Will Big Data Affect Opinion Polls?

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Abstract Statisticians feel recently a pressure for substituting sample surveys with new opportunities offered by Big Data. Some authors suggest that opinion polls and other random sample surveys have become obsolete in the new era of Big Data. The author discusses relationships between survey-based and Big Data-based approaches to the measurement of consumers' and public opinions. Special attention is given to traditional opinion polls.

1 Introduction

Opinion polls born in the early thirties of the twentieth century have gained a good reputation over the following decades and are still regarded as the main and the most popular way of measuring public opinion (other ways of expressing public opinions include: elections, media, interest groups and lobbying, public protests, straw polls). Dr. George Gallup (1901-1984), a pioneer of opinion surveys believed both in "collective wisdom", and in its representation - public opinion, which could be quantified and measured. He and his followers

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Archives of Data Science, Series A
(Online First)
KIT Scientific Publishing
Vol. 4, No. 1, 2018
DOI 10.5445/KSP/1000085951/11
ISSN 2363-9881

convinced politicians and media managers that opinion polls measure the "pulse of democracy" and make considerable contribution to democracy itself. Probably not many were concerned in those times that polls may become so influential, as they are claimed to be now. Since the beginning, however, polls have not only been praised for some accurate predictions, but also criticized for failures which they have experienced (e.g. Mosteller et al (1949); Robinson (1999)). The largest amount of criticism the polls have attracted in the last several years.

There is a number of reasons which could serve as an excuse for statisticians not to care about the decline in quality and trust of polls. First of all, all the failures which opinion polls have experienced over the decades were not able to undermine the essence and foundations of statistical inference based on random sampling. The strength of statistical inference has been highlighted by the vast majority of very accurate exit polls conducted on election days in many countries. Second, there are stages in performing opinion polls and in publishing their outcomes which are free from any involvement of statisticians. And as a consequence, statisticians are obviously reluctant to take any responsibility for the final results. Examples of such stages include: reporting the poll outcomes by the media which may have clear political preferences, and another phenomenon called "herding", which means the desire and activities of pollsters or media to adjust their poll results to the existing outcomes on the market. The American Association for Public Opinion Research (AAPOR) defines herding as follows: "Herding" specifically refers to the possibility that pollsters use existing poll results to help adjust the presentation of their own poll results (American Association for Public Opinion Research "Herding", `https://www.aapor.org/Education-Resources/Election-Polling-Resources/Herding.aspx`).

But even in those circumstances where some parts of the opinion poll measurement are exempted from statistical screening, in my opinion, neglecting or ignoring opinion polls by statisticians would not be a justified attitude. It is worth noting that opinion polls represent the kind of sample surveys which together with consumer's surveys are best known for many citizens. We all seem to be familiar with polls, as the media appeal to them every day: a popular Polish daily "Rzeczpospolita", for example, refers on average to 6-9 various polls in each issue. I suspect that if statistical inferences are identified at all by ordinary customers or voters in their everyday lives, they would probably relate to market surveys or opinion polls. Consequently, it is quite understandable that

the quality of any survey-based research would be evaluated from the perspective of successes and failures of opinion polls.
Sometimes this kind of thinking goes further and one can observe that because of the loss of the public's faith in polling in some countries, people lose confidence in quantitative surveys in general. That means that some of them could soon become skeptical about any statistical research regardless of its particular subject.

Hence my belief is that it is in the interest of the science of statistics not to neglect opinion polls, especially now, when they have lost much of their good reputation of the early years. Before big data replaces traditional public opinion measurements, if ever, our statistical community should indicate and offer new opportunities of collecting, processing, and analyzing data to pollsters and opinion poll analysts.

This paper includes a presentation and discussion of selected issues connected with implementation of external (non-sample) information, including metadata, paradata, and big data in conducting opinion polls. The first part of the paper concentrates on identifying the main sources of errors in contemporary polling performances, and showing how statisticians may contribute to improvements of the quality of opinion polls. The second part includes a short discussion about the current and the future influence of big data on traditional opinion surveys.

