We would thank all reviewers for their insightful comments!

Review #1:

Thank you for the thoughtful comment.

We would consider adding a more detailed discussion in the camera-ready version if the paper is accepted. The main reason that our approach cannot be directly applied to other feedback models (like the full-adoption feedback model) or other information diffusion models (like linear threshold model) is that the feedback information in these models are no longer independent. To be more specific, in the full-adoption feedback model, the feedback information contains the full cascade of the selected node. The feedback for different nodes can share the status of same edges and thus the feedback are dependent. For the linear threshold model, we consider the case where the feedback information contains only whether nodes are activated or not. Even if we are restricted to myopic feedback, the feedback for different nodes are not independent since they can share common neighbors. To the best of our knowledge, the adaptivity gaps in these models are still open and all previous approaches failed to deal with dependent feedback information.

Review #2:

Thank you for the thoughtful comment.

We agree that showing a hardness results of $1 - 1/e - \varepsilon$ would be very interesting, if it is indeed the case. However, we believe that this task could be potentially very tough and thus is out of scope of the current paper. The toughness comes from both the formulation of the problem and the proof of the results. The original NP-hardness results of maximizing a submodular function is actually reduced via PCP theorem. We do not know whether there are any ''simple" reductions can be used.

By the way, since most influence maximization algorithms are based on the greedy framework, our hardness result for greedy and adaptive greedy algorithms actually rules out a large number of existing algorithms.

Review #3:

Thank you for the thoughtful comment. For experiments, we will consider comparing adaptive greedy with non adaptive greedy, but this is not the main result of our paper. For the current study, our main purpose is to show the adaptivity gap, but due to the NP hardness we cannot get the optimal solution for any reasonably sized graph, so it is hard to validate our main theoretical results by experimental studies.