

BUSINESS' PARTICIPANTS MOTIVATION IN OFFICIAL SURVEYS BY FUZZY LOGIC

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Abstract

Business statistics, collected and published by official institutes, are important for policy makers and for businesses in their management decisions. In spite of that, business participation in surveys is decreasing. This causes a decrease in quality of data and increases demands for data imputation procedures, endangering the value of survey based data collection. Improving the motivation of respondents could significantly influence the validity of business survey research. To achieve this, we suggest applying fuzzy logic to both dissemination tools for statistical data and adaptive survey design methods to tailor survey design to the characteristics of businesses.

Adaptive survey designs (ASDs) take into consideration the fact that the impact of various design features varies significantly over respondents. When auxiliary information is available from e.g. registry data, survey designs may be tailored to optimize response rates through strategies designed to enhance motivation. In a crisp classification design businesses or respondents although having similar attribute values, may be classified into different classes and therefore receive different treatments. Applying fuzzy logic to an ASD may lead to a more robust and effective classification when aiming at improving unit and item response and decreasing measurement error through the stimulation of motivation.

Statistical institutes provide data on their data portals. However, data users typically find it hard to distill the relevant data and information on these websites, which could demotivate them to cooperate in surveys. Therefore, in dissemination we should include methods capable of processing imprecise queries and methods for mining rules in the data.

Keywords: Data collection, data dissemination, motivation, fuzzy logic

Introduction

Business statistics produced by National Statistical Institutes (NSIs) are very important for public policy making decisions but also for management decisions of businesses and other organizations. A significant part of the data necessary for these statistics is surveyed from business respondents. Participation of businesses in surveys, however, has been decreasing. This is a danger to survey-based data collection as it causes decreased quality of statistical data and increases demands for data imputation procedures. To ensure the quality of business survey research, improving the motivation of respondents to respond timely and accurately seems necessary (Torres van Grinsven et al., 2011, 2012).

The Generic Statistical Business Process Model (Vale, 2010) describes all required steps in data production in official statistics. Focusing on respondents' motivation, two parts are of main interest: data collection (survey design) and data dissemination. Respondents have to respond to many surveys but on the other hand often are not able to easily find relevant data on NSI websites. As a consequence "some businesses choose not to react to survey

requests (a problem of non-response) or invest insufficient effort (a problem of measurement error)” (Bavdaž et al, 2011, p. 7).

Tailoring business survey design could enhance response rates and survey quality as opposed to uniform design for all businesses (see e.g. Snijkers et al, 2013). In order to create a tailored survey design we should adopt an approach that is robust and ensures that similar respondents are always similarly treated. Businesses in a data user role cope with issues of how to find relevant data and information (Bavdaž et al, 2011). Therefore, they could prefer an intelligent data dissemination and mining tool capable of dealing with imprecise questions about the data and providing answers (data and mined information) in a useful and understandable way (Hudec, 2011; Kacprzyk and Zadrozny, 2009).

In both fields fuzzy logic (Zadeh, 1965) is a rational option that could provide the solution. The fuzzy logic works with overlapping sets, partial membership degrees and linguistic terms. It means that we could use fuzzy logic in classification of respondents and for example the creation of reminders for a tailored design; and on the other hand also for querying data on websites for dissemination (Hudec et al, 2012; Hudec, 2013a).

This paper discusses issues and perspectives of improving respondents’ motivation by fuzzy logic. The next section depicts the relation between respondents and the NSI. Following two sections are devoted to motivation in data collection and motivation of data users in the data dissemination part of statistical data production. Finally, concluding remarks are drawn in the last section.

