



Good will hunting. Predicting response quality using motivation in longitudinal surveys

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► To cite this version:

Valentin Brunel, Jean-Baptiste Portelli. Good will hunting. Predicting response quality using motivation in longitudinal surveys. European Survey Research Association, Jul 2019, Zagreb, Croatia. hal-02874071

HAL Id: hal-02874071

<https://sciencespo.hal.science/hal-02874071>

Submitted on 18 Jun 2020

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ESRA 2019 :

Good will hunting. Predicting response quality using motivation in longitudinal surveys

Valentin Brunel
Jean-Baptiste Portelli

Introduction

- Declining response rates and quality (Massey and Tourangeau 2013)
- What tools can we use to predict and target those challenges ?
- Motivation : what is it ?

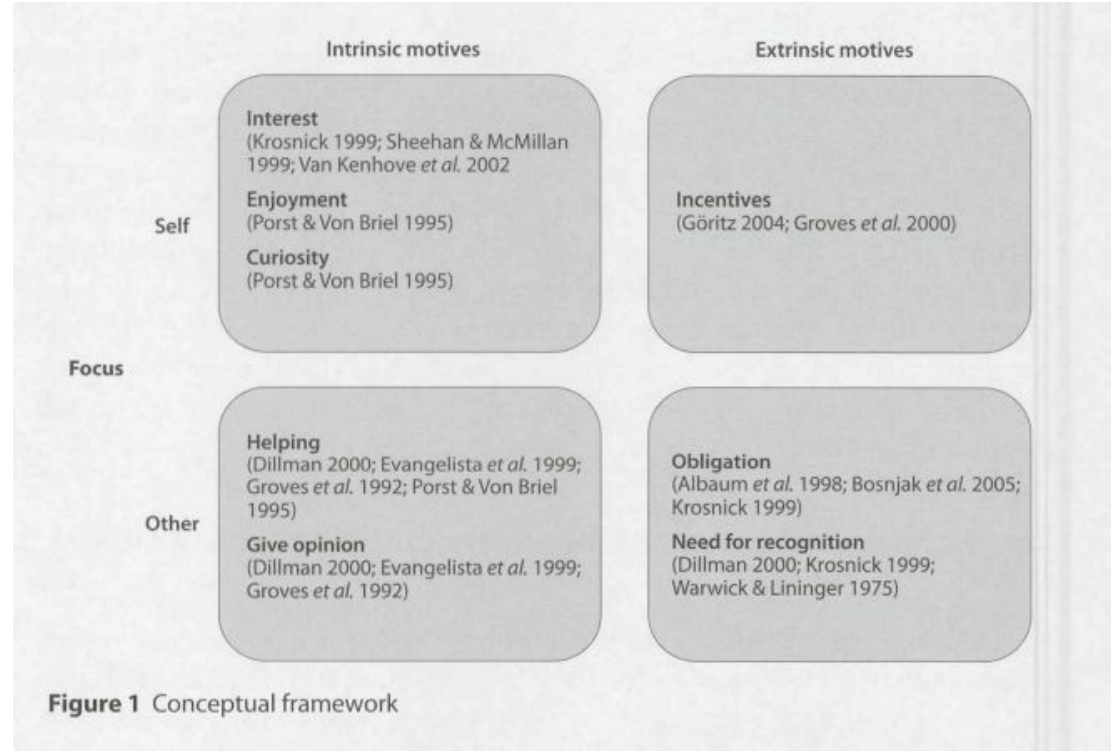
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[Massey Douglas S., Tourangeau Roger. 2013. "Introduction: New Challenges to Social Measurement." The ANNALS of the American Academy of Political and Social Science 645:6–22.](#)

Literature

- Most research on motivation is psychological
- Finding out what are the big drivers or sub-elements of motivation
- The objective in most cases is to maximize motivation

Literature



Elisabeth Bruggen, Martin Wetzels, Niels Schillewaert and Ko de Ruyter, Individual differences in motivation to participate in online panels : The effect on response rate and response quality perceptions, International Journal of Market Research Vol. 53 Issue 3, 2011

Literature

- Most research on motivation is psychological
- Finding out what are the big drivers or sub-elements of motivation
- The objective in most cases is to maximize motivation
- But this is not our case ! We will simply define “motivation” as the reason why people say they participate in a survey (“functionalist approach”, Dillman 2000).

