WHAT DO YOUR FRIENDS THINK EFFICIENT POLLING METHODS FOR NETWORKS USING FRIENDSHIP PARADOX

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ABSTRACT

The randomized surveying of members of a social network is the focus of this research. In order to accurately predict the winner of an election between two candidates A and B, traditional intent polling involves randomly sampling people and asking them: "Who are you going to vote for?" In expectation polling, respondents are asked who they anticipate will come out on top. In this article, we suggest a unique approach to neighborhood expectation polling (NEP) in which people are randomly picked and asked the following question: what is your estimate of the percentage of votes for A? When answering this question, sampled people will naturally glance at their neighbors, who are determined by the underpinning social network graph. This is how the NEP works. Therefore, the mean squared error (MSE) of NEP approaches is dependent on choosing the most appropriate collection of samples from the network. In order to do this, we suggest the following three NEP algorithms for the following cases: I the social network graph is unknown, but it is possible to run random walks, also known as sequential exploration, over the graph. (ii) the social network graph is unknown. In both scenarios, techniques rely on a graph theoretic consequence known as the friendship paradox are offered as potential solutions. Theoretical conclusions are developed about the dependency of the mean squared error (MSE) of the algorithms on the features of the network.For the purpose of demonstrating how well the algorithms work, we give numerical results obtained from both actual and simulated data sets.

I. INTRODUCTION

This study discusses the use of randomised polling techniques on a social network whose structure may or may not be known. In the event of predicting the result of an election among two candidates A and B, traditional intent polling involves asking people who have been evenly sampled the following question: who are you planning to vote for? In expectation polling, respondents are asked who they anticipate will come out on top. In this article, we offer a new method for conducting neighbourhood expectation polls in which non-uniformly selected people are asked the following question: "what is your estimate of the proportion of votes for A?" The next step is an official definition of the issue, followed by an explanation of the solution method and the associated work that inspired it.

Consider a social network that is modelled as the undirected graph G = (V, E), where each node v in V is assigned the label f(v) that falls between the values 0 and 1. A pollster has the ability to question an aggregate number of persons from this social network equal to S, which is

referred to as the sample budget. Case 1: The graph G = (V, E) is unknown; however, it is possible to investigate the graph in a sequential manner by employing a random walk. Case 2: The graph G = (V, E) is unknown, but the collection of nodes V may be randomly selected. Case 1: The graph G = (V, E) is known.

In order to solve the difficulty described above, we have come up with a category of polling techniques that we refer to as neighbourhood expectation polling (NEP). In the NEP, a collection of individuals from the social network G = (V, E) are chosen, and then those individuals are asked, "What is your estimate of the proportion of persons with label 1?" (What do you think the percentage of people who have label 1 is?)

When attempting to estimate a number that cannot be known for certain about the world, it is only natural for a person to turn to her neighbours.

Therefore, each person who was sampled would offer the proportion of their neighbors that had the label 1, and that fraction would be s S. To put it another way, the answer that the individual s S would provide to the NEP inquiry would be q(s) = |u N (s): f(u) = 1| |N (s)|. (2) After that, the NEP estimate of the proportion f is determined by taking the mean of all of the replies to the question P sS q(s) |S|.

II. RELATED WORK

After obtaining a set S of nodes through uniform sample selection with replacement, as was originally described in the classical intent polling2 method, the next step is to take the average of those nodes' labels and use it as an estimate of the fraction f defined in the method. This estimate will be referred to as the intent poll data estimate from this point forward (1). Intentional sampling has a number of drawbacks, the most significant one being that the minimum sample size required to obtain a - additive error is O(1 2) [3]. Our work is influenced by two recently suggested approaches, namely "expectation polling" [6] and "social sampling" [3], that aim to overcome this constraint in intent polling. Specifically, our work is driven by "expectation polling" [6] and "social sampling" [3].

To begin, in expectation polling [6,] each person who is sampled offers an approximation of something like the labeling held by the majority of the people in the network (that is, sampled individuals respond to the question "Who do you believe will win the election?"). The next step is for each person to glance about at her immediate surroundings and report the value that the vast majority of others share. When compared to the technique of intent polling, this approach is more effective in terms of sample size due to the fact that each person who is polled now offers the hypothetical answer of a whole neighborhood3,4.

