Artificial Intelligence facing Multidimensional Poverty in Elderly

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Abstract

Poverty is a multidimensional concept that, besides the economic status and financial resources, should consider the lack of access to resources enabling a minimum standard of living and participation in society. In particular, elderly people are likely to require help with some or everyday activities and the total costs of this help can be very high and absorb a significant amount of their income, especially when they are alone and not in good health. This work proposes a strategy based on Bayesian Network to identify the risk of poverty in elderly people, relying on multidimensional indicators learned from heterogeneous sources of information, including the difficulty of accessing services, social exclusion and health status. Data cleaning and integration that include socio-demographic indicators are proposed here, and an overall framework of analysis that can be exportable to several other categories of the population at risk of poverty is presented.

Keywords

Multidimensional Poverty, Elderly, Bayesian Network, Sustainability,

1. Introduction

Poverty is one of the most significant social problems in Organization for Economic Cooperation and Development (OECD) countries. The focus on financial resources alone does not capture people's quality of life as being poor means a lack of access to resources enabling a minimum

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standard of living and participation in societies: thus, a multidimensional approach is needed. Socio-economic vulnerability is accompanied by social networks impoverishment [1], and those in low socio-economic status have less chance of obtaining social support, *e.g.*, in terms of needed care [2]. This work considers a well-defined group of persons facing poverty – the elderly.

Starting from these observations, in this work, we consider data not only on income and wealth but also on material and social deprivation that are rarely collected or known by public welfare institutions, making it difficult to intercept those who require more support. The material deprivation captures the ability of individuals and households to afford specific types of goods and services. In contrast, social deprivation refers to a systematic exclusion of individuals, families and groups from participation in economic, political and social activities. This work proposes to include the difficulty of accessing services, social exclusion and health status while evaluating the risk of poverty. Moreover, it aims to investigate also how the co-presence of these conditions could even worsen susceptibility to poverty. This work starts by analysing a dataset on the elderly in Lombardy, which records their major needs, requests for assistance, and information about their social network before and during the COVID-19 pandemic. These data are cross-linked and integrated with other existing relevant data (such as the open access data from the selected municipalities, statistics, economic and health status conditions) and will be complemented with new data collected through dedicated questionnaires administered to the elderly to capture new indicators useful to predict the risk of poverty. The final aim of our proposal is to categorise the elderly risk of poverty by using the metaphor of an alert semaphore ("ampel" in German) as red, yellow and green code, *i.e.*, major, moderate and low or zero risk, thus providing a quick and exploitable prioritisation outcome, that can be exploited by welfare policy makers for poverty eradication and health promotion, especially to guide actions in case of emergencies, such as COVID-19 pandemic.

To this end, we propose a strategy based on Bayesian Networks (BNs) to exploit their ability to model dependency relationships among the variables. BNs are a probabilistic graphical model for representing knowledge about an uncertain domain where each node corresponds to a random variable, and each edge represents the conditional probability for the corresponding random variables [3]. One of the positive aspects of the BNs is the possibility to easily include prior background knowledge from the experts.

The paper is organised as follows. In Section 2, a brief state-of-the-art on multidimensional poverty and machine learning approaches to face this problem, especially in the case of the elderly, is reported. In Section 3 the data and source of data considered are presented. In Section 4, the proposed framework of analysis is described, and the adopted preprocessing on the considered data is reported in Section 5. In Section 6 the proposed implementation of the BN is reported, together with the preliminary results obtained. Finally, we conclude this paper and discuss the future direction in Section 7.

2. Background

Populations in OECD countries are ageing rapidly, their health worsens, and they may struggle with everyday activities. As World Health Organization (WHO) states, Long-Term Care (LTC) systems enable people experiencing significant declines in capacity to receive care consistent with their basic needs. LTC services help reduce the inappropriate use of acute healthcare services, help families avoid catastrophic care expenditures and free women – usually the main caregivers – to have broader social roles [4]. Incomes of the elderly are generally low: 23% of older people are likely to be at risk of relative income poverty, the same figure being 18% in the overall population, and this phenomenon interests 25 out of 35 OECD countries [5]. The financial challenges faced by older people with LTC needs can be very high and absorb a significant amount of their income. Home care and small out-of-pocket payments may be unaffordable without adequate social protection. LTC needs are relevant indicators to address from a multidimensional perspective, especially among the elderly. Women are more likely to be in poor conditions and, thus, at risk of socioeconomic disadvantage [6], the reasons being lower female participation in the labour market (working fewer hours and with lower salaries); moreover, women have primary responsibility for childbirth, child rearing and unpaid domestic work [7]. These factors place women at a disadvantage in a pension system that is tied to labour market earnings. All the factors associated with being female such as low income, being widowed, higher life expectancy than men and older age, are associated with requiring LTC [8].

Most studies emphasize the economic facet of poverty on the basis of monetary income [9, 10, 11]. However, income-based indicators are poor proxies of material conditions among the elderly [12, 13] whereas non-monetary ones improve our understanding of who is poor, with a shift from a unidimensional to a multidimensional approach [14],[15].