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Dillman, D. A. (2000). Mail and Internet surveys: The tailored design method. New York: Wiley.

What we aim to do

- Find out to what extent motivation can explain data quality and attrition
- Use those results to maximize data quality and minimize attrition

- Plus another, more methodological issue : comparing open-ended questions and close-ended questions in producing an effective and useful classification of reasons to participate

Our data

ELIPSS Panel, two waves :

1. pilot study (2012, 1000 panelists)
2. refreshment (2016, 2500 panelists)

5 years of data : longitudinal vision, commentaries, paradata, full-text, etc.



Our variables

786 variables :

- Questions asked when joining the panel
- Paradata (response status, duration, number partial non-response) for all surveys
- Socio-demographics (each year)
- “Pratiques numériques” questions (each year)
- End-of-survey questions of these surveys : close-ended questions on motivation
- Other

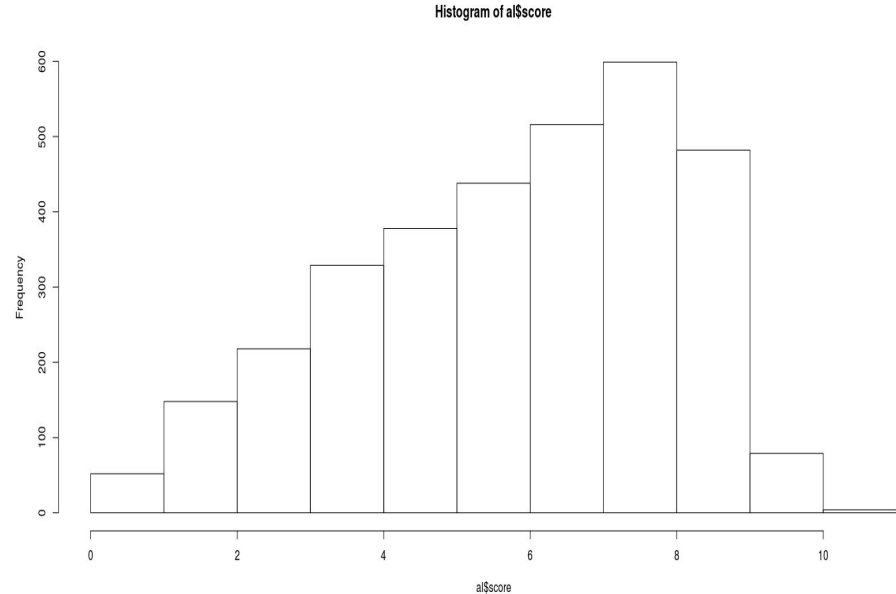
Descriptive statistics

What is motivation and how correlated is it to other variables ?

Descriptive statistics

Score constructed using :

- how much did you hesitate,
- did you subscribe yourself,
- did you check for additional information and where ?



Quali vs Quanti motivation

Other than the “quantitative” motivation score, we used a pair of questions asked to all panelists when entering : what is the reason why you chose to participate? Those questions had 6 possible answers:

- interest for research
- trust in institutions
- incentives (tablets or internet subscriptions)
- project's originality
- other

Quali vs Quanti motivation

Another approach of qualitative motivation : textual analysis. Could you describe your first impressions when hearing about ELIPSS?

First results : very high similarity of vocabulary...

...which makes all analysis difficult.

intéressant	990	adj
projet	621	nom
participer	398	ver
enquête	259	nom
trouver	248	ver
intéresser	243	ver
curiosité	239	nom
curieux	178	adj
tablette	161	nom
donner	149	ver

Quali vs Quanti motivation

However, we used Reinert (Alceste software) method, to identify classes of respondents, based on similarity of vocabulary.