Respondents and NSIs

“We find that a paradox is steadily developing in a rapidly changing world, in that statistical users are becoming ever more demanding for timely data, but are less willing to provide their own data to statistical institutes” (Ross, 2009, p. 6). The paradox presumably appeared from the fact that respondents have to cooperate in many official surveys but they often are not able to easily find relevant data or mine relevant information from databases exposed on NSI data portals. Besides, businesses would like to avoid any activity which seems to be less relevant or do not bring expected benefit for them like sending the same or similar data to different recipients (Erikson et al, 2012). This is not surprising having in mind the pressures on productivity and rational use of resources. As a consequence businesses either choose not to react to survey requests or invest insufficient effort to fulfil questionnaires (Bavdaž et al. 2011). This is depicted in Figure 1.

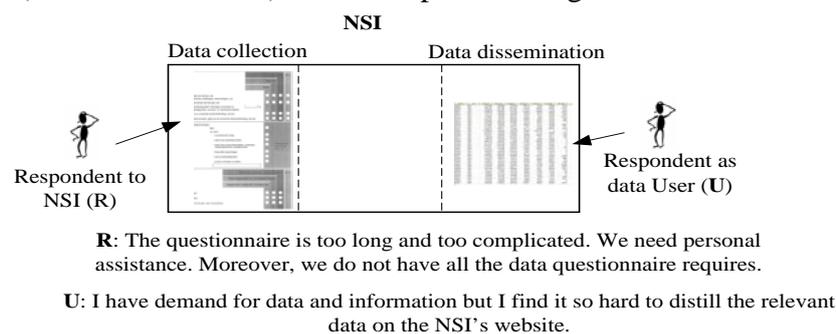


Figure 1: Statistical users

We would like to suggest ways for solving issues depicted in Figure 1. Analysing the consideration of respondent (R) we presume that the solution could be dividing respondents to groups and adapting surveys to each group. Adaptive survey designs (ASD) bring considerable advantage to the field of designing surveys by taking into consideration the fact that the impact of various design features varies significantly over respondents (Calinescu and Schouten, 2012). Adaptive survey designs (ASDs) have been introduced in Wagner (2008) and Schouten et al. (2011). ASDs have the potential to deliver a higher quality of survey

response than traditional survey designs that overlook this aspect (Calinescu and Schouten, 2012). In research on ASDs up to now sharp classification is used. In such a design thus respondents although having similar attribute values, may be classified into different classes and therefore receive different treatments.

Analysing the reasoning of data user (U) we could conclude that data dissemination by NSI data portals is a significant element for motivation to work with statistical data either in a positive or negative way (Hudec et al. 2012). If a data portal is well designed and users can easily find relevant data and information, they will be more motivated to provide their own data. Users want either raw data (large businesses) or extracted rules from data and information (small businesses) (Bavdaž et al., 2011). It is assumed that if we provide businesses not only with data but also information with meaning using appropriate data mining tools inspired by a human way of reasoning, they will be more satisfied and willing to provide their own data.

Linguistic terms used in fuzzy logic computations describe respondents and at the same time include a certain vagueness or uncertainty that crisp (sharp) procedures based on two-valued logic {true, false} do not understand and therefore cannot use (Galindo et al, 2006). In the crisp classification, an entity is selected or not, a rule is valid or not and objects belong only to one class. This might cause that respondents which contain similar values of analysed attributes are improperly ranked or classified. Certain respondents will fall out of the class where they should be. For example, we might set a certain date as the limit to respond in time. Every respondent that responded before that date will be classified to respond in time; yet respondents that respond just the day before that date, might have more similarities with a respondent that responds the day after than with a respondent that was also in time but responded two weeks before the deadline. Therefore, we could have a wrong impression of the attitude of the respondents (Křůčik et al, 2012).

Fuzzy set theory provides a framework for systematically handling the described vagueness (fuzziness). The vagueness and uncertainty discussed in this paper is not based on randomness; it cannot be presented as a crisp (sharp) value (Zimmermann, 2001). Main advantages to use fuzzy logic are discussed in Dubois and Prade (1997) and advocated in Kacprzyk and Zadrozny (2001). Abdullah et al (2004) emphasized that even though the fuzziness is closely related to phenomena in social sciences, the mathematics of fuzzy logic is mainly applied in engineering and computer science. This trend continues allowing engineering systems to be more and more sophisticated and powerful. We could reach the same level in social sciences if we support some tasks by fuzzy logic.