2 Opinion polls - recent successes and failures

Similarly to other areas of life, opinion poll measurements attract special public attention if they are accompanied by failures rather than successes. This kind of attitude should not surprise scientists who are used to dealing with various sorts of errors in their explorations aimed at identifying sources of errors and ways to avoid them in their future work. In the public perception, however, a long series of mistakes in certain scientific activities undermines confidence in both the methodology of the research and its performers. The loss of confidence may sometimes spill over into a broader area of research than the critical one. This relates to opinion polls where many people do not distinguish between generally high quality exit polls and based on the same methodology lower quality opinion polls, including pre-election surveys.

An exit poll is a survey of voters conducted on the election day which serves as a forecast of the election outcome produced immediately after the vote. In some aspects, an exit poll seems to be a simpler survey compared with pre-election polls. Primarily, because it focuses on what the respondents did a few minutes ago rather than on their changing intensions prior to the election. Unlike pre-election polls, the exit poll is free from a number of serious burdens typical for polls conducted between elections:

- Uncertainty which segments of the population of the entitled voters represented in the sample will actually vote on the election day,
- changes in election preferences of some voters between the day of polling and the election day (late swing),
- difficulties with choosing an efficient sampling frame and interview modes, and
- a considerably larger non-response rate in opinion polls compared with exit polls.

In some other aspects, however, especially related to sampling, the exit poll may constitute a real challenge for the pollsters. It is important to note that the sampling error in exit polls is generated by two sampling processes, not just one. There are two samples selected from two different populations which make up the basis for inference. One sample consists of polling stations, which are usually sampled using the stratified sampling scheme or more complex techniques (more about such techniques see Kozłowski (2014)). Second, sample consists of voters who had just left their polling stations. They tend to be sampled using the technique called systematic sampling (i.e. one out of every six/ten voters) based on the expected turnout. Ultimately, the total sampling error in exit polls aggregates the sampling errors of both sampling procedures.

Fortunately, there have not been many inaccurate exit polls in recent years. In Poland, for instance, the forecast accuracy based on exit polls has improved in the last ten years considerably. The total errors of exit polls in the last several elections did not exceed the following figures in relation to any candidate or party on the list:

- 1.0 % in both rounds of the presidential elections in 2010 (poll performed by TNS Polska),

- 1.6 % in the first round, and 1.5 % in the second round of the presidential elections in 2015 (IPSOS),
- 1.6 % in the parliamentary election in 2015 (IPSOS),
- 1.1 % in the Warsaw referendum to remove the mayor from her office in 2013 (TNS Polska).

Also in other countries the exit polls have good records. According to Singh (2017):

> *"At no point in the past quarter of a century has the largest party's seat total been wrong by more than* 15 *seats."*

The only example of genuine exit polls being wrong came in 1992, when for the Conservative Party the number of seats was underestimated by 35, and for the Labour Party overestimated by 27. In France in both rounds of the presidential election 2017 the margin of error in exit polls was very small and did not exceed 0.6 %. An analysis of the performance of exit polls is vital because the polls' estimates are subject to a rigorous verification on the basis of the complete data about the whole population of interest. This is a unique opportunity to test the efficiency of statistical inference in practice. Accurate forecasts obtained from exit polls constitute a strong evidence that the statistical inference based on a relatively small but carefully selected random samples really works. If so, what is the actual problem with pre-election polls? Do their inaccuracy problems refer only to practical difficulties?