=====

Reinert method :

Descending hierarchical classification, which separates progressively texts depending on their similarity of vocabulary. Texts with the same words will surface in the same class.



impression
simple
particulier

instant
intuitif
favorable
moment
positif
convivial
prononcer
réaction
facilité
accès
sérieuse
familiariser
attente
utilisation
parler
clair
simplicité
répondre
pratique
vraiment
simplement
main
construire
cest
jour

curiosité

intérêt
étonnement
méfiance
susciter
enthousiasme
questionnement
structure
expérience
sympathique
appréhension
envie
peur
motiver
interrogation
satisfaction
inconnu
étudier
ressentir
possible
information
émaner
tenir
sociétés
privé
panelistes
paneliste
ordre
opération
futur

curieux
intéresser
surprendre
surprise

étonner
sélectionner
intriguer
arnaquer
premier
méfiant
choisir
courrier
départ
agréablement
enquête
dépouvrir
présenter
demander
sceptique
connaître
commencer
tirer
domicile
sortir
rassurer
renseigner
réticent
renouveler

donner
avis
opinion
permettre
société
sujet
participer
chose
recherche
aimer
avancer
apporter
exprimer
français
répondre
social
étude
aider
enquête
population
important
partie
panel
sentir
heureux
sondage
tablette

intéressant

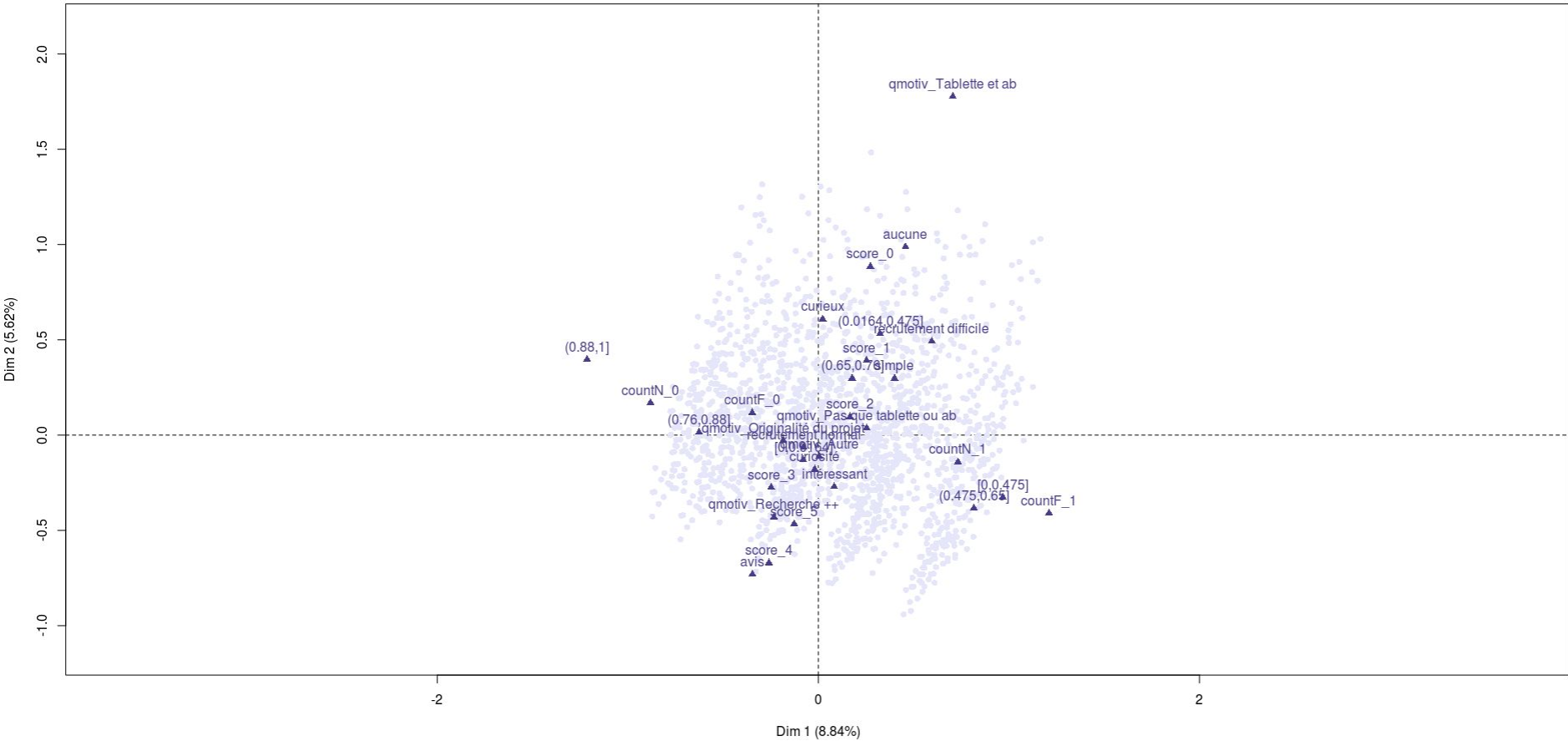
projet
sérieux
trouver
utile
air
sembler
paraître
innovant
enrichissant
po
contraignant
onrs
avenir
motivant
instructif
ambitieux
organisme
long
participatif
atrayant
suivre
pratique
amusant
organiser
étonnant
ca
terme
programme
attractif