Motivation in data collection

Data collected by NSIs is important for policy decisions. In order to achieve their institutional tasks, NSIs traditionally perform surveys. The quality of resulting data strongly depends on businesses' cooperation. As Erikson et al. (2012) pointed out, people do not consider surveys as important to society as before and therefore neither so important to participate in. The refusal rates and non-contact rates are rising all over the world. Business respondents often complain about response burden. Besides, they often reject participation in surveys (Giesen, 2011), or pay less attention to the survey task with the consequence of poor quality data (Bavdaž, 2010).

Current state

In survey-based research, the problem is most visible in declining response rates (de Leeuw and de Heer, 2002; Baruch, 1999) that have stabilized at a low level in organization research (Baruch and Holtom, 2008). Businesses increasingly complain about the response burden and often refuse to participate in both voluntary and mandatory surveys (Giesen, 2011). This is not surprising given the huge pressures on productivity and rational use of

resources. Even when they do participate, their attention to the survey task might not be sufficient, which leads to a more covert problem of poor quality of reported data. This increasing reluctance to cooperate endangers survey-based research and raises questions concerning the validity of the results of this line of surveys. When businesses refuse to cooperate, this may result not only in unit non – response (business refuse to reply on survey request), but also in item non- response (respondents do not fill all required fields in forms) and inaccuracy (measurement error - the observational gap between the ideal measurement and the response obtained (Groves et al. 2004)). Experience and research have shown that measurement errors in business surveys may be far from negligible (Bavdaž, 2010).

The extent of this survey error might be most easily evaluated in governmental surveys where recent studies suggest that as much as 30 % (e.g. Adolfsson et al, 2010) of the total survey cost is spent on data editing (imputation). The root cause of this problem seems to lie in its character of being an ‘irritation burden’ (European Commission High Level Group of Independent Stakeholders on Administrative Burdens, 2009), and not in the actual survey burden imposed on businesses that represents only around 0.5 % of the total administrative burden. Recent research suggests that problem of declining response rates and poor data quality indicates that the drive behind behavior – the motivation for the business survey task – is insufficient or lacking (Torres van Grinsven et al, 2012).

Current motivational practices, like reminders and (threats of) fines in the case of non-response, seem to achieve their aim of assuring business survey response (Torres van Grinsven et al, 2012). But there are much more possible ways to enhance motivation of businesses that can be tailored for an adaptive survey design according to a business’ characteristic and which, applied the correct way, might result to be much more effective to promote response rates, item response, timeliness and accuracy.

Torres van Grinsven et al (2011, 2012) have identified sources of motivation that are of importance for the business survey task, which are facets of the broader communication aspects of the survey design. Besides, they suggest that, indeed, motivation is an important factor influencing the survey outcome, and propose which types of motivation should be important for the business survey task (Torres van Grinsven et al, in review process). They suggest that survey outcome reflects the amount of motivation to perform a task through direction, intensity and persistency of the behavior; the higher the motivation: (a) the more favorable initial choices related to the task, (b) the higher amount of effort invested in the task, and (c) the more persistence at the task in the presence of obstacles; and that it depends on these three dimensions whether or not the survey outcome is the desired one: survey response providing timely and accurate data, though the importance of other factors, such as capacity and authority is acknowledged.

Example: As an illustrative example we have created output variable: respondents’ attitude to NSI. For this purpose we have created the following output classes: small, medium, medium high and high. Input consists of one qualitative indicator: Official statistics is frequently used in our business (Q1) and one quantitative indicator: trade value. It is not the same if businesses with small trade value and businesses with high trade do not respond timely and accurately or have a negative image of the NSI. Let’s describe the problem in the following way:

if trade value is small and Q1 is small, our interest in business respondent is small;

if trade value is small and Q1 high, our interest in business respondent is medium;

if trade value is high and Q1 is small, our interest in business respondent is medium high;

if trade value is high and Q1 high our interest in business respondent is high.

