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## SAGT 2021 notification for paper 51

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SAGT 2021 <sagt2021@easychair.org>  
To: Dengji Zhao <dengji.zhao@gmail.com>

29 June 2021 at 03:39

Dear Dengji Zhao,

We are pleased to inform you that your submission

Number: 51  
Title: Incentive Compatible Mechanism for Influential Agent Selection

has been accepted for publication at SAGT 2021.

Congratulations! We received a record number of 73 submissions, from which we decided to accept 30 papers. The reviews of your paper are included below. While the reviews may not always reflect the full discussion on your paper, we hope you find them helpful for preparing the camera-ready version of your paper. We strongly advise you to take into account the recommendations made by the reviewers towards improving your paper.

The camera-ready deadline is **\*\*July 12, 2021\*\***, which is quite soon. You will receive a separate email with instructions on how to prepare and upload your camera-ready version.

Best regards,

Ioannis Caragiannis and Kristoffer Arnsfelt Hansen  
SAGT 2021 PC co-chairs

SUBMISSION: 51  
TITLE: Incentive Compatible Mechanism for Influential Agent Selection

----- REVIEW 1 -----

SUBMISSION: 51  
TITLE: Incentive Compatible Mechanism for Influential Agent Selection  
AUTHORS: Xiuzhen Zhang, Yao Zhang and Dengji Zhao

----- Overall evaluation -----

This paper considers an influence selection problem. Given a DAG, the problem asks to select the agent that can be reached by the most number of agents. The challenge is that agents are strategic and can misreport their outgoing edges if it can help improve their probability of being selected. The goal is to design an incentive compatible mechanism with a good social welfare guarantee. In this paper, the authors make a further assumption that agents are only allowed to “under-report”, that is, they can only hide some of their actual outgoing edges, but cannot report new edges. Then the authors propose a Geometric Mechanism that is IC and achieves a social welfare approximation ratio of  $1/2$ . The idea is to look at every agent who, by remove *\*all\** of its outgoing edges, can become the most influential agent. The mechanism then selects each of such agents with a probability that is geometrically related to its “rank” in the set. Finally, in addition to the 2-approximati!

on guarantee, the authors also show a  $1/(1+\ln(2))$  upper bound on the approximation ratio for any IC mechanisms.

Overall I enjoy very much the model and results of this paper. The influence selection problem model is clean and well-motivated. The incentive compatible design problem seems hard at a first glance. But the proposed mechanism cleverly leverages the structural properties of the influential set and set selection probabilities that could achieve both IC condition and reasonable social welfare guarantee. The upper bound construction is also nontrivial. Overall the results paint a clear picture of what can and cannot be achieved in this influential agent selection mechanism design problem.

I have some further comments. There are not really drawbacks of the paper, but more of the ways that can possibly further improve the paper.

- I do not understand why the requirement that agents can only hide their connections is necessary. From what I can see, the geometric mechanism operates on each agent by first ignoring all of its reporting edges. Therefore it should be an IC mechanism against \*all\* possible misreports, including reporting new edges. So either this additional requirement is unnecessary and the mechanism is stronger than what's claimed, or, if I'm missing something here, I would suggest the authors add a small paragraph in the paper explaining why this requirement is indeed necessary.

- The paper also considers a fairness condition. But it's a rather weak condition that only requires the most influential agent should be selected with the same probability in two graphs that have enough similarities to each other. But within the same graph, some unfairness can still happen among agents. In particular, if there are two or more agents with the same maximum number of progenies, then the ones with larger indices will not be selected at all due to tie-breaking. This, to me, is a more serious fairness concern. On the other hand, I think this concern can be solved by the following simple step: first, shuffle the agents into a random order, then apply the GM with regard to this order. I think the new mechanism is still IC and can satisfy an additional fairness property that all most influential agents will be selected with the same probability. I'd suggest the authors think about this extension and add it if possible.

Minor comment:

1. In definition 5, each  $s_i$  in the influential set seems to denote the index of a node, then what does " $s_i \succ s_j$ " mean?

----- REVIEW 2 -----

SUBMISSION: 51

TITLE: Incentive Compatible Mechanism for Influential Agent Selection

AUTHORS: Xiuzhen Zhang, Yao Zhang and Dengji Zhao

----- Overall evaluation -----

This paper considers the probabilistic selection mechanism, where there is a directed acyclic graph (DAG)  $G=(V,E)$ . There are  $n$  agents in the graph, where each edge  $(i,j) \in E$  represents agent  $i$  follows agent  $j$ . Let  $P_i$  be the set of agents that "follow"  $i$ , i.e., for all  $j \in P_i$  there exists at least a path from  $j$  to  $i$ . The objective is to select the most influential agent (agent with  $\max P_i$ ) in this graph.