Approaching motivation through all dimensions

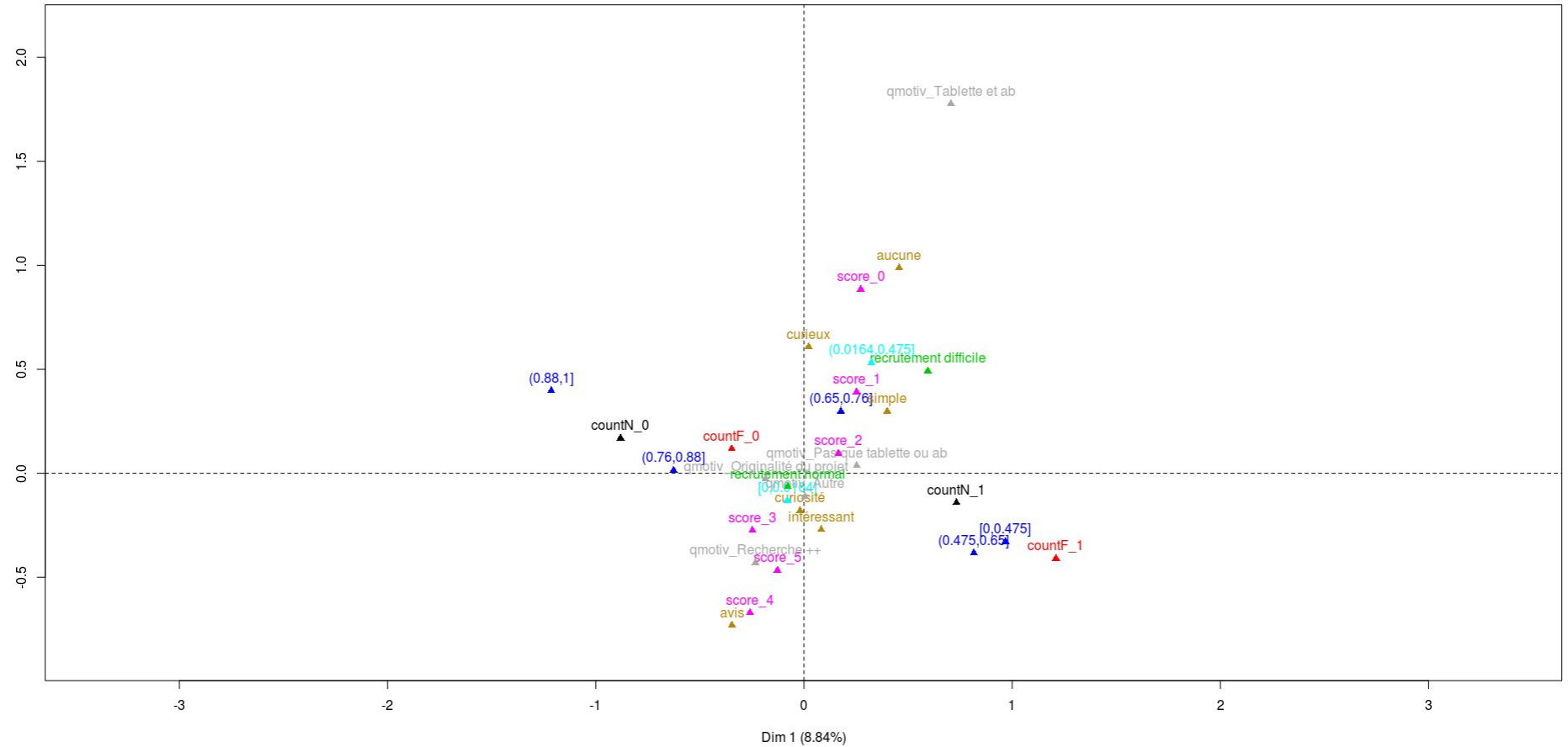
Using a MCA

- close-ended answers on motivation
- textual analysis categories
- quantitative score
- having not answered surveys
- having started but not finished surveys
- difficulty of recruitment
- proportion of over-time survey answering
- proportion of item non-response in main surveys

