Asking about private and sensitive attributes using item count techniques – methodological and theoretical challenges

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Abstract

Quality data about private, stigmatizing, socially unaccepted or illegal features and attributes is extremely difficult to obtain via traditional questionnaires and surveys. Some special statistical indirect methods of questioning have been developed to meet these challenges, in which respondents are not asked about the sensitive question directly. Indirect methods of questioning include randomized response techniques (RRTs), non-randomized response techniques (NRRTs) and item count techniques (ICTs). Among applied researchers item count techniques seem to gain the greatest interest and have been applied quite successfully in studies on criminal behaviors, risky sexual behaviors, prejudice and so on. Nowadays we have a lot of new theoretical item count models and still methodology and theory of item count techniques is being developed. This paper has two main purposes. The first is to present methodological and theoretical challenges of various item count methods, including trade-off between efficiency of the estimation and degree of privacy protection. Here we focus special attention on classic item count technique, Poisson and negative binomial ICTs and ICTs with a count or continuous control variable. The second aim of the paper is to analyze and compare different methods of estimation taking into account the fact that in real life surveys not all assumptions of theoretical item count models are fully satisfied. For this purpose we conduct a comprehensive Monte Carlo simulation study in which we distinguish between theoretical item count models and their real life counterparts. Here we focus attention on continuous ICTs. A sensitive variable under study is not directly observable (it is a hidden one) in these models and a neutral continuous control variable is used to mask the answer to the sensitive question. Assumptions about distribution of that control variable are crucial for maximum likelihood (ML) estimation via expectation maximization (EM) algorithm. In the paper we analyze how departures from theoretical assumptions about distribution of the control variable influence estimation results. We compare the obtained results for ML estimation in violated models with simple method of moments (MM) estimation which is not influenced in ICTs by distribution of the control variable.

Keywords: sensitive questions, indirect methods of questioning, item count techniques, ML estimation via EM algorithm

1. Introduction

Quality data about private, stigmatizing, socially unaccepted or illegal features and attributes is extremely difficult to obtain via traditional questionnaires and surveys. Troublesome sensitive features include drug use, beating children, politically incorrect views, bribery of officials, atypical sexual behaviors, abortion, tax frauds, illegal work and so on. It is well known that in direct methods of questioning respondents tend to under report negative sensitive attributes and over report the positive ones (Blair and Imai, 2012).

To deal with sensitive questions in surveys and assure privacy protection indirect methods of questioning have been developed, in which the sensitive question is not asked directly. The oldest indirect methods of questioning are randomized response techniques (RRTs) introduced by Warner (1965). An exemplary RRT questionnaire may look as follows.

Please take out any banknote you have from your wallet . But do not show it to me.

If the last digit of the serial number on your banknote is 0,1,2,3,4 or 5 answer the question:

Is it true that you once bribed an official?

If the last digit of the serial number on your banknote is 6, 7, 8 or 9 answer the question:

Is it true that you have never bribed an official?

So the interviewer does not know which question the respondent is answering and their privacy is being protected. Theory of RRTs has been developed immensely during several decades. An excellent systematic review is presented by Le et al. (2023). But despite advanced theory, mainly basic earlier randomized response models (Warner, 1965, Greenberg et al., 1969, Boruch, 1971, Fox and Tracy, 1986) are used in practice (e.g. Blair et al., 2015, Chu et al., 2018, Rueda et al. 2020). The main disadvantage of RRTs is that they need some randomization device and the process is quite complicated. It also has to be mentioned that respondents do not always fully understand RRT procedure. They do not always understand the role of the randomization device either. Therefore RRTs have also met some criticism among applied researchers (Tourangeau and Yan, 2007; Coutts and Jann, 2011, John et al., 2018).

To free oneself from the need to use a randomization device a non-randomized response techniques have been introduced for dealing with sensitive questions in surveys by Yu et al. (2008). An exemplary NRRT questionnaire looks as follows.

Below you have two questions:

- *Have you ever bribed an official?*
- *Were you born in the even month of the year?*

Choose one of the following statements:

- *The answers to the two questions are the same, i.e. both questions are answered YES or both are answered NO.*
- *The answers to the two questions* are different, i.e. one question is answered YES and one question is answered NO.

Theory of NRRTs is still being developed and new models are being introduced (Tian, 2014, Wu and Tang, 2016, Arnab et al., 2019, Liu and Tian, 2019, Kowalczyk, 2022). Applications of non-randomized response models are mainly experimental so far (Wu and Tang, 2016, Erdmann, 2019; Hoffman et al., 2020).

Another indirect method of questioning about sensitive questions is item count technique, also known as list experiment or unmatched count technique. In classic ICT developed by Miller (1984) survey respondents are randomly assigned to either the control or treatment group. Respondents in the control group are given a list of several neutral questions, say K, with binary outcomes. An exemplary questionnaire in the control group looks as follows.