Probably some statisticians would answer "yes" to the last question. They could argue that there is little room for scientific proposals aimed at improving the overall quality of opinion polls. I do not think that they are right. After all, statistics has always dealt not only with theory or modelling various phenomena but also with practical aspects of quantitative measurements. Therefore, statisticians should not ignore any part of the total error involved in the results of opinion polls. All parts, regardless of their nature and sources, ought to remain in the focus of their research interests. This kind of attitude has made statistical communities take actions several times in recent years when opinion polls suffered from harmful defeats. Obviously, not every pollster's failure is followed by a special investigation. In 2015 alone, political pollsters failed to make the correct election predictions in the U.K., Poland, Israel and Argentina.

At least the three recent investigations launched after the failures of polls should be mentioned (listed in chronological order):

- Domański et al (2010), a report followed by pollsters' failure to predict presidential election outcome in Poland in spring 2010;
- Gallup (2012), a thorough review of Gallup's 2012 pre-election presidential polling aimed at determining the factors responsible for underestimating Barack Obama's popular vote strength;
- Sturgis et al (2016), an inquiry report into pollsters' failure to forecast Conservative victory, whereas most polls suggested a neck-and-neck race.

All these reports tried to identify new factors which accounted for the polls' inaccuracy. The majority of the factors are common for all three reports, but some seem to be country-specific. Below are shortly discussed the former ones. One of the main difficulties in predicting election outcomes has always been uncertainty about who will actually cast the ballot on the election day. Even if a pre-election surveys were able to capture the voting preferences in the population of voters perfectly, the obtained numbers and proportions would be completely useless if only 40 % eligible voters (like in Poland) or 60-70 % (in Germany, France (in presidential elections but lower for parliamentary elections (48.7 % in June 2017)) and UK) take part in voting. The turnout has been declining for many years, and moreover, some statistical procedures to deal with this problem which were efficient in the past, have not been working nowadays.

One of the most popular concepts, based on a series of additional questions to respondents, called likely voter technique (or model), was successfully applied in many previous elections. However, these days it has become clear that it requires corrections and changes, or – as The Gallup Organizations announced (Gallup (2012)) – a complete re-evaluation of the likely voter procedures. British experience is very similar, confirmed by the following recommendation:

> "*Too much reliance is currently placed on self-report questions which require respondents to rate how likely they are to vote, with no strong rationale for allocating a turnout probability to the answer choices* [. . .] " (Sturgis et al, 2016, p. 5).

This is one of the crucial challenges for statisticians who need to improve likely voter technology or replace it by other models and procedures combining various sources of data. Another problem which is likely to contribute to the total survey error relates to inadequate sampling frames and improper ways of interviewing respondents. In Britain some pollsters use non-probability online panels of pre-recruited individuals and some others prefer a mix of landline and mobile phones. However, none of these modes turned out to be satisfactory. With regard to online interviews, which not always have a good population coverage, the recruitment procedures to online panels via methods such as banner advertising, online panel portals, and referrals (Callegaro et al (2014)) have been criticized. Telephone interviews, on the other hand, suffer from other drawbacks. The Random Digi Dialing (RDD) sampling frame, which was successfully applied in commercial surveys and opinion polls through decades, is not sufficient nowadays, as many people rely on mobiles only. Moreover, Gallup (2012) has revealed that in the United States the listed landline samples were demographically different to respondents from the RDD list-assisted landline plus mobile sample frames. The differences between people who are on landline only and those who have only mobile phone are deeper and are not confined to demography. It is argued that in the US the cell phone only population is more likely to be younger, include more minorities (nearly 2/3 of Hispanic adults), engage in more risky behaviors, and earn less as compared to the wider U.S. landline population (Insight Association (2017)). Also in other countries, including Poland, attempts to identify voters by RDD of mobile and landline phone numbers are subject to the risk of over- or underrepresentation of some population segments. The growing proportion of people available on landline phones do not have the same structure as the whole population of voters. Some individuals possess more than one mobile instead. As a consequence they have different probabilities to be selected to random samples based on RDD. In the United States The 1991 Telephone Consumer Protection Act bans autodialing to cell phones which makes all kind of telephone surveys more costly and time-consuming. The quality of telephone and online samples may of course be improved by applying adjustment procedures based on weights which are correlated with peoples' political interests and preferences. An additional challenge consists in identifying reasons for differences between the results obtained from online and telephone interviews. Sturgis et al (2016) find some indications that the phone polls were somewhat more accurate during the 2015 British election campaign than on-line surveys.