However, from the perspective of mechanism design, the strategic agent might have incentives to delete its edges to make itself become the most influential agent. So this paper considers designing an incentive-compatible and "fair" mechanism to output a probability distribution over agents which has a good approximation ratio. At a high level, fairness is defined as follows: for an agent  $v$ , if in two graphs  $G$  and  $G'$ , the structure of  $v$ 's follower are same, then the probability that  $v$  is selected needs to be the same.

The main contribution of this paper is to give a  $1/2$ -approximate incentive-compatible and fair mechanism and to prove a  $1/(1+\ln 2)$  upper bound for any incentive-compatible and fair mechanism in DAGs.

\* Strengths:

It seems that no works consider selection mechanism design in the DAGs setting (according to the introduction and related work). So I think this work might be a good start. The observation and techniques also sound.

\* Weaknesses:

My main problem is the statement in the intro (especially about the most related work Babichenko et al. [4]). But it would not impact the main result in this paper.

In sec 1.1, it is mentioned that the previous upper bound is  $4/5$ , and the lower bound is  $1/\ln 16$  ( $\approx 0.36$ ). However, as far as I have checked, Babichenko et al. [4] focus on the forests, not DAGs and they didn't have the constrain on "fairness". So these bounds could not be applied in the setting of this paper.

Take the upper bound as an example, the upper bound in Babichenko et al. [4] is derived by the construction of two trees, but I believe this paper assumes the DAG is connected (e.g., the Observation 1). If the upper bound and lower bound could indeed be applied in this paper, the authors need to state them more clearly.

Some other comments:

1. The definition of fairness makes sense, but could you find some references to support your setting?

2. It would be better to say the setting of your paper is considering not "exact" mechanism, which means the probabilities might sum-up to less than 1. (The word "exact" comes from Babichenko et al. [4]. They state it clearly even in the abstract.)

3. Could you give an upper bound of your mechanism? Is it also 1/2 or the analysis of the lower bound could be improved?

4. The notations  $\{s_1, \dots, s_m\}$  in Definition 5 made confused. If  $\{s_1, \dots, s_m\} \subset [n]$ , then what means  $s_j \prec s_i$ ?

----- REVIEW 3 -----

SUBMISSION: 51

TITLE: Incentive Compatible Mechanism for Influential Agent Selection

AUTHORS: Xiuzhen Zhang, Yao Zhang and Dengji Zhao

----- Overall evaluation -----

The paper studies the problem of influential agent selection in a graph, that is given a directed graph we select an agent (node) and the value of the solution is the number of ancestors of that agent (progeny). The authors focus on DAGS as the problem has been studied before in trees and forests. The agents' private information is their outgoing edges and they can only misreport by revealing a subset of them to the mechanism. The authors design a randomized mechanism that is incentive-compatible that achieves a 2 approximation of the optimal objective, i.e. the agent with the maximal progeny. In

addition, the authors prove that the mechanism satisfies a notion of fairness.

Their mechanisms proceed as follows: it identifies a set of agents, the influential set, that can misreport their type to be the optimal solution in the new graph, i.e. have the maximum progeny. Then the mechanism selects an agent at random with decreasing probability in terms of their true progeny. In particular, the agent with the lowest progeny is allocated with probability 1/2, the second-lowest 1/4, and so on. The approximation ratio proof follows from the fact that the maximum progeny can never be more than twice the progeny of any agent in the influential set. Furthermore, the authors prove an upper bound of any incentive-compatible mechanism that satisfies their definition of fairness.

Overall, I find the research topic interesting. Nevertheless, most of the results follow from the natural property that any agent that can potentially have an incentive to deviate already has high progeny compared to the optimal solution. Also, the presentation of the paper should be improved, especially the introduction section.

Typos:

Page 2 Paragraph 1 : any other agents->agent

Page 2 Paragraph 2 : studies mainly explores->explore

Page 4 Paragraph 3 : revelation principles-> principle

Page 5 Paragraph 1 : most of the probabilities are-> probability is

Page 6 Paragraph 2nd before last: one out-edges-> one out-edge

page 11 paragraph 1: all agent -> each agent