Below you have three questions. How many of them will you answer yes to? Do not tell which ones, only how many.

- *Do you like going to the cinema?*
- *Do you like fishing?*
- *Do you like reading books?*

Respondents in the treatment group are given a list of the same neutral questions as in the control group plus one sensitive question with binary outcomes, i.e. they are given a list of K+1 questions in total. An exemplary questionnaire in the treatment group looks as follows.

Below you have four questions. How many of them will you answer yes to? Do not tell which ones, only how many.

- *Do you like going to the cinema?*
- *Do you like fishing?*
- *Do you like reading books?*
- *Have you ever bribed an official?*

In the control group respondents report a number from 0 to K (in the above example 0,1,2 or 3) and in the treatment group a number from 0 to K+1 (in the above example from 0, 1, 2, 3 or 4). Item count technique has many advantages. It is very simple and easy for implementation. It does not need any randomization device. It can be used in telephone surveys, internet surveys and of course face-to-face surveys. And most importantly, usually respondents know how their privacy is being protected.

It has to be emphasized that classic ICT has also some drawback connected with the situation when respondent has to report either 0 (this phenomenon is called the floor effect) or K+1 (this phenomenon is called the ceiling effect). In these two cases respondent's answer to the sensitive question is being revealed, so his or her privacy is no longer being protected. The floor effect is especially dangerous for positive (well seen, socially expected) sensitive features and the ceiling effect is especially dangerous for negative (illegal, socially unaccepted) sensitive features.

Apart from the fact that respondent's response is disclosed when floor or ceiling effect occurs, another problem to consider is degree of privacy protection. Degree of privacy protection is directly related to the number of neutral questions in the questionnaire. Large number of neutral questions complicates the questionnaire and decreases efficiency of the estimation but at the same time increases degree of the privacy protection. And the small number of questions, conversely, decreases degree of the privacy protection but at the same time increases efficiency of the estimation and simplifies the questionnaire. So there is always a trade-off between degree of privacy protection, efficiency of the estimation and simplicity of the questionnaire.

Theory of ICTs is still being developed. Proper mathematical background and maximum likelihood (ML) estimation via expectation maximization (EM) algorithm was introduced to classic ICT by Imai (2011). New item count models are still being developed (Trappman et al., 2014, Tian et al. 2017, Krumpal et al. 2018, Liu et al., 2019, Kowalczyk and Wieczorkowski 2022, Kowalczyk et al., 2023). ICTs are also very popular among applied researchers and are often used in real life surveys (e.g. Walsh and Braithwaite, 2008, Janus, 2010, Comsa et al., 2013, Sheppard, & Earleywine, 2013, Wolter and Laier, 2014, Kuha and Jackson, 2014, Hinsley et al., 2019).

As it was mentioned earlier, a major disadvantage of classic ICT is the occurrence of the floor and ceiling effect. In the next section two models which are free from the ceiling or/and floor effect are presented in more detail. In section 3 discrepancies between theoretical models and their real life counterparts are described and results of a comprehensive Monte Carlo simulation study for continuous ICT referring to the departures from strict theoretical assumptions are presented. Section 4 concludes.

2. Item Count Techniques free from floor and/or ceiling effects

2.1 Poisson and negative binomial item count techniques, Tian et al. (2017)

To deal with the ceiling effect Tian et al. (2017) introduced a new item count methods called Poisson and negative binomial ICTs. In their models survey respondents, similarly to classical ICT, are randomly assigned to either the control or treatment group. Respondents in the control group are given one neutral question, answer to which is denoted by X, with possible count outcomes 0,1,2,…. An exemplary questionnaire in the control group looks as follows.

How many times did you go out of town last month?

Neutral count control variable is directly observable in the control group. In the treatment group respondents are given two questions and are asked to report only the sum of their answers. One question is neutral and exactly the same as in the control group. The other question is the sensitive one, answer to which is denoted by *S*, with possible binary outcomes. An exemplary questionnaire in the treatment group looks as follows.

Below you have two questions:

- *How many times did you go out of town last month?*
- *Have you ever bribed an official? Assign 1 for Yes and 0 for No.*

Do not answer the questions separately. Report only the sum of your answers to the two questions.

In the treatment group both variables, neutral *X* and sensitive *S*, are hidden ones. Sensitive variable *S* follows Bernoulli distribution with unknown parameter π being the unknown sensitive population proportion under study. In the whole model sensitive variable *S* is not directly observable.