Among all kinds of errors which contribute to the total error of sample surveys, non-sampling errors attract nowadays increasing attention. For years statisticians concentrated on the sampling error which is clearly and consistently located in mathematical formulae of statistical inference. The term was used by the famous statistician Leslie Kish (Platek and Särndal (2001)). Probably too long sampling error was "*over-researched*" and all kinds of non-sampling errors neglected. Interestingly, this kind of approach was criticized already half a century ago by the most notable Indian statistician Prasanta Chandra Mahalanobis who in 1951 wrote:

> *" In fact, the general attitude is to look upon the non-sampling error as something, which does not concern the statistician, or in any case is a kind of dirty job, which a highbrow statistician need not bother about."* (Mahalanobis, 1951, p. 4).

Currently all people who are involved in sample surveys either in economics or in measuring public opinions are more aware of possible consequences of non-sampling errors. In opinion polls two kinds of non-sampling errors seem to be most burdensome. They are nonresponse error and measurement error.

Falling response rates are primarily explained by the large number of various surveys people face in recent years, mistrust or doubts of respondents whether or not the survey is legitimate, poor reputation of political polls (generally connected with low reputation of politicians), lack of incentives to take part in the survey, weakening human interaction between interviewers and the respondents over time:

> *" The sample survey has been transformed from being a comfortable face-to-face conversation to a highly impersonal experience"* (Dillman et al, 2009, p. 1).

Widespread access to the internet offers everyone various opportunities to express his or her views on many issues . Opinion polls conducted in a traditional form have lost their charm, especially for younger generations. As a consequence, it is not surprising that the non-response rate quite often reaches as much as 90 % or more. Seven years ago the non-response rate was low, attaining 85 % – 93 % in pre-election polls in Poland (Domański et al, 2010) and nowadays is even lower. This in turn implies that the actual sample may be considerably different from the initially designed one. Some population segments may have a disproportionate or no representation at all in the sample. Furthermore, this can potentially make the whole inference invalid, as the estimates are likely to be biased. The consequences of nonresponses are less harmful only if they can be regarded as observations missing at random. In this particular case, although the estimates suffer from lack of precision, they remain unbiased (for details see e.g. Szreder (2010, chapter 6)). However, in practice such fortunate situations are seldom. More frequently nonresponse is associated or correlated with some other population variables. This results in underestimating or overestimating the population characteristics of interest.

One of the most efficient ways to reduce the nonresponse error involves enriching sample information by other relevant information which could be used in weighting schemes or calibration procedures. It could be either sample information about other characteristics of the units or non-sample information, including external secondary data. Weights are used in surveys not only for adjusting for nonresponse, but also for correcting the sample structure in order to improve the precision of inference. The effectiveness of all such measures aimed at substituting nonresponses depends on the relevance and quality of the auxiliary data. This seems to be another challenge for statisticians or data analysts – to propose sources of relevant information and ways of incorporating the acquired data to statistical inference. Although there is a considerable amount of scientific literature dealing with non-response, the reality in which the response rate is often in the single digits, creates new problems.

Unlike in commercial surveys, respondents taking part in opinion polls tend to be sensitive to mainstream propaganda, and as a consequence some of them feel that they should give answers that are socially or politically desirable. This phenomenon has not received sufficient attention yet. Generally, the scientists had good reasons to assume that deliberate misreporting was not large and did not introduce a systematic bias into the findings. This has been changing in recent years. A systematic and one directional bias that occurred in the majority of polls which failed to predict the outcome in the British EU referendum and in the last presidential election in the US puts new emphasis on this problem. Currently, misreporting may have a different impact than it used to have before. However, this requires new research studies and new solutions aimed at recognizing the motives of respondents for misreporting and at reducing the possible consequences of this phenomenon.