Indicator trade value is fuzzified into two fuzzy sets using the uniform domain covering method (Tudorie, 2008) adapted to the case of two fuzzy sets. Indicator Q1 is fuzzified by directly assigning membership degree to all five values.

The obtained solution for selected businesses (extracted from Křůčik et al, 2012) is presented in Table 1. For example respondent 8 is very close to fully meet the condition high relevance for the NSI. This means that some tailored motivation strategy could result in the change of their opinion of using statistical data from value of 4 to value of 5.

Table 1: Some of classified businesses – quantitative and qualitative data

Respondent	Q1	Trade value	$\mu(S)$	$\mu(M)$	$\mu(MH)$	$\mu(H)$	Relevance
1	5	60301	0	0	0	1	0,9
2	5	87555	0	0	0	1	0,9
3	5	58912	0	0	0,0347	0,9653	0,891325
4	5	56777	0	0	0,1422	0,8578	0,86445
5	5	53870	0	0	0,2885	0,7115	0,827875
6	5	52097	0	0	0,3778	0,6222	0,80555
7	5	50314	0	0	0,4675	0,5325	0,783125
8	4	66298	0	0,25	0	0,75	0,7625
9	4	60734	0	0,25	0	0,75	0,7625
10	5	45838	0	0	0,6928	0,3072	0,7268
11	5	42216	0	0	0,8751	0,1249	0,681225
12	5	6927	0	0	1	0	0,65
13	5	19747	0	0	1	0	0,65
14	5	34978	0	0	1	0	0,65
15	3	91027	0	0,5	0	0,5	0,625
...							

For example if we want to motivate businesses to actively use statistical data we can offer them some percentage of discounts (if NSIs charge preparing and providing data) according to their importance for NSI (trade value) and their significance as customers. Let respondents belonging to class high receive 9% discount of price for provided data and respondents belonging to class medium high 6.5% discount. In a crisp classification respondent 4 will receive a discount of 6.5% (or 9% depending of classes definitions) although it is closer to the class high than medium high. In our approach we can offer a discount of 8.6% (if the definition of crisp class forced this business to class high then the business is not motivated to improve its relation with NSIs).

Entities with similar values of examined attributes are similarly classified and treated using only four fuzzy rules which are easily readable and modifiable by decision makers in motivation. However, we can use crisp classification but in that case we should create larger number of classes. Therefore, model will not be as easily maintainable and understandable for decision makers in motivation as it is in the case of flexible classification.

Perspectives (Further research and development)

Respondents show a certain response style that may lead to different levels of response errors. On the other hand, this means that ways to enhance respondents' motivation might vary in effectiveness according to different types of respondents. Therefore, a tailored design has the potential to deliver a higher quality of survey response than traditional survey designs that overlook this aspect (Calinescu and Schouten, 2012). In most surveys all sample units receive the same treatment and the same design features apply to all selected people and households. When auxiliary information is available from e.g. registry data, like type of industry or size of the business, survey designs may be tailored to optimize response rates through strategies designed to enhance motivation. In these so called adaptive survey designs thus different people, households or businesses may receive different treatments. Wagner (2008) introduced the term adaptive design, describing the differential survey designs tailored to the characteristics of sample units, using rules specified before data collection. Recently, a tailored adaptive design was compared with a standard uniform survey design in an

experimental setting by Statistics Netherlands for a household survey (Luiten and Schouten, 2013). This tailored design was directed towards the improvement of the representativeness. The results showed that the tailored fieldwork strategy was successful in maintaining the level of response, while significantly augmenting representativeness

We propose such a differential fieldwork strategy, trying to maintain survey response at a level necessary for precise survey estimates (Schouten, 2010), yet aimed at maximizing motivation and using fuzzy logic for classification and ranking. The intention of maximizing motivation is increasing the overall quality of the survey response. Representativeness, as measured in Luiten and Schouten's (2013) experiment is one possible way of measuring this quality.

