We thank the reviewers for their insightful comments and suggestions. Reviewer-specific comments to follow.

Reviewer 1. Thank you for your enthusiastic review and for finding this work highly relevant to the NeurIPS community; we agree that gross-substitute functions are an important class of functions and that the adaptive complexity has practical use-cases using parallelization.

Reviewer 2. Thank you for your positive review and great suggestions. The question of GS + matroid is a very interesting direction for future work. Thank you for bringing this up and we agree this is missing in the current version of the manuscript and will address this in the next version. Regarding “the switch from submodular + matroid to GS + cardinality", the techniques in [7] for submodular + matroid consist of two parts, the adaptive sequencing technique together with a continuous greedy technique. The adaptive sequencing technique by itself is sufficient for submodular + cardinality but continuous techniques are required for matroid constraints. Here, for GS + cardinality, we modify the adaptive sequencing technique and do not use continuous techniques, which are very slow in practice.

Regarding “richer classes of gross substitute functions", we believe that the OXS valuations on graphs we consider are among the richest classes of GS functions. Indeed, to the best of our knowledge, all existing lower bounds for gross substitutes, including those in this paper, are constructed using OXS valuations, which implies that OXS valuations are among the hardest GS functions to optimize.

Reviewer 3. Thank you for your review. It seems like there is a simple misunderstanding about the algorithm which we discuss below. We hope that in light of our response you will consider revising your score.

- Regarding motivation for adaptivity: We would be happy to include a short paragraph summarizing the motivation and tie to the broad line of work on adaptivity discussed in related work.
- “what happens if, in line 8, the set $\{i \text{ s.t. } |X_i| < (1-\epsilon)|X|\}$ is empty": **See line 186, 187**: $i^\star$ is the largest position i such that a large fraction of the elements in X has high contribution to $S \cup A_{i-1}$. If $\{i \text{ s.t. } |X_i| < (1-\epsilon)|X|\} = \emptyset$, this implies that for all $i \in [k^\star]$, a large fraction of elements in X have high contribution to $S \cup A_{i-1}$, in which case we add the entire sequence of elements $A_{k^\star}$ to the current solution S.
- “shouldn't X in line 4 receive $N \setminus S$ and not N?": Both are correct. It is fine to have X also receive the elements $a \in S$ as they have marginal contribution 0 to the current solution, i.e. $f_S(a) = 0$, which implies that these elements will all be removed from X in the first iteration of the inner-while loop. To recap, after one iteration of the inner loop, X will not contain elements from S either way.
- “...X_1 will be the empty set. As a result line 9 will add a low value item to S." This is incorrect. If X_1 is the empty set, then we have $i^\star = 1$. **Line 9** states that $S \leftarrow S \cup \{a_1, \dots, a_{i^\star-1}\}$. Thus, if $i^\star = 1$, we have $i^\star - 1 = 0$ and line 9 adds zero elements to S.
- “The paper does not really explain the algorithm." We refer the reviewer to **line 9**, which might add zero elements to S. We believe that the description of the algorithm clearly explains what happens in the case pointed out and that Reviewer 3 made a minor mistake when running the algorithm, which caused the confusion.
- “Section 4 gives some lower bounds but does not add really *any* new information on top of what the intro already told us.": The intro only informally states the lower bounds. Section 4 gives the precise statements of theorems for the lower bound. We believe that it is very important for every paper to contain precise statement of the main results.
- “it seems to me that trimmed greedy obtains value very close to GSAS in most of the figures." This is incorrect. In over half of the figures, GSAS outperforms TRIMMED-GREEDY by a factor of at least 2 on almost all values of k. (See **Figures 1a, 1b, 1c, 1d, and 3.**)
- “It would also help to compare to OPT": From **Theorem 3**, we know GSAS is arbitrarily close to OPT and hence, they are empirically indistinguishable. We will clarify this in the next version of the manuscript.
- “the average number of rounds that GSAS ended up performing.": Thank you for the suggestion. GSAS uses significantly fewer rounds than k in our experiments. We will include this in the next version of the manuscript.
- “k was never explicitly defined as the cardinality parameter": Thank you, we will fix that.
- “it is confusing that Theorem 1 is gives a deterministic statement": Since the elements are chosen u.a.r. among all elements with high contribution, the guarantees hold deterministically.
- “is not polished enough to published": Please note that we worked very hard to make the paper polished and easy to follow. We note that both Reviewers 1 and 2 thought the paper is very well written. We believe that a main reason for this comment is the inablility to run the algorithm over an example due to a minor mistake in understanding. We hope that with the explanations and examples provided in this rebuttal the algorithm makes sense.