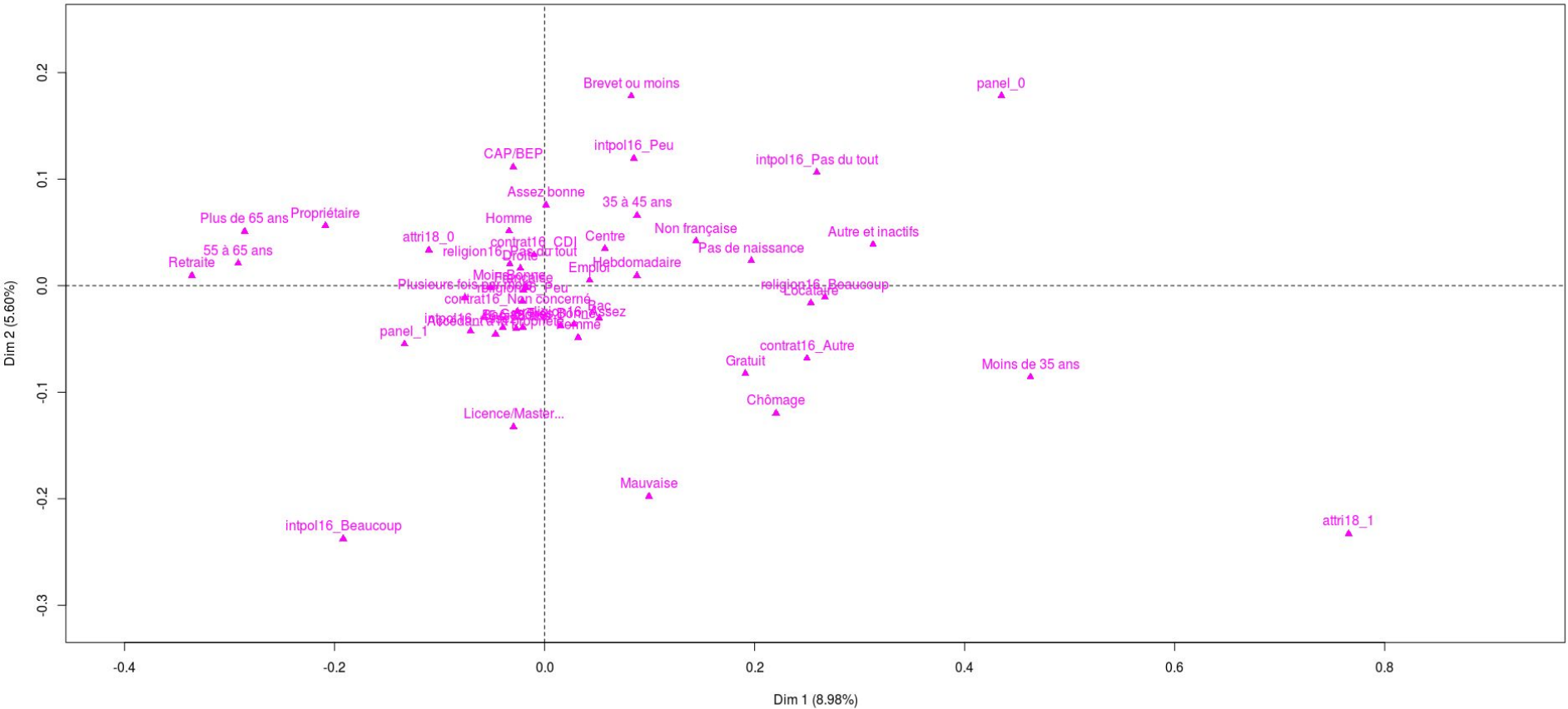
Graphe de l'ACM



Graphe de l'ACM



Graphe de l'ACM



Approaching motivation via different dimensions