Applying fuzzy logic to a classification and ranking to support an adaptive survey design, might lead to more robust and effective design when aiming at improving unit and item response and decreasing measurement error. Fuzzy logic allows us to examine "levels of grey" like the degree of matching of a selection condition, the extent to which a rule is satisfied, and the inclusion of objects to several overlapping classes with different matching degrees. In addition, including logical structures into an aggregation function significantly improves respondents' evaluation, ranking and classification. Fuzzy logic approach is able to classify respondents using several kinds of valuable data at the same time (quantitative, categorical and even textual). It ensures that respondents with similar values are always similarly treated. Concerning realization, respondents belong to groups for an adaptive design with certain intensity. This intensity could be used to ensure that similar respondents are similarly treated.

Motivation by fuzzy logic was examined in the customer relationship management (Meier et al, 2005; Werro et al, 2005) to motivate customers by robust and easy to use fuzzy classification. However, up to now no research was focused on respondent motivation by fuzzy logic in official statistics data collection. Our goal is among others to integrate ideas and results from static flexible classification (Werro et al, 2005), dynamic flexible data classification by fuzzy queries (Hudec and Vujošević, 2012) and improve fuzzy logic approach by real sets (Radojević, 2008), and to apply them on adaptive survey designs. All these approaches could bring robust, easy to use, and logically consistent approach for solving issue recognized in ASDs.

Motivation in data dissemination

Statistical institutes have created large amounts of data that contain knowledge potentially valuable for businesses. However, business data users are not always interested in sheets of figures, but they also search for information like relational knowledge in the data that is usually shaded by large amounts of data sets. Data with meaning could be more useful than pure data.

Current state

In this field several approaches have been suggested for improving dissemination in different ways such as WEB 2.0 (Smith, 2011) or presenting selected indicators in tables and maps (Jern et al., 2011). The eye tracking method (Wulff, 2007) can evaluate users' habits and reveal if it is difficult for users to navigate to relevant information and how to improve the design of portals. Although all these approaches significantly improve data dissemination capabilities of NSIs, data dissemination in a way which mimics human approximate reasoning (without precise measurement but very powerful tool) is still missing.

As was mentioned above data users (businesses) search for (raw) data or extract rules (relations, dependencies, summaries) from data. For example, business wants to obtain available data for municipalities that have *small pollution, medium altitude and high unemployment*. The suitable answer is list of municipalities ranked downward according to

the degree of satisfying this condition. As an example for extracting rules, let's have business that wants to know to which degree rule *most of municipalities with high altitude above sea level have low gas consumption* is satisfied. Rule checks assumption that these municipalities mainly use other sources for heating. Moreover, the meaning of query or rule for mining information is expressed by linguistic terms, in a way understandable at the first glance.

Imprecise queries for data and information cannot be straightforwardly converted into numeric constraints. Therefore we should create bridge between users and databases. Concerning the first user demand, fuzzy queries (based on fuzzy logic) is option which offers the solution (Hudec, 2013a). Regarding the second user demand, recent development in linguistic summaries which are based on fuzzy logic is promising (e.g. Hudec, 2013b; Kacprzyk and Zadrozny, 2009).

Example: User wants to know whether each region is more hilly or flat. This question is expressed by the linguistic *summary most of municipalities have small attitude above sea level*. The result for all eight regions of the Slovak Republic is presented in Table 2 ranked downwards starting with region having the highest value of the rule validity (flatness of region). We see for example that region Trenčín is more flat than hilly. The same holds for region Košice but it is a slightly hillier than region Trenčín. The first advantage in this case is keeping data that are not free of charge or sensitive hidden from users. In the example only mined information for each region calculated from municipal data is presented. No data of municipalities (used in calculation of rule's validity) is revealed to user.

