

1 We thank all the reviewers for the detailed perusal and valuable suggestions. Please find our responses below.

2 **Reviewer 1** *On technical novelty:* On observing the role of max flows in modeling diffusion processes, we took  
3 inspiration from Chen et al [2020]’s study and formulated a new robust influence maximization model. Our first step in  
4 establishing the tractability of the model’s influence function  $f^{corr}$  (Theorem 1) involves adapting a key result in Chen  
5 et al [2020], but our study as a whole concerns much more. Towards optimizing  $f^{corr}$ , we show it is a submodular  
6 function. This does not follow from the literature; indeed, if  $g(\cdot)$  and  $h(\cdot)$  are submodular set functions, the pointwise  
7 minimum  $\min(g(\cdot), h(\cdot))$  need not be a submodular function in general (see the book on submodular functions by  
8 Bach, 2013). But in our case of  $f^{corr}(\mathcal{S}) = \min_{\theta \in \Theta} \mathbb{E}_{\theta}[R(\tilde{\mathbf{c}}, \mathcal{S})]$  as a pointwise minimum of submodular functions  
9  $\mathbb{E}_{\theta}[R(\tilde{\mathbf{c}}, \mathcal{S})]$  over  $\theta \in \Theta$ , it is submodular. Beyond study of the optimization problem, our robust model enables a study  
10 of how costly the independence assumption in IC can be (Sec 4.2). Further advantages follow from Corollaries 1-3.

11 *On Corollaries 1-3:* Cor 1 reveals several distinguishing features of our model: (a) in contrast to IC, we can efficiently  
12 compute the (worst-case) node activation probability for any node  $i$  via  $\pi_i^*$ ; (b) with  $f^{corr}(\mathcal{S}) = \sum_{i \in V \setminus \mathcal{S}} \pi_i^*$ , we find  
13 that the adversary’s problem is additively separable- “the worst-case sum is the sum of the worst-cases” (see Eqn (6));  
14 (c) there is a simpler computation for  $f^{corr}$  (using shortest path computations instead of the LP, see line 219 on page 7).  
15 Cor 2 reveals that only a subset of the paths from  $\mathcal{S}$  to node  $i$  propagate influence to  $i$ , unlike in IC where all paths  
16 contribute. Cor 3 describes how to simulate  $\theta^*$  and makes an interesting comparison with LTM - a surprising byproduct  
17 of our original aim for a robust treatment of IC. Since all these pertain to  $f^{corr}$  they were included in Sec 3.

18 *Scenarios, broader impact:* While a graph captures observable network connections, there may be latent variables  
19 causing segments of a network to exhibit correlation in propagating influence. For example, in spreading news articles  
20 on Twitter, each article resonates with members in complex, correlated ways due to hidden variables (like political party  
21 affiliation, demographics), so our work finds those members whose influence is robust to the choice of article promoted.

22 **Reviewer 2** *On motivation and other models, references:* There is a vast literature on network models, and IC  
23 is particularly well-studied in influence maximization. Our interest was in examining the classical independence  
24 assumption by formulating a model most antagonistic to IC in that the diffusion process is governed by an adversary  
25 (for motivation and broader impact, please refer to the para above). For references, we chose the ones most relevant to  
26 IC and its robust treatments, due to space. We will be happy to cite more works, including those suggested.

27 *On accelerated greedy:* The accelerated greedy technique [23] can be used to maximize any monotone submodular  
28 function and only requires an oracle that evaluates the function. So we use it to maximize  $f^{corr}$ ; we will provide details.

29 *On notations:* In Sec 3,  $\theta$  is a distribution over  $2^{|E|}$  graph realizations, where any fixed graph realization is a vector  
30  $\mathbf{c} \in \{0, 1\}^{|E|}$ .  $\theta(\mathbf{c})$  denotes the probability mass assigned to  $\mathbf{c}$ . We denote the underlying random variable as  $\tilde{\mathbf{c}}$ .  
31 Expectations are always taken over  $\tilde{\mathbf{c}}$  with pmf  $\theta$  (written  $\tilde{\mathbf{c}} \sim \theta$ ).  $\mathbf{p} = (p_e)_{e \in E}$  is a vector with  $|E|$  components where  
32  $p_e$ , equivalently  $p_{ij}$ , denotes the activation probability of edge  $e = (i, j) \in E$ . All of this should clarify the typo on line  
33 103, for which we apologize.

34 *Beyond qualitative statement through plots:* The POC in Sec 4.2 provides a technical treatment to compare  $\mathcal{S}_{ic}$  and  
35  $\mathcal{S}_{corr}$  under correlations. As the comparison is graph-dependent, a completely general conclusion cannot be drawn.

36 **Reviewer 3** *On extensions:* Our techniques can handle the case where a subset  $T \subset E$  of the edge activations are  
37 known to be mutually independent while dependency information on the rest ( $E \setminus T$ ) are unavailable. In particular  
38 when  $|T| \leq \log |E|$ , the worst case influence function remains computable in polynomial time. If the adversary is  
39 additionally allowed to choose  $p_{ij}$  within  $[a_{ij}, b_{ij}]$ , the problem remains tractable. In general tractability under other  
40 ambiguity sets  $\Theta$  is not guaranteed (e.g., further constraining the correlation structure can make it NP-hard to check  
41 non-emptiness of  $\Theta$ , see Georgakopoulos et al, Probabilistic Satisfiability, 1988); we will need a separate investigation  
42 towards these aspects. Efficient extension to an adaptive model can also follow from our work. Our paper may be  
43 viewed as a start to this line of work in robust influence maximization. We will discuss the above extensions.

44 *Visualization:* Since the datasets used are too large to visualize the seed sets, we have reported some properties of these  
45 seed-sets. While small examples have been provided in Section 4.2, we will provide a few snapshots of larger examples.

46 **Reviewer 4** *Interpretability:* The variables in our LP have meaningful interpretations as  $\pi_i^*$  can be viewed as the worst  
47 case probability that node  $i$  is reachable from a seed set  $\mathcal{S}$  (Corollary 1). The overall optimization problem thus is  
48 meaningful and conforms to requirements in Doshi-Velez et al, 2017.

49 *Polynomial character of LP:* Our LP in Theorem 1 being of efficient size (with  $|V|$  variables and  $k + |V| + |E| \leq$   
50  $2|V| + |E|$  linear constraints) can be solved in time polynomial in the inputs  $|E|$  and  $|V|$ .

51 *On follow up work:* Please refer to our answer for reviewer 3 ‘On extensions’. We will also add more on broader impact.

52 *Line 19, 37, 39, 103:* We will add references and preamble to line 103 based on our answer ‘On notations’ to reviewer 2.