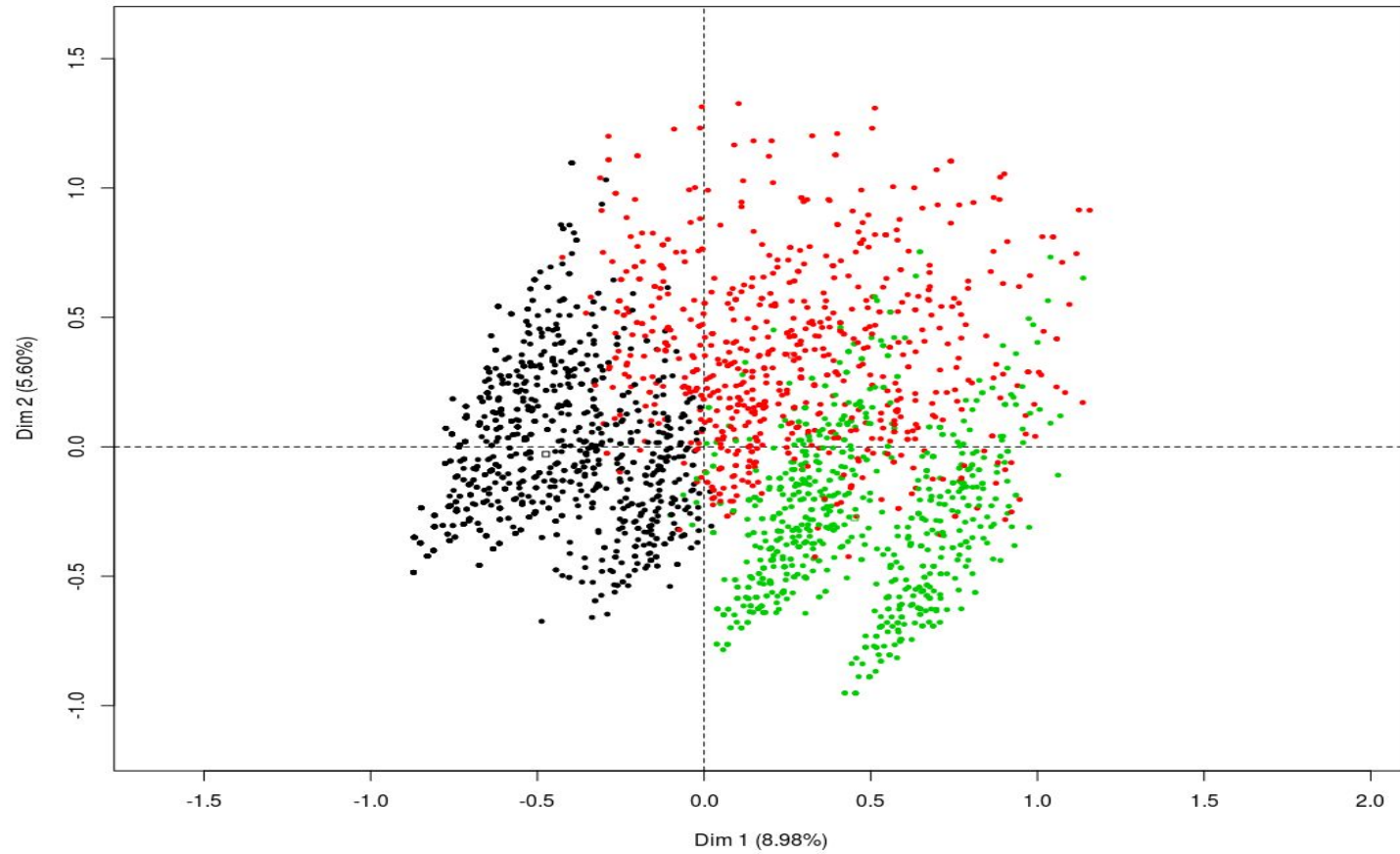
The main result is the opposition between subjective motivation and objective measures of motivation.