A simple estimator of the unknown sensitive population proportion π (proportion of people in the population that possess the sensitive attribute) is obtained via method of moments (MM) and takes form: $\hat{\pi}_{MM} = \bar{Y} - \bar{X}$, where $\bar{Y}$ is the treatment sample mean and $\bar{X}$ is the control sample mean. Method of moment estimator is very simple, it is a difference in means between treatment and control groups. And it does not depend on the distribution of the neutral control variable. But MM estimator has also some serious drawbacks. It may take values outside the parameter space, i.e. estimate may be smaller than 0 or greater than 1. Additionally, by using method of moments one cannot assess probabilities of possessing the sensitive attribute by individuals. To combat these obstacles Tian et al. (2017) also proposed maximum likelihood (ML) estimation via expectation maximization (EM) algorithm. Count data are usually modelled by Poisson or negative binomial distribution, therefore in this approach it is assumed that *X* follows either Poisson or negative binomial distribution. ML estimation via EM algorithm starts with fitting the distribution to the observed data, i.e. answers to the neutral control question. It can be done by traditional goodness of fit tests based on the control group. Then based on a particular distribution (Poisson or negative binomial) complete data log-likelihood function is constructed and EM algorithm is performed. In E step hidden (unobservable) individual data for sensitive variable are replaced by their conditional expectations $s_j = E(S_j|Y_{obs}) = P(S_j = 1|Y_j = y_j)$. In the M step, the ML estimators of all model parameters are obtained based on complete data set. Both steps depend on the distribution of the controlled variable. E and M steps are repeated until convergence.

Due to the fact that values of *X* are by definition not limited from above, there is no formal ceiling effect in this model. But still methodological question arises what type of a control neutral question should be asked, i.e. what control variable *X* should be used. A control variable with large variance (e.g. referring to the question: “How many pair of shoes do you have?") increases degree of privacy protection but at the same time decreases efficiency of the estimation. A control variable with smaller variance (e.g. referring to the question "How many marriages have you been in?"), conversely, increases efficiency of the estimation but at the same time decreases degree of privacy protection. So there is always a trade-off between degree of privacy protection and efficiency of the estimation.

2.2 Item count technique with a continuous or count control variable based on two treatment groups, Kowalczyk et al. (2023)

Poisson and negative binomial ICTs eliminated the formal ceiling effect that is present in classic ICT but the floor effect still remains. By answering 0 respondent reveals their answer to the sensitive question and therefore is no longer protected. Kowalczyk et al. (2023) proposed item count technique with a continuous or count control variable with two treatment groups. In their model both formal ceiling and floor effects are eliminated. Moreover, the method is more efficient. Here survey respondents, unlike in previous ICTs, are randomly assigned to two different treatment groups. So there is no control group in this model. In both treatment groups respondents are given two questions. One question, answer to which is denoted by X, is neutral. And the other question, answer to which is denoted by S, is the sensitive one with possible binary outcomes. It is important that answer to the control neutral question should result in values that are distanced from 0, like e.g. age of adult respondents (it has to be greater than 18), average hours of sleep (on average one cannot sleep two hours a day) etc. An exemplary questionnaire in the control group looks as follows.

Below you have two questions:

- *How many hours did you sleep in total during last two days (include also halves and quarters)?*
- *Have you ever bribed an official? Assign 1 for Yes and 0 for No.*

Do not answer these questions separately. Report only the difference between your answers, i.e. subtract the answer to the second question from the answer to the first question.

An exemplary questionnaire in the second treatment group looks as follows.

Below you have two questions:

- *How many hours did you sleep in total during last two days (include also halves and quarters)?*
- *Have you ever bribed an official? Assign 1 for Yes and 0 for No.*

Do not answer these questions separately. Report only the sum of your answers, i.e. to the answer to the first question add the answer to the second question.

In both treatment groups both variables, neutral *X* and sensitive *S*, are hidden ones. Therefore in the whole model neither the sensitive variable *S* nor the control variable *X* is directly observable. *S* follows Bernoulli distribution with unknown parameter π being sensitive population proportion under study.

A simple estimator of the unknown sensitive population proportion π is obtained via method of moments and it takes form: $\hat{\pi}_{MM} = \frac{1}{2}(\overline{Y_2} - \overline{Y_1})$, where $\overline{Y_1}, \overline{Y_2}$ are the sample means in the first and second treatment groups respectively. As in previous model, method of moment estimator is very simple and it does not depend on the distribution of the neutral control variable. It also possesses some drawbacks. Obtained estimator may not be efficient. It may take values outside the parameter space, i.e. estimate may be smaller than 0 or greater than 1. And by using method of moments we cannot assess probabilities of possessing the sensitive attribute by individuals. Kowalczyk et al. (2023) also presented maximum likelihood estimation via expectation maximization algorithm. It starts with fitting the distribution to data. Due to the fact that control variable is not directly observable in this model some modifications of standard methods were given. Akaike Information Criterion, Bayesian Information Criterion, and goodness-of-fit Kolmogorov-Smirnov test adapted for ICTs with two treatment groups were presented. Based on particular distribution complete data log-likelihood function is constructed and EM algorithm is performed. Each step in EM algorithm depends on particular distribution of the control variable. In the E step hidden (unobservable) individual data for sensitive variable are replaced by their conditional expectations $s_j = E\left(S_j | Y_{obs}\right) = P\left(S_j = 1 | Y_j = y_j\right)$. And in the M step, the ML estimators of all model parameters are obtained based on complete data. E and M steps are repeated until convergence.