Second, in social sampling [3], the answer of each sampled person is a function of something like the labeling, degree, and sampling probabilities of her neighbours. This is discussed in more detail in the next paragraph. This approach is used in [3], which not only produces numerous unbiased estimators for the fraction f, but also sets limits for the variances of those estimators. In comparison to NEP, the most important drawback of the social sampling approach is that it necessitates the persons who are sampled to have a large degree of prior knowledge about the network that is being studied. Because of this, it is possible that a realistic implementation of social sampling might not be practicable in contexts where there is minimal knowledge on a very big

network. Therefore, the NEP may be viewed of as a technique that asks the questions that seeks a finer steps toward achieving to expectancy polling while simultaneously being easier and more intuitive than social sampling.

The friendship paradox, which is a kind of network sampling bias found in undirected networks, is the essential concept that underpins our proposed NEP estimators for cases 1 and 2 (as specified in the problem specification). More specifically, the friendship paradox is a sort of network sampling bias. Recently, "how network biases may be successfully employed for estimating problems?" has been a popular topic of discussion in a number of applications that are connected to networks. One of these applications is the "friendship paradox."

For instance, [14], [15] demonstrate how the friendship paradox may be used for precise estimate of a heavy-tailed degree distribution. Similarly, [16], [17] demonstrate how the friendship paradox can be used for prompt detection of an epidemic of illness. The findings that we obtained for cases 1 and 2 may likewise be categorised under this overarching concept. In addition to its use in estimation problems, the friendship paradox has been investigated in the following contexts: perceptual and cognitive biases in online communities [18], [19], [20], information diffusion and opinion creation [21], [22], [23], [24], influence maximisation and stochastic seeding [25], [26], [27], node properties other than the degrees [28], [29], [30], instructed social media networks [18], [28], [31], and node characteristics other than the degree courses [25], [26].

III. PROPOSED SYSTEM

After obtaining a set S of nodes through uniform sample selection with replacement, as was originally described in the classical intent polling2 method, the next step is to take the average of those nodes' labels and use it as an estimate of the fraction f defined in the method. This estimate will be referred to as the intent poll data estimate from this point forward (1). Intentional sampling has a number of drawbacks, the most significant one being that the minimum sample size required to obtain a - additive error is O(1 2) [3]. Our work is influenced by two recently suggested approaches, namely "expectation polling" [6] and "social sampling" [3], that aim to overcome this constraint in intent polling. Specifically, our work is driven by "expectation polling" [6] and "social sampling" [3].

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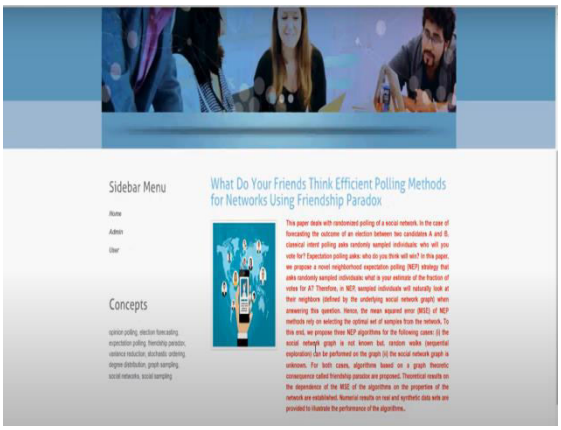
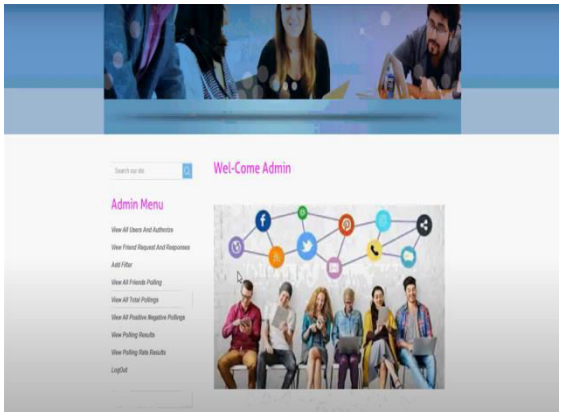
IV RESULTS