The MCA seems to oppose 3 groups of people : clockwise, starting from top left :

- good-willing panelists
- hard-to-reach, not too interested from the start
- unconcerned, non respondents

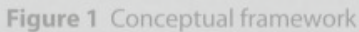
The first axis is motivation enduring in time, the second motivation during recruitment.

Plan factoriel



Approaching motivation via different dimensions

One could here find other dimensions noted in the literature : extrinsic self (incentives), extrinsic other (recherche), intrinsic other (give opinion), intrinsic self (interest, curiosity).



A statistical model to predict non response

- Model to predict attrition under-performed (16.5% bar of well-classed panelists)
- Thus we turned towards predicting non-response to at least one survey as our variable of interest.

Our model

Variables selected :

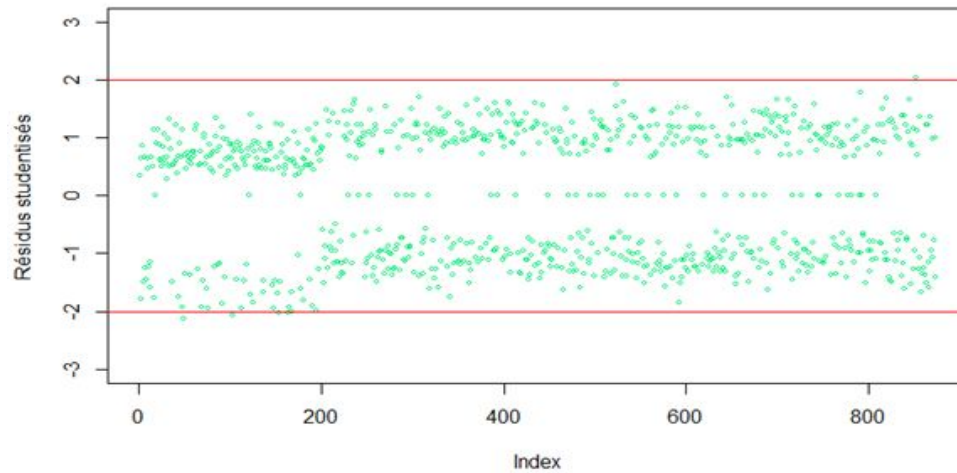
- durationsum2_cl: response time to an inquiry
- ea16_A2A_REC_cl)): age divided in 5 slices
- housing16: occupancy status of the dwelling (owner or tenant)
- qmotiv2: qualitative initial motivation variable in 4 groups (Research, Originality of the project, Tablet and subscription, other)
- score_cl: initial motivation score in slices
- difficulty_recruitment: difficult to find during recruitment, measured by survey institute

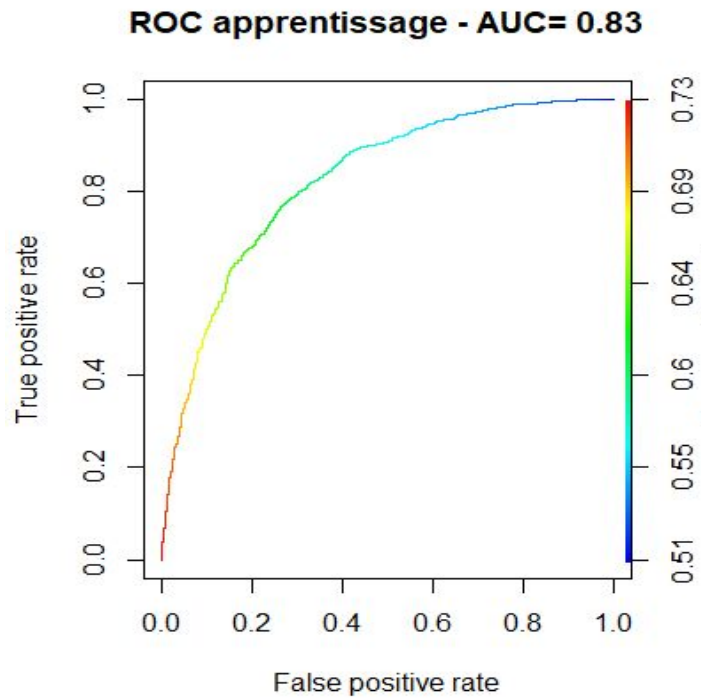
Our model

Coefficients:

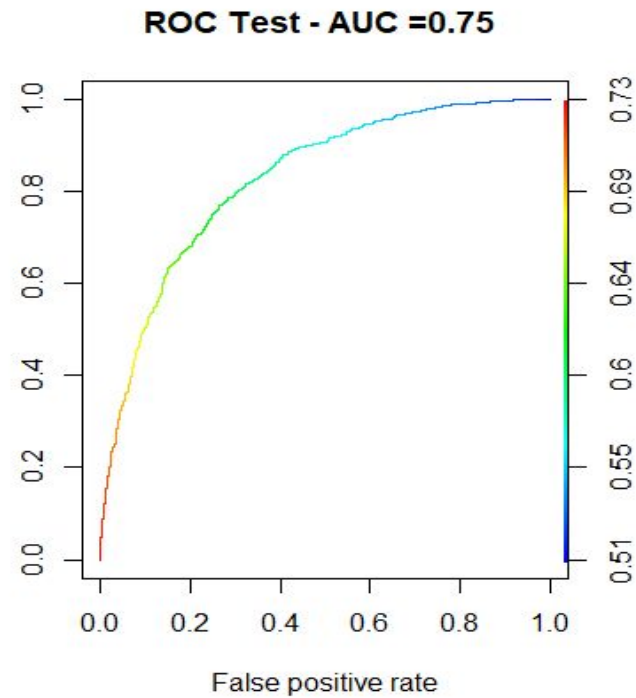
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	18.1974	3956.1805	0.005	0.99633
score_cl(1,2]	-0.38742	0.44544	-0.870	0.384440
score_cl(2,6]	-0.44104	0.33451	-1.318	0.187341
score_cl(6,8]	-0.37790	0.33641	-1.123	0.261291
score_cl(8,11]	-0.55896	0.33864	-1.651	0.098823 .
ea16_A2A_REC_cl(7,9]	-0.28524	0.14118	-2.020	0.043346 *
ea16_A2A_REC_cl(9,11]	-0.51901	0.15435	-3.363	0.000772 ***
ea16_A2A_REC_cl(11,99]	-0.78053	0.23635	-3.302	0.000959 ***
durationsum2_cl(0.25,0.35]	-0.18228	0.18209	-1.001	0.316795
durationsum2_cl(0.35,0.4]	-1.17636	0.18044	-6.519	7.06e-11 ***
durationsum2_cl(0.4,0.45]	-2.16779	0.17701	-12.247	< 2e-16 ***
durationsum2_cl(0.45,1]	-3.76696	0.24150	-15.598	< 2e-16 ***
qmotiv2Originalité du projet	-0.68006	0.25698	-2.646	0.008137 **
qmotiv2Recherche	-0.68388	0.23604	-2.897	0.003763 **
qmotiv2Tablette et ab	-0.59665	0.24347	-2.451	0.014262 *
difficult_recrutementrecrutement normal	-0.70899	0.15675	-4.523	6.09e-06 ***
logement16Accédant à la propriété	0.09051	0.13705	0.660	0.508974
logement16Locataire	0.35847	0.13614	2.633	0.008462 **
logement16Gratuit	0.28292	0.25257	1.120	0.262640

Our model





Rate of well ranked = 67%



Rate of well ranked = 63%

Our model

Although the model described above is not perfect, we can present the typical profile of a panelist's behavior with respect to his or her likelihood of not responding to an investigation can be identified. These criteria are:

- a low initial motivation score
- An initial motivation to acquire tablets and subscription
- Difficulties in contact during recruitment
- a young age
- tenant status

Conclusion

- Motivation, even initial, can be useful in predicting and preventing non-response. Surprising result : data collected sometimes seven years earlier.
 - Paradata as a great indicator of motivation and a very useful tool : looking for other variables...
 - Usg those elements could prove interesting in organising panel calls and stimuli. Focus on panelists with more risk of leaving/not answering.
-
- Textual analysis of motivation, even with a very homogeneous corpus, looks promising.