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A study of MLP for the imputation of the "Attained Level of Education" in Base Register of Individuals

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- o Context
- Data description
- Sampling weights in surveys
- Methods (Log-linear MultiLayer Perceptron)
- o Experimental study
- o Results
- o Conclusions



- The Attained Level of Education (ALE) of the Permanent Italian Census relies on a high amount of **administrative information**. Nevertheless, it is necessary to resort to sample survey data to cope with delay of information and coverage gaps.
- Istat adopted a mass imputation approach integrating administrative and survey data for the ALE estimation of the Italian resident population, based on a sequence of log-linear imputations.

Due to the complexity and heterogeneity of the available information, the solution of the problem with standard statistical methods requires an in-depth knowledge of data structure and an expensive initial phase of data analysis and treatment.



GOAL: experiment the use of a **MLP** with the twofold objective:

- reducing human workload
- improving estimation accuracy



- The High-Level Group for the Modernization of Official Statistics of UNECE (HLG-MOS) launched a Machine Learning project in 2019 with the aim of investigating of the use of machine learning for official statistics (Timely, Accurate and Reliable estimates).
- Istat worked on a comparison between the official imputation approach for ALE estimation, based on loglinear models and the Multilayer perceptron model (De Fausti et al., 2022).

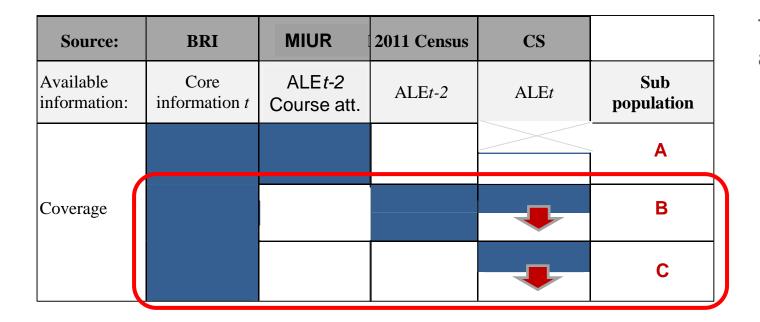
ALE distribution on the Italian resident population is a standard output of the new yearly Permanent Italian Census, a good estimate of the ALE **frequency distribution** is crucial

we extend the study on MLP to include **sampling weights**



Data description

- The procedure for the ALE prediction is obtained by integrating different data: Administrative (BRI and MIUR), 2011 traditional Census and Census Survey (CS)
- O Different patterns of information determine the partition of the population of interest into three subgroups.



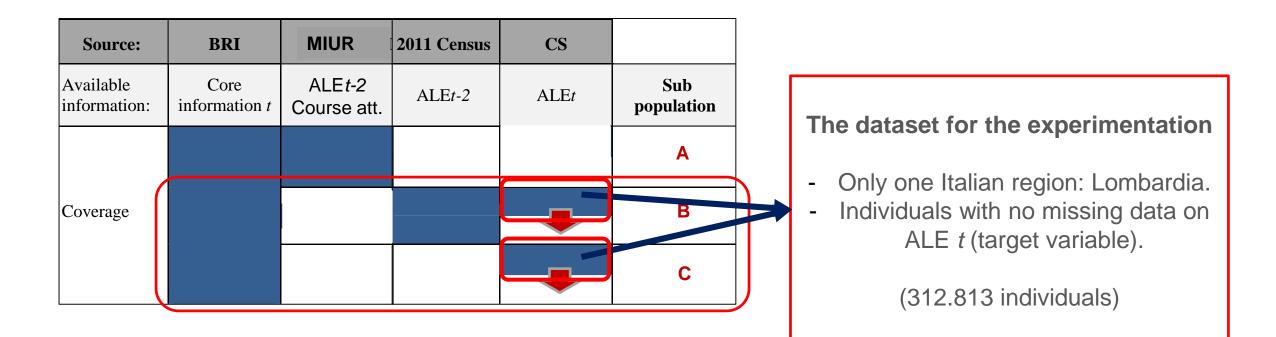
The main difference is between group A and the others:

- Group A is composed by "Active" people. Only administrative information are used.
- Groups B and C are "Inactive" people. The aim is to reproduce the ALE distributions observed in the CS within profiles.



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NSIs use complex sampling designs to carry out **probability sample surveys**.

The joint effect of (i) unequal inclusion probabilities and (ii) use of auxiliary information for survey estimation determines unequal survey weights.

In Standard approach survey weights are used directly in estimates or incorporated into estimators.

The model estimated for ALE imputation includes survey weights

In Machine Learning approach the inclusion of survey weights has received little attention in the literature.

 In order to leverage survey weights during the training phase of our MLP, we used a loss function weighted with sampling weights

$$loss_{w} = -\sum_{ic} w_{i} T_{ic} log(P_{ic})$$

sampling weights



Methods

Official procedure: Log-linear model.

For each sub-population:

- conditional probabilities $h(I_t|X)$ are estimated on weighted count data
- ALE is imputed by randomly taking a value from this distribution

ML procedure: MultiLayer Perceptron.

- o Single neural network
- Weighted loss function
- ALE is imputed by randomly taking a value from the distribution (better macro-level estimates)

- MLP: Same input variables used in Log-Linear model
- 2) MLP All-in: All the variables in the dataset without any selection or reclassification (to study the possibility of using a more automated approach)



Experimental Study

- Estimates are computed using a **k-fold approach** with k=5: The dataset is partitioned into 5 subgroups and:
 - a) the model is estimated on the training set, consisting of 4 of the 5 subgroups;
 - b) the results are applied on the test set, composed of the remaining subgroup;
 - c) Tasks (a) (b) are repeated 5 times so to reconstruct the entire data set.
- The results of estimates are compared. Quality measures are concerned with:
 - predictive accuracy of each unit (micro level)
 - accuracy of estimated aggregates (macro level: Kullback-Leibler divergence).
 - For each model the **process is repeated 100 times** to consider the model variability and the resulting indicators are averaged over those repetitions.