Home Page

Admin Login



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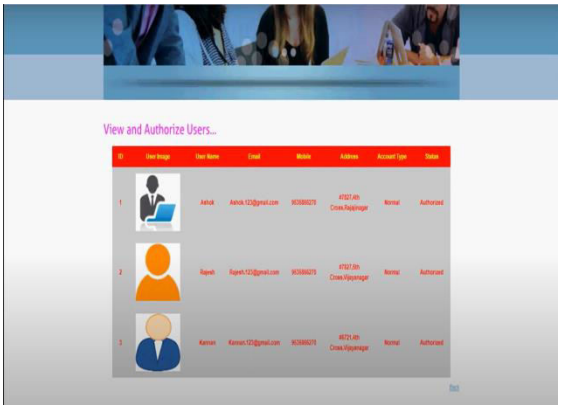
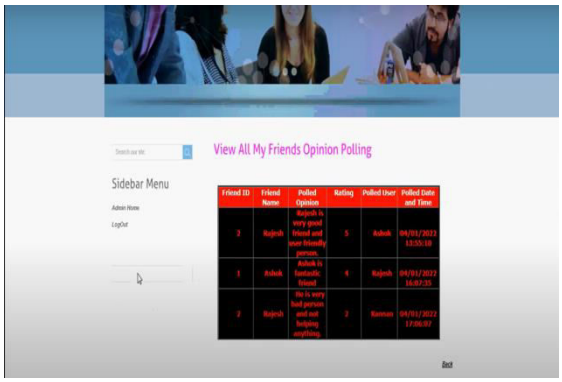
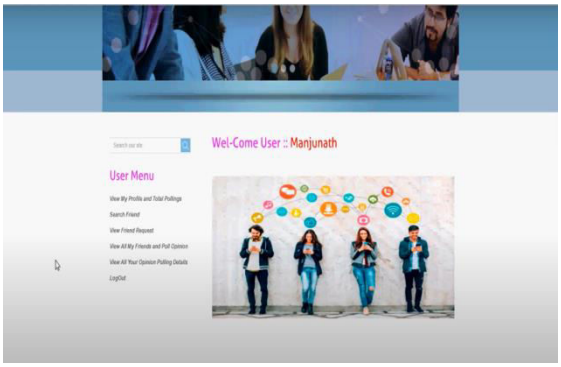


Authorized uses

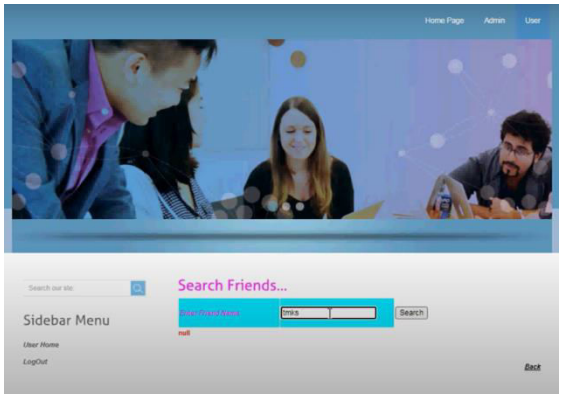


View friend opinion pooling

Registration of user



User welcome page



Search Friends

V CONCLUSION

This paper considered the problem of estimating the fraction of nodes in a graph that has a particular attribute (represented by a binary label) and, proposed a novel class of polling methods called Neighborhood Expectation Polling (NEP). In NEP, each sampled individual responds with information about the fraction of her neighbors in the social network that has label 1. We considered the cases where either: 1) the pollster has no knowledge about the social graph but, has the ability to perform random walks on the graph 2) uniformly sampled nodes from the unknown social graph are available.

Two NEP algorithms were proposed (for case 1 and case 2) exploiting a form of network bias called friendship paradox. Theorems 3 to 8 characterized the bias, variance and mean-squared error of the estimate as well as how they depend on the properties of the underlying network (correlation between node labels and degree, expansion, average, minimum and maximum degree, etc.) were derived.

These results are useful for a pollster to incorporate prior knowledge about the underlying network to choose the best algorithm (in terms of statistical efficiency) and guarantee its performance. Extensive empiriand simulation results are provided to illustrate the performance of

the proposed methods under different network properties. These complement the theoretical analysis and provide insights into how the proposed algorithms would perform under different conditions. Both theoretical and experimental results indicate that the friendship paradox based NEP algorithms are capable of obtaining an estimate with a smaller mean-squared error with only a smaller (compared to alternative methods) number of respondents.

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