In general, in continuous ICTs (when *X* follows a continuous distribution) any positive real number $a,\ a > 0$ can be assign to the sensitive question, i.e. we can ask to assign a for Yes and 0 for No answer. Degree of privacy protection and efficiency of the estimation is influenced by the choice of the control variable *X* and the choice of a. Once again, the larger the variance of the control variable the higher degree of the privacy protection but at the same time the lower efficiency of the estimation. The larger value of a the higher efficiency of the estimation but at the same time the lower degree of privacy protection. One always has to look for the balance between degree of privacy protection and efficiency of the estimation. In continuous item count models we can balance efficiency and privacy protection by taking into account both a and *X.*

3. Discrepancy between theoretical models and their real-life counterparts

In theoretical models described earlier regarding ML estimation it is assumed that the control variable follows a particular distribution. In practice we can fit a theoretical distribution to the observed data. But it is not the same as data generated according to this particular distribution. In other words, in real-life surveys answer X to the non-sensitive question can be modeled by a theoretical distribution that best fits the observed data, which is not the same as theoretical idealized assumption that X follows this distribution

As it was stated in the previous section, maximum likelihood (ML) estimators have many advantages. They are asymptotically efficient, ML estimates always take values within the parameter space, i.e. between 0 and 1, and use of EM algorithm allows for obtaining assessments of conditional probabilities of possessing the sensitive attribute at individual level (although these individual assessments may be subject to large errors). Method of moments estimators on the other hand may not be efficient, may take values outside the parameter space, and does not allow for assessments of probabilities of possessing the sensitive attribute at individual level. Numerical comparison of these estimators can be found in Tian et al. (2017) and Kowalczyk et al. (2023). In this paper we expand this analysis to include cases in which the actual data do not perfectly fit the assumed idealized theoretical distribution. We focus here on continuous item count models, i.e. models based on two treatment groups in which control variable follows a continuous distribution. This is due to the fact that this problem is of special importance here, because in these models control variable is not directly observable.

So now we introduce to the theoretical continuous item count models some assumptions violations. More precisely, we introduce perturbation to the theoretical distribution of the control variable X. We consider the case, in which actual data regarding neutral control question with probability $1 - \alpha$ follow the assumed theoretical continuous distribution and with probability α follow some different continuous distribution. Let us notice that for $\alpha = 0$ we obtain original theoretical model. As a rule, probability α of perturbation should not be too large.

To compare performance of different estimators we conduct a comprehensive Monte Carlo simulation study with 10,000 replications for each set of model parameters. We compare three types of estimators, maximum likelihood ML (via numerical EM algorithm), method of moments (MM) and restricted method of moments (RMM) estimators. Due to the fact that MM estimators may take values outside the parameter space, it is appropriate to restrict each such estimate to interval [0,1]. More precisely, when MM estimate is smaller than 0 we adopt 0, when it is larger than 1 we adopt 1, when it is from 0 to 1 we do not change it. The new resulting estimator is called restricted method of moments RMM estimator.

In all figures presented below π relates to the actual sensitive population proportion, *n* relates to the sample size, and α relates to the probability of perturbation. Usually to be able to call some feature sensitive, it cannot be the case that a very large part of the population possess it. So in the literature related to sensitive questions it is often assumed, what we also follow in this paper, that $\pi \leq 0.3$. By definition perturbations should not be too large. Therefore we consider $0 \leq \alpha \leq 0.25$. For $\alpha = 0$ there is no perturbation and neutral control variable follows assumed theoretical distribution (data fit theoretical distribution perfectly).

In all figures presented below efficiency of different estimators is measured by relative root mean square error (RRMSE). Squares refer to maximum likelihood (ML) via EM algorithm estimators, dots refer to method of moments (MM) estimators and triangles refer to restricted method of moments (RMM) estimators.

In figure 1 we consider a normal theoretical distribution of the control variable with perturbation also being a normal distribution but with two times larger variance. As we can see, even after introducing a perturbation, ML estimators are still more efficient than MM estimator. Differences are most visible for small sample sizes and small sensitive proportions. This may be due to the fact that MM estimates may result in values outside the parameter space, which is especially dangerous for small sample sizes and small sensitive proportions. For larger sample sizes and larger sensitive population proportions differences between ML, MM and RMM estimators diminish. Situation is very similar for a normal theoretical distribution of the control variable with perturbation also being a normal distribution but with two times smaller variance (figure 2).