Micro-level accuracy in the 5 test sets averaged over 100 runs

K-fold	Log-linear	MLP	MLP All-in
1	71.20	71.52	73.05
2	71.25	71.65	73.06
3	71.15	71.35	73.21
4	71.18	71.41	73.28
5	71.02	71.39	73.16
Mean	71.16	71.46	73.15
Standard Deviation	0.077	0.110	0.088



Macro-level accuracy: Kullback-Leibler divergence (KLD) in the 5 test sets averaged over 100 runs

K-fold	Log-linear	MLP	MLP All-in
1	0.008	0.019	0.022
2	0.017	0.014	0.045
3	0.015	0.044	0.057
4	0.032	0.018	0.114
5	0.024	0.020	0.102
Mean	0.019	0.023	0.068
Standard Deviation	0.008	0.011	0.035



Results: Macro-level accuracy by citizenship

Macro-level accuracy by citizenship: Kullback-Leibler divergence (KLD) averaged over 100 runs (Fold 2)

	Italian			Not Italian		
ALE in 2018	Log-linear	MLP	MLP All-in	Log-linear	MLP	MLP All-in
Illiterate	0.029	0.023	-0.014	0.093	0.206	-0.080
Literate but no att.	-0.014	0.025	0.047	-0.829	0.226	-0.480
Primary education	-0.176	-0.071	-0.181	0.103	-0.654	-0.262
Lower secondary	0.043	-0.075	-0.757	0.479	-0.115	2.671
Upper secondary	0.148	0.151	0.965	1.385	0.361	0.774
Bachelor's degree	0.002	-0.021	-0.204	-1.249	-0.881	-1.726
Master's degree	0.021	0.032	0.259	0.585	1.273	0.053
PhD	-0.043	-0.053	-0.079	-0.133	-0.090	-0.256
KLD	0.009	0.011	0.035	0.433	0.325	0.694

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This paper aims at investigating the behavior of **MLP as a tool for improving quality and efficiency** of the statistical process of ALE estimation. In order to leverage **survey weights** we modified the cross-entropy loss function using the sampling weights to create a pseudo-population.

- For the imputation of ALE the results of the MLP are very similar to those originated from log-linear models in terms of predictive accuracy and macro-level estimated frequency distribution.
- This study encourages to deepen the opportunity given by the use of ML methods of a more automated approach for the prediction of the variable ALE.
- In future work we want to explore the opportunity to manage longitudinal information in the MLP approach in order to obtain consistent estimates over time.



Thank you

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Id NAME	DESCRIPTION	Log-linear					
	DESCRIPTION	Α	В	С	MLP	MLP All-in	
1	COD_IND	Record id					
2	GENDER	Gender		1	1	1	1
3	AGE_CLASS	Age classified into 14 levels	1	1	1	1	
4	AGE	Age in years					1
5	BIRTH_MU	Municipality of birth					1
6	BIRTH_CO	Country of birth					1
7	MUN	Municipality of residence					1
8	PROV	Province of residence		1		1	1
9	CIT_CLASS	Citizenship (Italian/Not Italian)	1	1	1	1	
10	CIT	Country of citizenship					1
11	ABC_2017	Subpopulation (A, B C)				1	
12	APR	ALE from APR classified into 4 levels			1	1	1
13	ALE2017	2017 ALE (combination of Administrative and 2011 Census)	1	1		1	1
14	FR18_CLASS	Aggregated type of school and year of attendance in 2017/2018	1			1	
15	FR18	Type of school and year of attendance in 2017/2018					1
		Resident in Italy in 2011 not caught by					

Results - Micro-level accuracy

NOT WEIGHTED

K-fold	Log- linear	MLP	MLP All- in
1	72.15	72.05	73.49
2	72.14	72.18	73.59
3	72.27	72.27	73.67
4	72.10	72.24	73.54
5	72.08	71.93	73.45
Mean	72.15	72.13	73.55

		Log-		MLP All-
	K-fold	linear	MLP	in
0	1	71.20	71.52	73.05
WEIGHTED	2	71.25	71.65	73.06
EIGI	3	71.15	71.35	73.21
8	4	71.18	71.41	73.28
	5	71.02	71.39	73.16
	Mean	71.16	71.46	73.15

NOT WEIGHTED

compared with the weighted benchmark

K-fold	Log-linear	MLP	MLP All-in
1	71.31	71.22	72.51
2	71.35	71.35	72.64
3	71.29	71.28	72.57
4	71.33	71.39	72.62
5	71.18	71.06	72.45
Mean	71.29	71.26	72.56

Results - Macro-level accuracy: KLD

NOT WEIGHTED

K-fold	Log-linear	MLP	MLP All-in
1	0,007	0,011	0,012
2	0,008	0,019	0,014
3	0,009	0,027	0,013
4	0,026	0,014	0,024
5	0,009	0,023	0,010
Mean	0,012	0,018	0,015

	K-fold	Log- linear	MLP	MLP All- in
	1	0.008	0.019	0.022
WEIGHTED	2	0.017	0.014	0.045
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NOT WEIGHTED

compared with the weighted benchmark

K-fold	Log-linear	MLP	MLP All-in
1	0.009	0.030	0.024
2	0.017	0.030	0.020
3	0.016	0.063	0.035
4	0.036	0.022	0.031
5	0.024	0.036	0.028
Mean	0.020	0.036	0.028