paragraph, the quantity ρ_n had very*
48 *specific rates of decay with n , while here the claim seems to be for any rate of decay. This could benefit from some*
49 *clarification.*

50 We agree the sentence is not precise: we indeed prove things for specific regimes and the sentence will be reformulated.