We also consider (figures 3-6) normal theoretical distribution with perturbation being log-normal and log-normal theoretical distribution with perturbation being normal. In both cases perturbations with larger and smaller variance are considered.

Out of all presented cases only in the case of log-normal theoretical distribution and perturbation being normal with two times higher variance, ML estimators proved to be less efficient (figure 5) than MM estimators for large sample sizes, small sensitive population proportions and perturbation larger $\alpha > 1$ than 0.1.

Figure 1: Relative root mean square error of various estimators in normal ICT with perturbation being normal distribution with two times higher variance

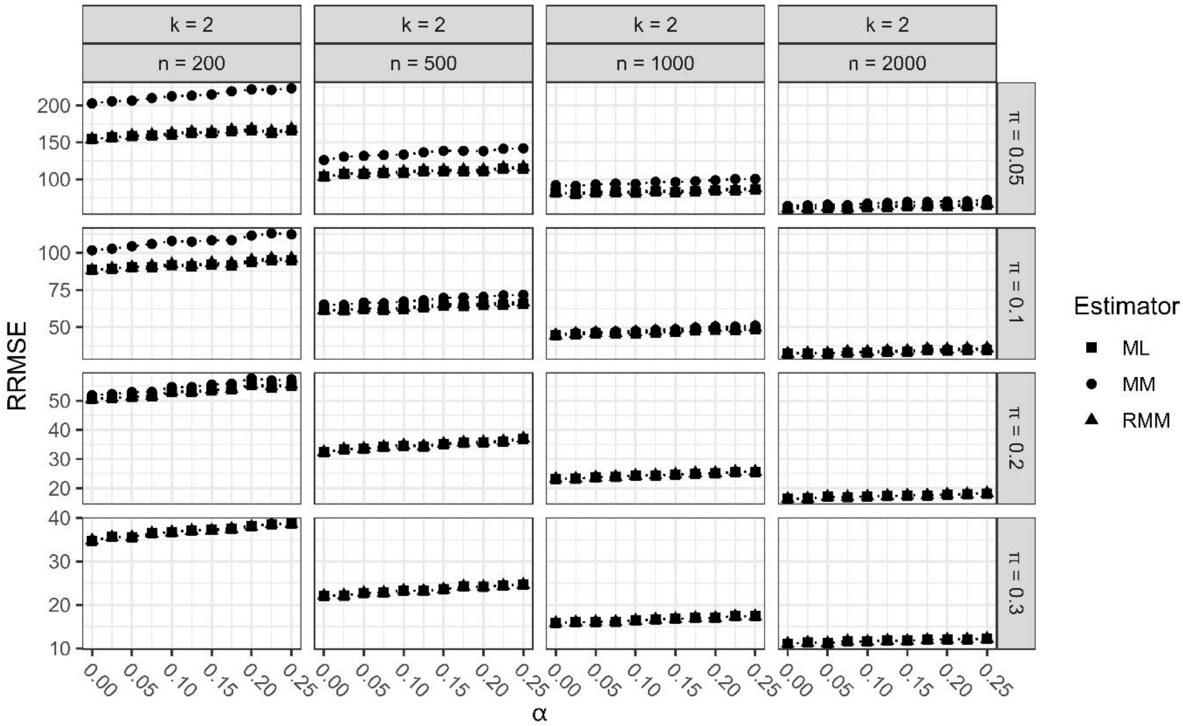


Figure 2: Relative root mean square error of various estimators in normal ICT with perturbation being normal distribution with two times smaller variance