3 Influence of big data on opinion surveys

The most important sources of error described in section 2 which are responsible for declining accuracy of opinion polls should be considered from the perspective of additional information they need. Sampling frames, modes of interviewing, sampling techniques, non-response errors – all of them could benefit, in terms of higher quality of the final outcomes of opinion polls, if sample data were combined with external information.

Depending on nature and content one can distinguish several categories of external information, including metadata, paradata, and the broadest concept called big data.

Metadata is commonly understood as “data about the data”, which means that it summarizes basic information about the collected data: Its structure, content, and context. Examples of metadata are survey instruments, interviewer instructions or software used for data processing. This kind of data was probably first recognized and used by official statistics, but soon attracted attention of researchers in many kinds of surveys, including opinion polls. In recent years the collection and implementation of metadata have been facilitated by the Internet and software developments. Taking into account problems with declining response rates and with possible misreporting their views by some respondents, the impact of metadata has increased. This kind of additional information could be particularly useful in constructing election forecasts which require more information than the usual opinion poll. Also it may turn out to be useful in confronting estimates obtained from telephone interviews and online surveys. However, what can be regarded as challenge for statisticians is a lack of theoretical background and common standards of using metadata in sample surveys.

Paradata, on the other hand, refers to more detailed information and is more difficult to be recorded. The term paradata describes all types of data about the process and context of data collection. According to Kreuter (2015) the expression “paradata” was first used in the survey research context by Couper (1998) to describe automatically generated process data, such as data from computerized interviewing software. This kind of information include: Contact data (day, time, outcome), keystrokes (response times, edits), interviewer personal observations (a degree of respondents interest). Proper use of this sort of data can contribute to the reduction of the total error in opinion polls. For example, an analysis of the time the respondent took to “click” and answer the following questions may suggest how interested he or she was in the survey, and consequently what quality of data he or she has provided. Similarly in telephone or face-to-face interviews information about availability of respondents can provide some additional knowledge to researchers. For example, in one of the pre-election face-to-face British Social Attitudes survey in 2015, Labour was six points ahead among respondents who answered the door at the first visit, whereas the Tories enjoyed an 11-point advantage among interviewees that required between three and six home visits (Clark and Parraudin (2016)). Despite the growing opportunities to collect various kinds of paradata in recent years, its future impact will depend on the expected progress in working out a systematic approach to handling this kind of data.

Both metadata and paradata constitute elements of a broader concept which is known as big data. The term big data describes such ways of acquiring new knowledge and learning the reality which can be achieved in large scale using new opportunities of capturing and processing large-size data files. Some authors who deal with this subject expect revolutionary changes not only in survey-based research but also in our lives. Viktor Mayer-Schönberger and Kenneth Cukier in their famous book (Mayer-Schönberger and Cukier, 2013, p. 26, 31) argue that

> “ [. . .] *the concept of sampling no longer makes as much sense when we can harness large amounts of data* [. . .] ”

and they add

> “ *Reaching for a random sample in the age of big data is like clutching at a horse whip in the era of the motor car.”*

These statements are debatable. The authors, who are impressed by huge volumes of available data, mainly internet-derived data and social media data, seem to suggest that quantity can compensate for lack of quality. They are of course aware of the nature of big data. They realize that big data is often unstructured, messy, and maybe of poor quality. If one argues that in such circumstances big data is superior to well designed and performed sample survey, that means that the person is likely to pay too much attention to sampling error and neglect the magnitude of non-sampling errors. In modern sample surveys the latter ones are much more difficult to combat than the sampling error. If a survey fails, the principal reasons are usually connected with non-sampling errors. These errors can come up both in sample surveys and in surveys aimed to cover the whole population under study. And, therefore, one of the main challenges is to seek efficient tools for reducing non-sampling errors. If "sacrificing a little of accuracy" – according to Mayer-Schönberger and Cukier (2013) – means ignoring some categories of non-sampling errors before they are analyzed, then a well-designed and carefully performed sample survey will presumably provide a better information quality about the population of interest than big data analyses.

