Non-Representative Polling
Mobile User Polling Data for the German Federal Election 2017

Election Forecasting Project

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Abstract

Using online surveys to forecast election outcomes imposes severe challenges to pollsters. Non-representativ samples and likely-voter bias skew gathered information and require adequate adjustment. This paper sets out to discuss different approaches to adjust a non-representative online polls on the upcoming german federal election and how they can be applied to a poll conducted with mobile phone app users.

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1 Introduction

The digitialization is challenging the way polling was done for many decades. Calling people on their landline phones has become difficult as response rates dropped and households equiped with landline phones are getting less and less (Skibba 2016). In response, polling institutions have resorted to other methods for polling ranging from face-to-face interviews to mobile phone calling. However, these methods either face similar difficulties to ensure representativeness or are too expensive for regular polling. In order to tackle these obstacles, pollsters are increasingly using online polls, including highly non-representative polls (W. Wang et al. 2015).

The eventual aim of pollsters in online as well as traditional polling is to collect sample data that reflects the view of a population of interest. The major difference between both methods is that with most online polls representativeness cannot be ensured before the actual poll takes place. In online surveys respondents are more likely to be from certain age groups or with a particular political background depending on the website where the survey is conducted. Such a non-representative poll can, however, be statistically adjusted (post-stratification) to match the demographic composition of the population.

Additionally, online election polls, like traditional ones, face a another problem. Pollsters are naturally not only interested in the population as such, but in the population of actual voters. By the time a poll is made representative in demographic terms it is still in question whether it reflects the group of people who cast their ballots. This is, however, crucial in order to make an accurate prediction. Traditional polling tries to account for this using likely voter models and could perform fairly well ("Understanding Gallup's Likely Voter Models" 2010, Keeter, Igielnik, and Weisel (2016)). Online surveys will also have to be adjusted to actual voting population in order to provide accurate predictions.

In the paper at hand we want to explore and analyse how different approaches to adjust online polls perform. Our first approach will be a two step procedure where the polling data is first made representative of the population and then likely voter methods are used to resemble the probable voters population. Our second approach attempts to combine both steps into one by post-stratifying the online poll with exit polls and voting statistics from previous elections. For this we work with individual level data from mobile-phone app users who were surveyed on their vote intention in the German federal election 2017. As the ultimate election will only be after the end of research, we use other forecasts of the 2017 federal election as a benchmark.

The structure of the paper is as follows: Chapter two will survey the literature on non-representative polls and approaches to employ such data to forecast elections. Subsequently, we present our data and discuss possible problems with this data set. Afterwards we present the methodology we want to use for adjusting our data at hand.

2 Related Literature

Traditional polling and in particular election polling has relied heavily on telephone surveys for the last decades. To ensure representativeness the standard was randomized digit dialing (RDD). The selection of random respondents was intended to eliminate the sample bias of the survey. However, for several reasons this approach has become unreliable. First, response rates have declined heavily (Keeter et al. 2006; Holbrook, Krosnick, and Pfent 2007). ("Assessing the Representativeness of Public Opinion Surveys" 2012) reported that in the U.S. the response rate was down to 9% in 2012, compared to 36% in 1997. This is mainly a result of technical changes like the possible identification of caller. As a result polls have a tremendious non-response bias which cannot be handled with classical approaches anymore. Second, more and more people don't get landlines telephones after moving to new places or just give them up as mobile phone and other means of communication have increasingly become popular. This induces a sample bias which the RDD approach intended to eliminate. Hence, classical representive polling is becoming less reliable and this trend will rather continue than cease. Unsurprisingly, missing the representativeness of a survey as been identified as a core reason for recent polling failures, e.g. in the UK General elections 2015 (Mellon and Prosser 2015).

Can non-representative polls like online polls fix this? Since the famously failure of Literature Digest poll in 1936 U.S. presidential election, pollsters have been sceptical of non-representative polling (Squire 1988, Goel, Obeng, and Rothschild (2017)). This scepticism is still shared among many pollsters. Yeager et al. (2011), for example, argue that phone surveys are still more accurate then online polls. However, they only employ simple correction approaches.

