We kindly thank the reviewers for their detailed reviews, valuable feedback and suggestions for improvement. We try to answer their questions and concerns as best as possible below.

Reviewers 1/2/3: Arbitrary permutation group, high-order outputs. A common concern from all reviewers is that the adaptation of our results to arbitrary permutation (sub)groups should be discussed more. We agree and will provide more discussion and clarification in the final paper. In the *invariant* case, our Stone-Weierstrass (SW) approach can actually be easily adapted to handle arbitrary subgroup of the full permutation group (since the separation of points is still valid, etc.), we will explain this. However this extension is not valid in the *equivariant case*, which is our main result. Indeed, our proof of the new SW theorem relies on an "ordering" of the coordinates of arbitrary equivariant functions, and therefore requires the full permutation group to be available. We agree that a fully general version of the SW theorem under arbitrary finite group action would be desirable, however the proof is out of our reach as of today. Nevertheless, we believe that the proposed theorem, and its application to graph neural nets (in which full permutation is natural), is an important first step toward a more general theory, especially since many practical applications of GNNs consider the equivariant case. We emphasize again that equivariant universality is, in our point of view, fundamentally more difficult than the invariant case: indeed, all the classical algebraic tools such as the powerful theory of invariant polynomials used by [3] or the classical SW theorem do not apply, and new tools need to be developed from scratch.

The reviewers also ask for clarifications over the possibility of high-order *outputs* in the equivariant case, as opposed to a signal over the nodes. It is indeed another limitation of our SW theorem, for the same reason that our proof requires an "ordering" of the output. In a way, this limitation is similar to the distinction between "point clouds" (which in dimension one can be represented by a vector up to permutation), and graphs. In the same way that the universality proof is significantly more involved for graphs input than for point clouds input [4], high-order outputs may be significantly more difficult to handle than vector outputs. We will add this discussion in the paper, and mention it in the abstract.

Reviewer 1. The main concern of the reviewer seems to be related to arbitrary group actions as well as high-order outputs, please see the paragraphs above. Additionally, we would like to kindly mention again that the equivariant case is somehow fundamentally different from the invariant one, since most algebraic tools do not exist anymore. While we agree that at first glance the equivariant result can seem incremental with respect to the invariant one, we strove to demonstrate the significant difference between the two by including "sketches of proof" in the paper. We will emphasize this in the final version.

Reviewer 2. The main concern of the reviewer is the applicability to a broader class of permutation groups, see paragraph above.

Reviewer 3. The main concern of the reviewer is the relation between the studied GNN and other known architectures, and experimental comparison. As mentioned in the paper, the architecture that we study is actually not new: it is a one-layer instantiation of the GNNs proposed by [2]. In its "deep" original version, it covers all type of "Message-Passing" GNNs, but not spectral GNNs which use powers of the adjacency matrix. We will clarify this in the final version.

We would like to kindly emphasize again that our paper is theoretical in nature. As with Multilayer Perceptron, we cannot expect the studied one-layer GNNs to outperform deep architectures, and do not aim to, hence the limited experimental section for illustrative purpose only. Moreover, the original paper [2] already performs many experiments (in the deep case), showing the practical interest of these GNNs. Nevertheless, we still believe that our results have a theoretical interest for the community, since universality was not known in the equivariant case, which covers many practical applications. In particular, some key ideas can be extracted from our work: for instance, the notion of "self-separability" introduced for the equivariant SW theorem could serve to adapt the results of the recent preprint [1] (which came out after the submission deadline) to the equivariant case.

Finally, the reviewer suggests that we extend the comparison between GNNs and group invariant NNs.: the only difference is that we consider the full set of permutation while group invariant NNs consider any arbitrary subgroup. This is related to the first paragraph of this document, and we will add a clarification in that direction.

References

[1] Z. Chen, S. Villar, L. Chen, and J. Bruna. On the equivalence between graph isomorphism testing and function approximation with GNNs. *Arxiv preprint arXiv:1905.12560*, pages 1–19, 2019.

[2] H. Maron, H. Ben-Hamu, N. Shamir, and Y. Lipman. Invariant and Equivariant Graph Networks. In *ICLR*, pages 1–13, 2019.

[3] H. Maron, E. Fetaya, N. Segol, and Y. Lipman. On the Universality of Invariant Networks. In *International Conference on Machine Learning (ICML)*, 2019.

[4] M. Zaheer, S. Kottur, S. Ravanbakhsh, B. Poczos, R. Salakhutdinov, and A. Smola. Deep Sets. (ii):1–26, 2017.