Table 2: Validity of the rule expressed by linguistic summary for each region

Region	Validity of the linguistic summary
Bratislava	1
Trnava	1
Nitra	1
<i>Trenčín</i>	<i>0.7719</i>
<i>Košice</i>	<i>0.6314</i>
<i>Bánska Bystrica</i>	<i>0.2116</i>
<u>Žilina</u>	<u>0</u>
<u>Prešov</u>	<u>0</u>

Further, a linguistic summary could expose a ranking of areas with most large businesses in a certain industry or countries of most frequent exports. The rule is: *export by countries has high number of reports*. Table 3 shows most frequent export countries obtained from the Slovak Intra-EU trade database (Křůčik et al, 2012). When policy makers, businesses, etc. are not interested in data but in aggregated information, then linguistic summaries are the solution.

Table 3: Countries with high number of reports

Country	High number of reported trade
AT	1
CZ	1
DE	1
HU	1
PL	1
<i>FR</i>	<i>0,9533</i>
<i>IT</i>	<i>0,777</i>
<i>RO</i>	<i>0,3277</i>
<i>SI</i>	<i>0,1222</i>
<i>NL</i>	<i>0,0449</i>
<i>GB</i>	<i>0,0394</i>
<i>BE</i>	<i>0,0137</i>

Perspectives (Further research and development)

Mathematically, relevant equations which support flexible data queries and rule extraction are created and explained in many papers e.g. (Hudec 2009; Kacprzyk and Zadrozny, 2009; Werro et al, 20005). Nevertheless, research in fuzzy logic continues to examine further issues in theory and limitations for application e.g. (Radojević, 2008; Radojević, 2013). The next step is creation of full web applications. It is task for experts in fuzzy logic; design of web application and in motivation. Although fuzzy logic has proved its advantages, surveys among key data users among businesses about their needs and tailored advertisement of new approach is required.

It is obvious that processing flexible queries introduces additional computation burden due to the additional amount of calculations concerning data and information retrieval (Kacprzyk et al, 2000). On the other hand, this additional amount of calculations is balanced with additional valuable information mined from a database in a way that is more suitable for data users.

Having in mind computational burden and respondents' motivation, one possible solution is restricted access to flexible data dissemination according to the level of the users' cooperation as respondents. Full access could be offered only for respondents which fully cooperate in surveys. Partial access could be offered to respondents which have small delay or several non-responded data. No access for respondents which are far to meet requirements of NSIs. Anyway, demo version should be offered for all respondents. It will be interesting to calculate the influence of flexible and human oriented data dissemination to respondents' willingness to cooperate in mandatory and voluntary surveys.

Conclusion

Business respondents play the pivotal role in data collection and are key users of aggregated statistical data in data dissemination. Therefore, efforts in improving respondents' motivation by fuzzy logic could convey benefits for both sides. Respondents will work in a more human oriented way, tailored to their characteristics and wishes, in searching for relevant data and rules, and in filling questionnaires and therefore, will be more motivated to cooperate in surveys. For NSIs it means collection of data of better quality reducing the computation burden focused on managing reminders and data imputation. This is especially important in continuously tightening of budgetary constraints. Merging social sciences with fuzzy logic and information science could considerably improve the quality of statistical data.

In dissemination the solution capable of giving answers to imprecise queries and questions related to statistical data is a way for increasing motivation to explore data produced by NSIs. In flexible queries selected entities are ranked downwards from the best to the worst. Linguistic summaries answer questions related to data and keep data that are not free of charges or sensitive hidden. Fuzzy logic can solve more user demands and therefore improve the image of NSIs as data providers.

In data collection, fuzzy logic can help identifying key respondents using several criteria at the same time (quantitative, textual, and categorical) and ensure that similar respondents are always similarly treated in a tailored or adaptive survey design. Flexible sets with overlapping boundaries are a framework for preparing adaptive survey designs and therefore create motivation tailored to each group of respondents.

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