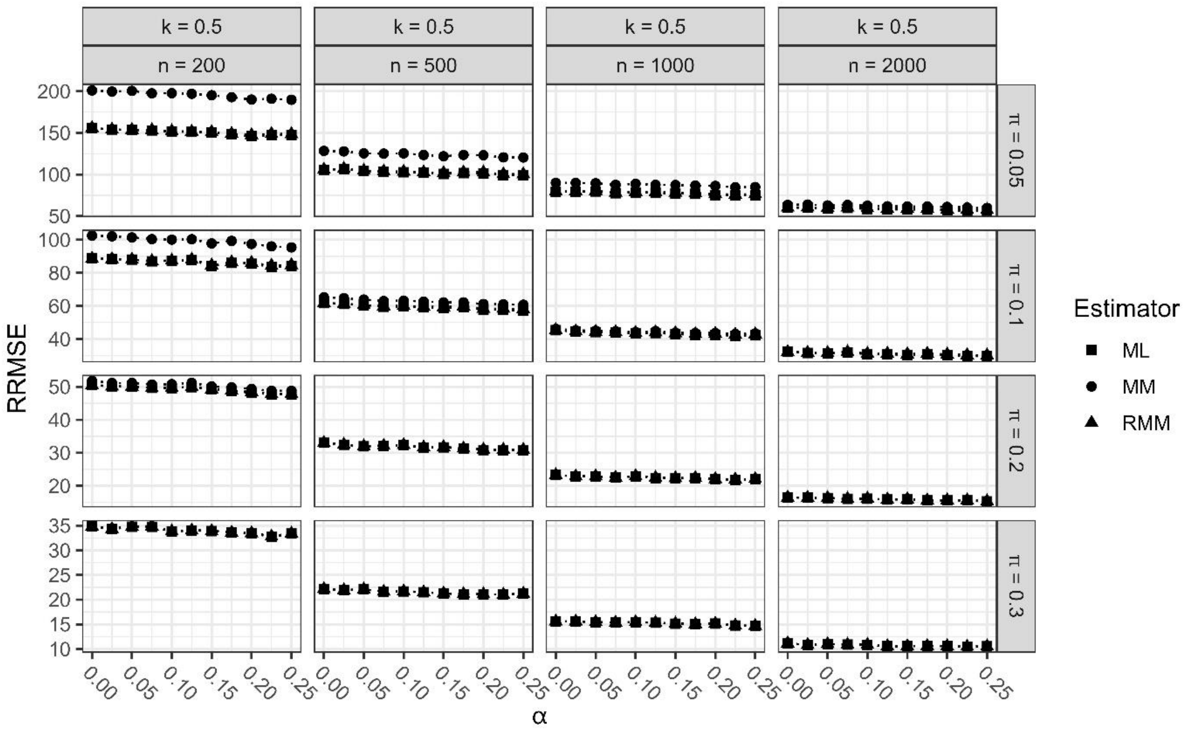


Figure 3: Relative root mean square error of various estimators in normal ICT with perturbation being log-normal distribution with two times higher variance

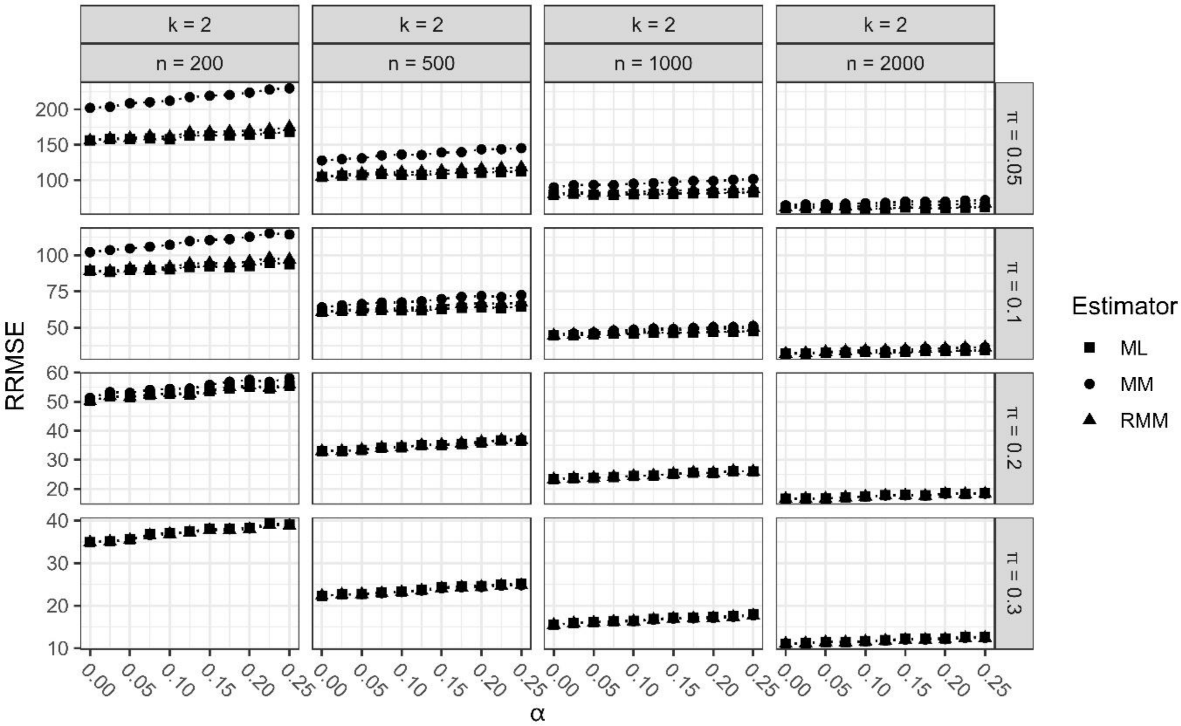


Figure 4: Relative root mean square error of various estimators in normal ICT with perturbation being log-normal distribution with two times smaller variance