Substituting a random sample by gathering as much data as possible ("N = all") – according to the concept of Mayer-Schönberger and Cukier (2013) – is also controversial. There are many populations where small fractions, if they have no representatives in the sample, may seriously affect inference. Even as much as 99 % of a population covered in the survey may not be sufficient to make reliable statements about some variables.

The slogan "We are the 99 %" of the Occupy Wall Street movement refers to one of these variables - the global wealth (and distribution of family wealth in the USA). According to Credit Suisse the top 1 % of the adult wealth holders worldwide own more than half of the global wealth. If a researcher fails to cover the richest one per cent of the population, his estimates related to the world's wealth will certainly be inadequate.

Another example relates to the problem of insufficient information from a large proportion of regional constituencies (polling districts) for making inference about the final outcome of the national election. Some people have experienced deep disappointment when the results from 80 % or 90 % of local constituencies announced during the night following the election day turned out to be essentially different from the final outcome. A small number of large polling districts influenced substantially the results from 90 % smaller districts. Therefore, if one allows absence of a small but sensitive proportion of observations, then even a large amount of available data will possibly not cover the lack of information about the variables of interest.

Entering big data in the areas previously occupied by statistical surveys and opinion polls does not have to be viewed in terms of mutual competition between the two approaches. Big data and the traditional sample surveys seem to be complementary rather than competitive. Big data resources and techniques, including artificial inteligence may effectively complement sample data. But the question, how this can be achieved, has lead to intense debates (Blumenthal (2005)).

Some authors go further and try to work out alternative schemes for sampling and new models of social science data acquisition and analysis (for details see Hill et al (2013)). They seek opportunities of implementing new technological developments and taking advantage of more accessible data sources compared with the pre-big data era.

In my opinion, the following two tendencies are likely to develop simultaneously. On the one hand, we should expect proposals of new methods and techniques for using additional information in order to deal with the main problems which are responsible for the poor accuracy of many polls. And on the other hand, combinations of data which may be obtained from social media and internet records will probably change the object which is supposed to answer the questions involved in opinion polls. It may not be a respondent any more, but a growing amount of data which reflect his/her attitudes, behavior patterns and opinions. Big data and new technological devices designed for data mining may become in the near future a reliable source of information sought by pollsters. It is more likely to be an evolutionary process in which new theoretical frameworks will be integrated with practical considerations and experiences, rather than a revolutionary breakthrough.

4 Conclusions

Opinion polls have recently suffered many defeats. In a number of countries they failed to predict election outcomes, and as a consequence were subject to a strong criticism of their methodology and practice. Although all this criticism has not undermined the foundations of statistical inference, it affects the reputation of the science of statistics in general. Therefore, it should not be surprising that many scientists and politicians look forward to new approaches to measuring public opinion. There has been observed an increasing interest in big data, in particular. It is expected that large and up-to-date files of data will be helpful in reducing those parts of the total error which are most difficult to combat. It relates mainly to non-sampling errors, including non-responses and deliberate misreporting by some respondents.

In my opinion, big data offers a great deal of opportunities for enriching information about voters opinions and attitudes. Unlike in economics where causal effects are of primary concern, in opinion polls which focus on describing and forecasting the population under study the main advantages of big data seem to be obvious. In other words, the measurement of opinions is more connected with statistical learning on the basis of new available information than seeking causal effects. And therefore combinations of various data sources about people's behaviors or opinions, and identified associations should improve the accuracy of opinion polls. It is not, however, a straightforward process.

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