W. Wang et al. (2015) in contrast are much more optimist about the possiblities of non-representative polling. They used polling results from XBox users which were highly unrepresentative of the population to forecast the 2012 U.S. presidential elections. By employing a sophisticated multi-stage approach to stratify and calibrate the data they were able to generate accurate forecasts of the elections. However, they their methodology relied on a huge data set. But Goel, Obeng, and Rothschild (2017) argued that smaller non-representative online surveys can also be accurate. They conducted polls on Amazon Mechanical Turk and a mobile phone app and achieved a level of accuracy sufficient for most applications. Their work shows that online survey can be used in a meaningful way, if appropiate methods are used to stratify and calibrate the non-representative data.

3 Data and Potential Biases

3.1 Europulse Survey

In this paper we are using data from Dalia Research, an online polling firm who is conducting market and opinion research through smartphones exclusively. To ensure to collect data from a broad variety of target populations Dalia is using a diverse set of app and website categories such as sports, news, entertainment or games. To control how serious participants answer the survey an algorithms analyses the consistency and the response behaviour and computes a "trust score" to every respondent. Dalia praises its methodology as distinctively accounting for potential biases such as interviewer effect, social desirability bias or interviewer data entry errors. (Dalia Research 2016)

Our forecasting project utilizes data of Dalia Research's Europulse Survey which is conducted quarterly in all EU countries. The survey consists of seven waves, but for this project we only use two waves of the survey from December 2016 and March 2017. The first wave is freely available on Kaggle, the second wave was provided to us directly by Dalia Research. Each wave consists of about 11000 individuals, of which roughly 1900 were from Germany which is the fraction of respondents we will focus on in the following analysis. The data is already pre-stratified by Dalia Research based on micro zensus data for age and gender.

The Europulse data is not particularly collected for election forecasting purposes but contains data on a variety of questions such as online behaviour, media consumption and personal views on political and societal development in the European Union and the country of origin. Moreover, the survey contains information on the respondents personal background, demographic data and his or her financial situation. These data can be utilized in order to improve the representativeness of the survey through weighting. This will be explained more detailed in Chapter four.

The variables collected in Europulse to use the data for election forecasting are similar to traditional polling questions. First of all respondents are asked if and for which party they will vote in the upcoming election and for which party they voted in the previous election. Moreover, they are asked on the level of agreement with several political parties and the degree of certainty to cast a ballot, overall and for a particular party.

3.2 Potential Sources of Bias

As with all surveys there are several sources of potential bias included in the methodology used by Dalia Research. Several of such issues that come from flawed measurement or representation of the surveyed population are listed in the figure below (Groves et al. 2009).

With regard to measuring voters intention to vote for a particular party, Europulse uses a similar