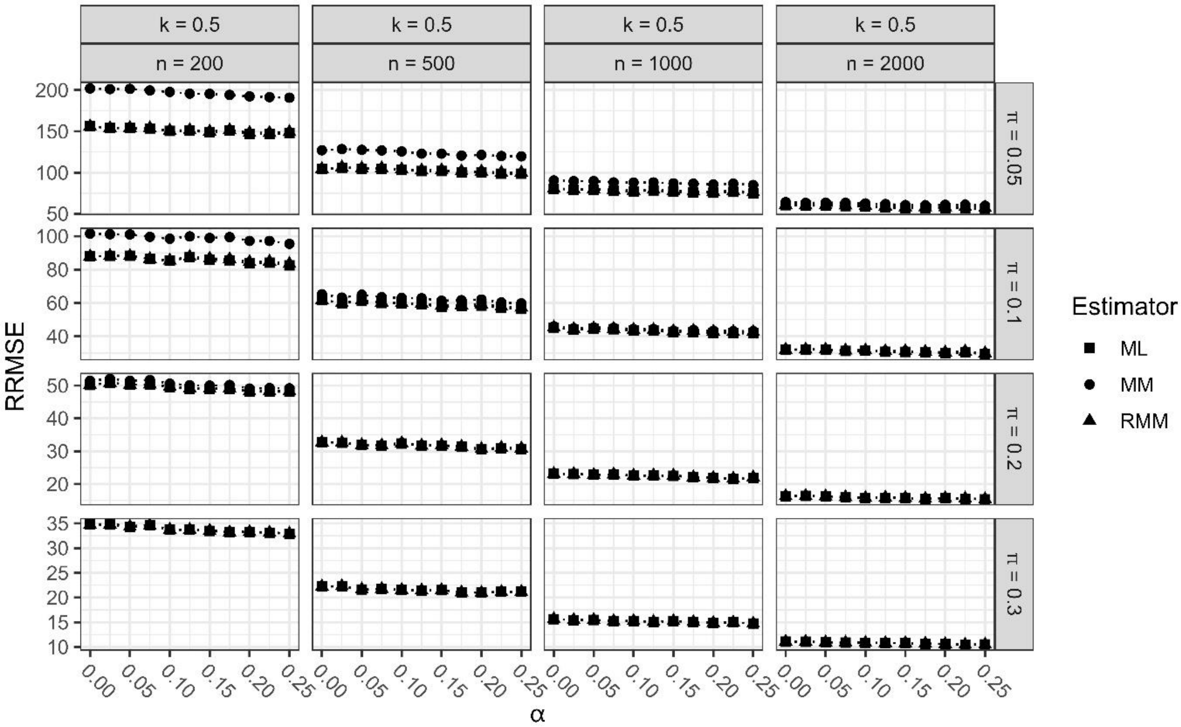


Figure 5: Relative root mean square error of various estimators in log-normal ICT with perturbation being normal distribution with two times higher variance

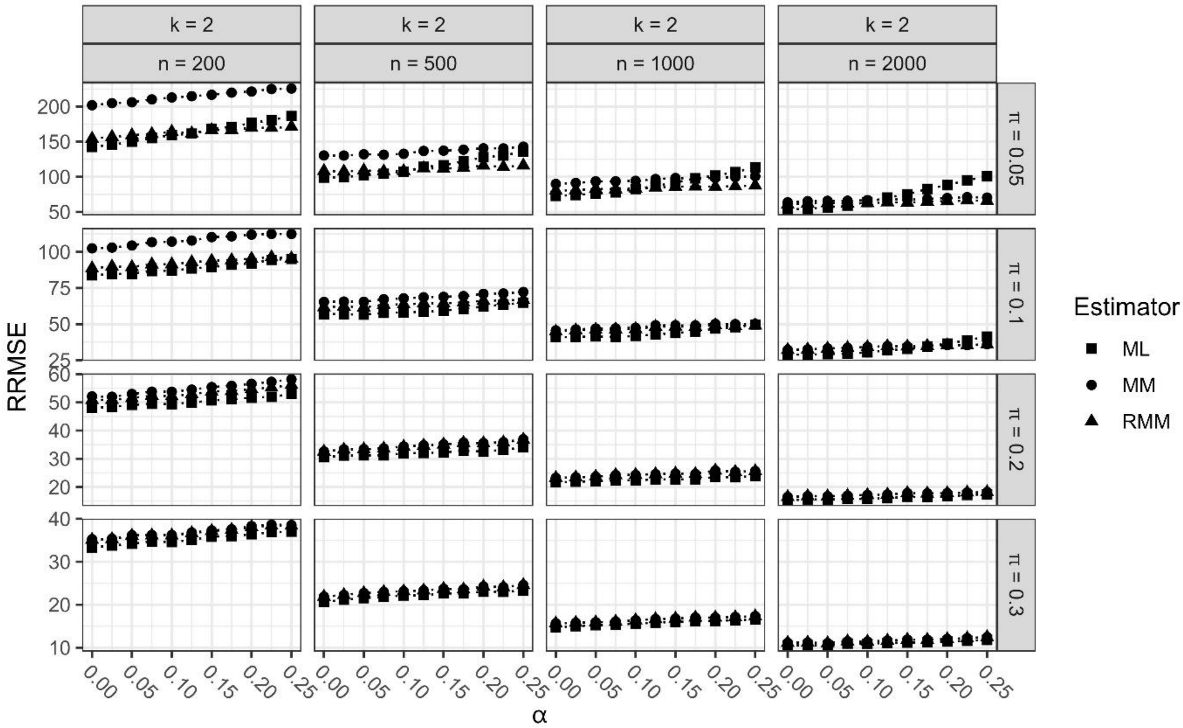
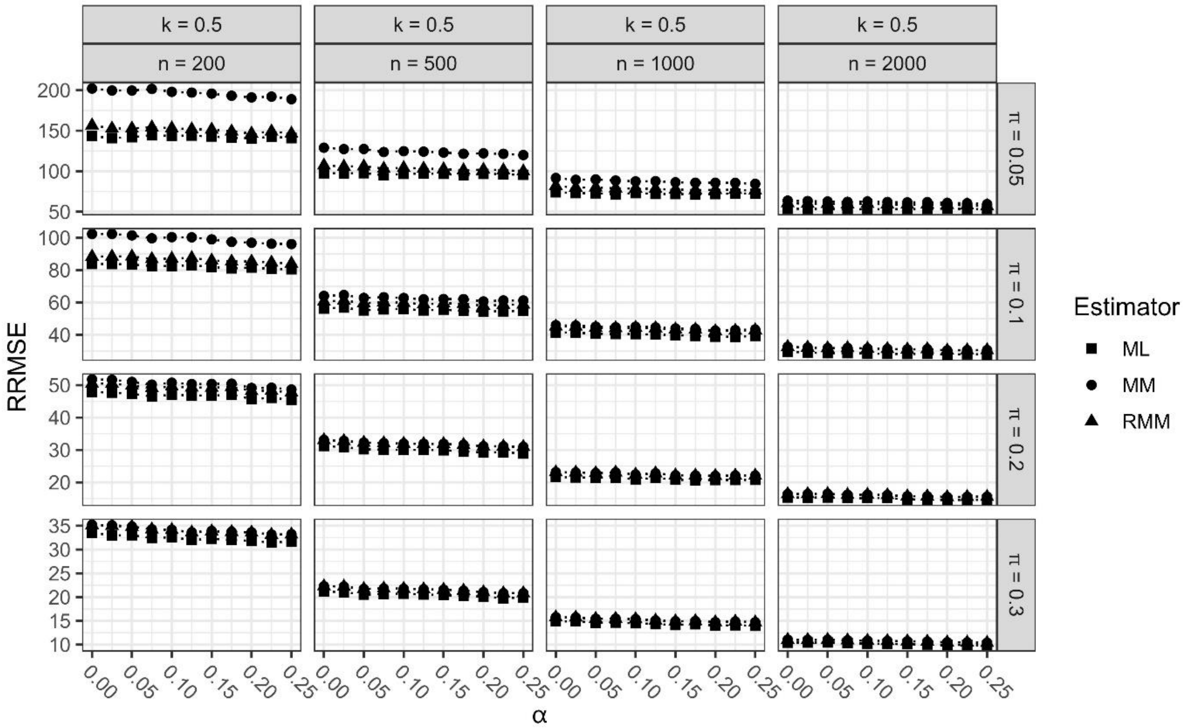


Figure 6: Relative root mean square error of various estimators in log-normal ICT with perturbation being normal distribution with two times smaller variance



In total, out of considered 144 cases (different sets of model parameters), ML estimators under presented distribution perturbations, $\alpha \leq 0.25$, still proved to be more efficient than MM estimators in more than 140 cases.

4. Conclusions

Item count techniques are quite simple and very easily for implementation. They can be used in telephone surveys, internet surveys and of course face-to-face surveys. They do not need any randomization device. The questionnaire can be written in a simple and understandable way. And respondents usually know how their privacy is being protected. In all item count models one should look for a compromise between degree of privacy protection, efficiency of the estimation and simplicity of the questionnaire. It is impossible to increase efficiency of the estimation and degree of privacy protection at the same time. There is always some trade-off between them. Item count models have sound mathematical and statistical foundations. The sensitive variable under study is not directly observable in these models. Both method of moments and maximum likelihood estimators via EM algorithm can be used for assessment of the unknown population sensitive proportion, i.e. assessment of the proportion of the population possessing the sensitive feature. Application of ML estimation via EM algorithm allows also for assessments of conditional probabilities of possessing the sensitive feature at individual level. Small departures from the assumed theoretical distributions introduced to the item count models do not influence estimation much. Under introduced perturbations, estimators obtained by numerical formulas for ML via EM algorithm are in most presented cases still more efficient than MM estimators.

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