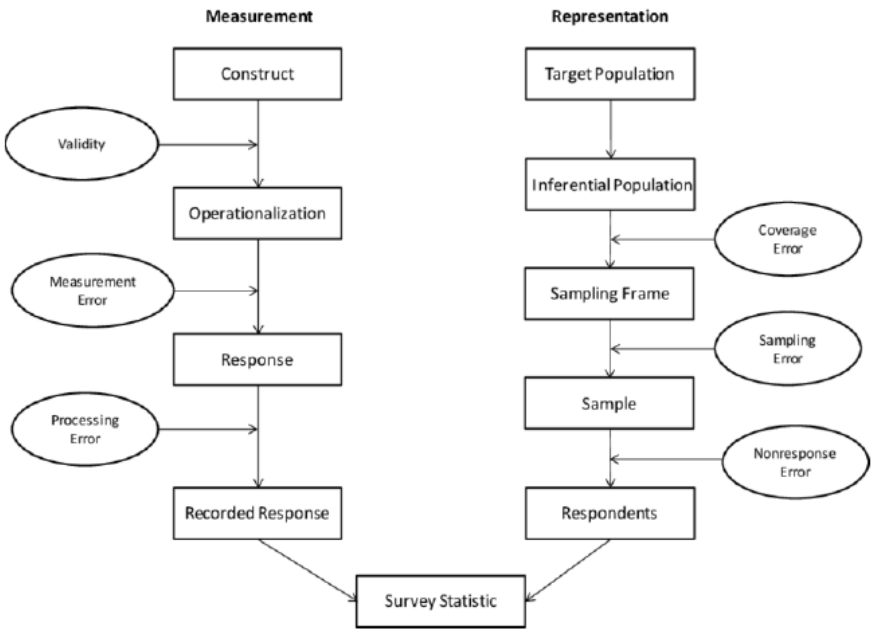


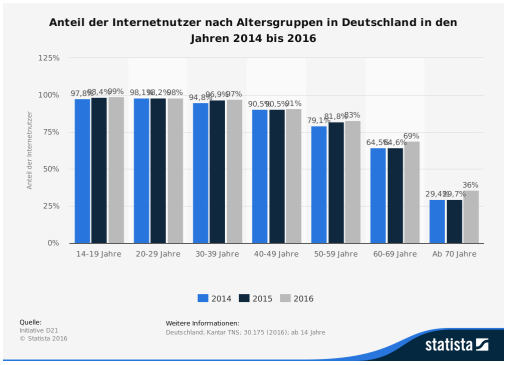
Figure 1: Potential sources of survey error

approach as traditional surveys. As such it asks directly which party a respondent intents to vote for at the upcoming election. Whether such questions measure correctly the actual voting behaviour at the election day is questionable but the approach does not differ from other polling methods to ensure validity. Moreover, online surveys such as Europulse can reasonably claim to avoid other sources of measurement error such as social desirability bias or interviewer bias. Since such surveys are often anonymous social pressure on the respondent is smaller and interaction with the interviewer can not bias the respond.

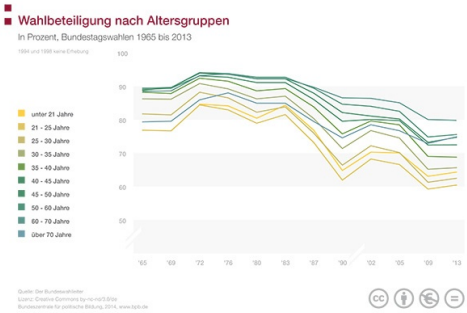
Regarding representativeness the Europulse survey is exposed to issues that face-to-face or RDD interviews do not have. First of all, Europulse' framework does not select participants completely random but offers visitors of certain websites or app-users the opportunity to participate the survey. This approach carries various risk to representativeness. With regards to population-coverage the entire group of users across all survey plattforms should be representative to the German population. However, this ist likely not to be the case for Europulse. Since online users in general tend to be younger than the German average while the voting population is older than average the Europulse sample is likely to be strongly biased with regards to the voting population.

In addition, through self-selection the sample will be most likely be biased towards the sub-sample of the plattform users that is more prone to surveys in general, e.g. people with higher education or scientific interest. [Source?]

Dalia Research tries to account for such problems using a two-step approach. Using the self-reported demographic information they stratify their sample for different age groups and gender in



(a) Internet usage by age



(b) Voter turnout by age

order to render it representative for the German population. In a second step they use data from the German Census an compute weights for combined cluster of age, gender, education and whether the respondent lives in an urban or rural area. These weights can finally be used to post-stratify the sample to match the demographic composition of the population.

Despite these efforts it is questionable if the data can match scientific standards of representativeness. Most important, since it is not conducted particularly as an election poll, it is likely to come with several other biases such as likely voter bias or late swing. (Mellon and Prosser 2015) Hence, in order to utilize the data to election forecasting further weighting and post-stratification will be conducted. Different methods to do so and their technical details will be explained in the following.

3.3 Data for Post-stratification and Weighting

The data used for post-stratification and weighting come from several sources. To adjust our sample to demographic composition of the German population we use data of the German Zensus 2011. The data is freely available and we obtained combined frequencies for characteristics such as age, gender, education, employment status and confession. The Census claims to reflect the actual demgraphic distibution of the German population and hence is suitable in order to post-stratify our sample to demographic criteria.

Furthermore, we collected data from election polls conducted by Forschungsgruppe Wahlen e.V., Infratest dimap and from the official German election statistics (Neu 2013). While the latter contains only information on turnout and the demographic dimensions age and gender, Forschungsgruppe Wahlen e.V. has also issued election results and turnout along groups with different education, different employment status and confession. Such data the closes estimate of the actual voting population and their voting behaviour across demographic groups and across the spectrum of political parties. We will employ such data to account for likely voter bias in the Europulse data at hand.

DIESE GRAFIKEN NOCH TEXTLICH EINBAUEN

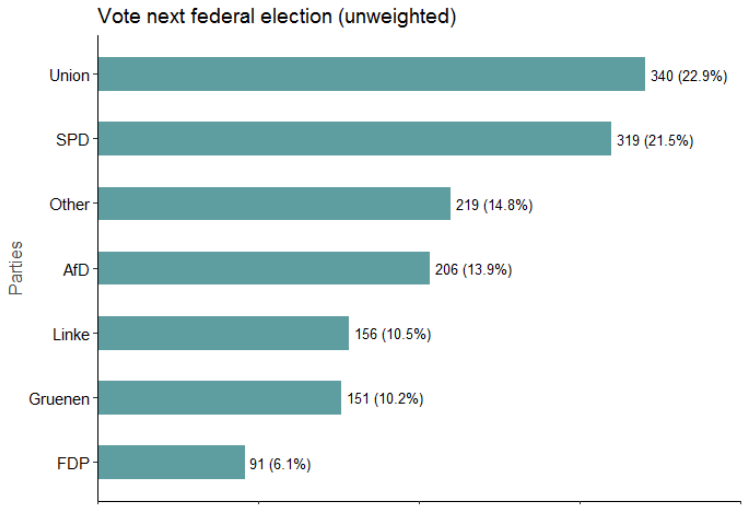


Figure 2: Federal election 2017 vote intent (Unweighted Europulse)

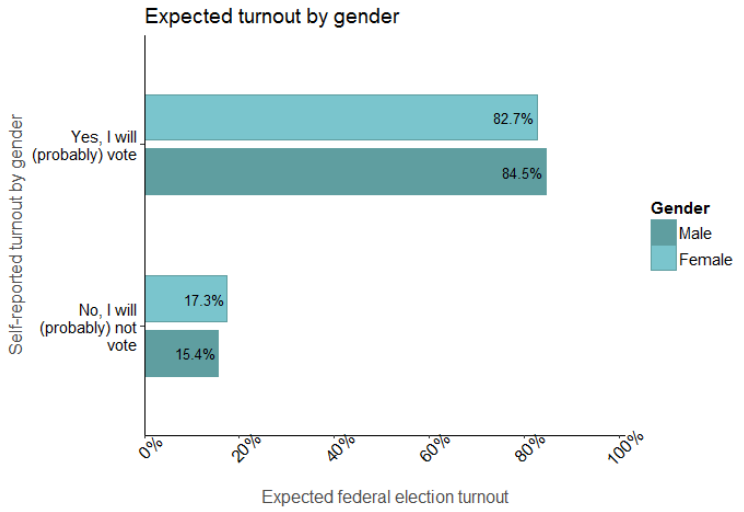


Figure 3: Self-reported turnout (Unweighted Europulse)

4 Methodology

We want to employ two approaches generate election forecasts from the data we have. In the first approach the survey data is adjusted in a two step procedure: First, the representativeness of survey data is increased by finding appropiate weights. Then a likely voting model is used to get to the election forecast. Our second approach does this in one step: The survey data will be directly adjusted to the likely voter population based on exit poll data from the last German federal election.

In order to follow both procedures, we need methods to compute weights for sub-groups of the survey sample aiming at increased representativeness. A classical way to get these weights is *raking*.

With raking weights are assigned to each respondent in order to match the marginal distribution of characteristics in the 'true' population. For example, if we know the distribution of education level and employment status in the population, for each we can compute a weight so that the weighted survey sample has the same distribution of these characteristics as the 'true' population. Basically, raking computes a joint distributions for each combination of characteristics.

In formal terms, we can describe each combination of an individual and a characteristic with $x_{i,j} \in \{0, 1\}$ where i stands for the individual and j for the characteristic. To illustrate, if $x_{i,j} = 1$ an individual may be female and if $x_{i,j} = 0$ an individual is not female. Hence, each characteristic is modeled with a binary variable. c_j expresses the prevailance of a characteristic in the population and raking estimates the weights w_i such that:

$$c_j = \frac{\sum_{i=1}^{n} w_i x_{i,j}}{\sum_{i=1}^{n} w_i} \forall j \tag{1}$$

The weights can than be used to compute the raking estimates for each observation in the survey y:

$$\hat{y}^{rake} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

However, raking is not ideal. It is often used if only marginal probabilities are available. This is also the case for some of our data. However, if the joint distribution of characteristics is known we can use *post-stratification* instead. In contrast to raking, post stratification takes into account the distribution of combination of characteristics in the population. In other words: It sub-divides the population into stratas for each combination Unfortunately, publically available data often only includes the distribution of pairs of characteristics or in rare cases triples (e.g. age, gender and past vote). Ideally, we would like to know the distribution of the population for each strata (combination of the characteristics).

Formally the post-stratification estimator can be expressed as follows (Goel, Obeng, and Rothschild 2017):

$$y^{post} = \frac{\sum_{j=1}^{J} N_J \hat{y}_j}{\sum_{j=1}^{J} N_J} \tag{3}$$

where $\hat{y}^{post}$ is the estimator of y in the strata j and N_J the size of the j-th strata in the population. But even if the size of N_J is known for each strata, the number of strata's grows exponentially with each characteristic included. If we use for instance two gender categories and four age groups we have eight stratas, if we add past vote (7 categories) we have immediately 54. As a result we might only have a few individuals for each strata or even none. Hence, a few respondents in the strata female, old (60+) and FDP voter in 2013 will have an overproproportional influence on the strata estimate.

If possible, we might use *model-based post-stratification* to counter this effect. In this approach the estimates for each strata are not based on the average in the strata, but the result of a multinomial logistic regression. In order to arrive at this regression results, demographic variables in the sample can be used. In order to execute this we will orient ourself at the work of Goel, Obeng, and Rothschild (2017).[1] The larger question here is, whether it makes any sense at all to use model-based post-stratification if we only have the strata size for triples at best.

4.1 Approach number one

For stratifying the data we orient ourself at the work of XXX. The basic idea is to compute clusters of voters along several demographic categories and use their past votes to compute weights.

First, if possible we use post-stratification (see Lumpley, ch. 7?) to compute weights for subgroups in the sample. Post-stratification tries to make a sample representative of the actual population by ensuring the relative size of subgroup resembles the relative size of the same subgroup in the 'true' population. For forecasting the 'true' population is not known, as it is a question of who will actually turn out to vote.

How we plan to make poll representative

Compare different stratification approaches

Likely problems we will encounter: 1. empthy clusters or clusters with low number of observations. Implications: If empthy, there is a real problem. If the number of observation is low, e.g. below 20, the weigths will will amplify the impact of this small group in the total forecasting result.

Benchmark -> other publically available polls. This is straight-forward, but also problematic as it might induce a herding effect. The final evaluation is only possibe after the election

4.2 Approach number two

5 Data Overview

how representative our data already is

1. raw data forecast. Compared to other forecastes the data under represents the CDU as well as the SPD. (Verify)
2. Show distribution of respondents on different demographic clusters and compare to zensus / exit polls / election statistics

[1] They are developing an r package for this (postr) and might be willing to share their r script (as they already anounced to make ot public).

3. Raw (voted last election)

6 Results

What the result is of making it representative

1. Election forecast Weighted with exit polls
2. Election forecast weighted with election statics
3. Election forecast weighted with zensus

Compare the three different weighten approaches

Comment Moritz: I think we have to weight the data with Zensus data in any case at least for gender and age as long we don't want to use the Dalia weights; then we can either use election statistics or exit poll data (that we don't have)

My approach would be:

1. Weighting with Zensus (accounts for self-selection of the survey)
2. Different mixes of weighting with election statistics with education (accounts for likely voter bias)

7 Conclusion

Summary of the core finding

Further implications

8 References

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