In 2010 the Multidimensional Poverty Index (MPI), was officially published by Oxford Poverty and Human Development Initiative[1] in collaboration with Human Development Report Office of the United Nations Development Programme (UNDP) [16]. The MPI Indicator is the first attempt to represent the multidimensional poverty. It considers poverty through ten indicators divided into three dimensions: health, education and standard of living. The dimensions are equally weighted, and so are the specific indicators. Later, in 2015[2], they come to the MPI side by side:

1. the concept of measuring well-being made up of eleven specific dimensions;
2. the concept of social cohesion, consisting of measures concerning inclusion, capital and social mobility;
3. the Social Institutions and Gender Index (SIGI), concerning discrimination factors.

Multidimensional measures of deprivation are composed of different indicators fitting into a synthetic scale [17, 18], which is deemed to reflect basic living standards and the exclusion from the minimum acceptable way of life in one's own society. Several methodologies to assess

[1] ophi.org.uk
[2] www.oecd.org/dac/post-2015.htm

poverty from a multidimensional perspective exist, including methods aiming to implement aggregate data from different sources, and statistical approaches – *i.e.*, principal component analysis, or cluster analysis – which reflect the joint distribution of single deprivation indicators and aim to a bottom-up definition of synthetic scales [19]. Such approaches are adequate if they capture the joint distribution of deprivations, identify the poor ones (*i.e.*, dichotomising the population into poor and non-poor), and provide a single cardinal figure to assess poverty. Although there is little research on Machine Learning (ML) and Artificial intelligence (AI) application to poverty estimation, thanks to recent advances in data obtainability, big data and ML are nowadays adopted to predict poverty in low-income countries. Besides the choice of the best algorithms, other crucial aspects, such as data quality and the presence of bias due to subjective and indirectly related data, exist, pushing to choosing other data sources such as remote sensing datasets [20]. A second issue is related to the difficulties in finding labelled data. Ensemble models were employed, assuming as ground truth for ML training the Proxy Means Test (PMT) labels, without verifying the accuracy of the PMT labels [21]. Finally, in the presence of a noisy dataset, it is crucial to select robust features to feed ML algorithms and to understand how these features can contribute to the identification of poverty clusters, which is not obvious when using complex heterogeneous data. Among different ML techniques for poverty classification, decision tree [22], random forest [21], and ensemble approaches [23] are the most used.

3. Datasets description

This work relies on four different datasets to acquire multidimensional indicators of poverty in the case of the elderly and to detect the mutual correlation among them.

1. **AD** (AUSER Dataset): this is an unconventional and valuable dataset collected by AUSER[3], an Italian association that promotes active ageing. These data have been collected by volunteers in nine municipalities in the Lombardy region, which records the major needs of the elderly, requests for assistance, and information about their social network, both before and during the COVID-19 pandemic (years 2019, 2020, and 2021). The nine municipalities and the elderly that refer to them are reported in Figure 1.
2. **CD** (Context Data): Demographic and socio-economic retrospective data, collected from public open data, that enable socio-demographic comparisons of groups of citizens in different municipalities.
3. **RD**: Retrospective Data on health, disability and ageing, collected during concluded projects, TAPAS [24] and IDAGIT [25], on a similar population of elderly in Lombardy, that enables addressing the impact of health, disability and comorbidity on wealth and vice-versa.
4. **ND** (New Data): for a selected representative sample of the elderly, ad-hoc surveys are administered through a structured questionnaire to acquire information on elderly social deprivation, their health and well-being.

[3]www.auser.it

Table 1
Municipalities where the data have been collected.

AUSER Senior Center	Number of elderly	Male	Female	Number of volunteers	Male	Female
LECCO	2615	676	1939	223	148	75
LODI	1200	453	747	122	83	39
COMO	864	289	575	183	126	57
CINISELLO	208	78	130	33	18	15
CERNUSCO SUL NAVIGLIO	253	72	181	59	30	29
PIOLTELLO	163	48	115	32	20	12
PREALPI-MILANO	60	17	43	15	9	6
COLOGNO	132	46	86	16	14	2
GALLARATE	408	138	270	24	16	8
	5903	**1817**	**4086**	**707**	**464**	**243**

4. The proposed framework of analysis

The framework of analysis presented here has two main objectives:

- identifications of novel indicators of poverty risk and of their mutual interference based on longitudinal data that grasp information from daily difficulties and that could reveal new social criticalities that social services, municipalities and other public institutions will have to face;
- definition of an AI model that, managing heterogeneous data, will provide a poverty risk prediction, simplified in a three-level semaphore alert: red (high), yellow (medium) and green (low or absent) risk. Besides the human and social benefits, it is noteworthy that such a prioritisation will allow a high-level organisation of the management bodies to care for people with vital long-term care needs, which will result in a significant impact on poverty.

In this work, a Bayesian Network (BN) model is proposed to define different levels of risk of poverty. We start considering the **AD** dataset, which can be considered a novel, unconventional and valid data source. This dataset requires essential preliminary steps of data preprocessing to clean and normalise the data entries and to be enriched with the collected Context Data (**CD**). Starting from these two merged datasets, we create the Enriched Dataset (**ED**), where each record corresponds to one elderly person and all the related information.

Starting from the **ED** dataset, the framework will be applied in three incremental steps of detail: i) we decide to adopt the Gini Index[26] as initial target of the BN. This index represents the income inequality, and not directly a multidimensional deprivation index, which is our focus, however it shares common ground with poverty indexes, permitting, while we are collecting new data, a first validation of the proposed framework; ii) the data from **RD** TAPAS and IDAGIT is integrated, and the expert's domain knowledge is consolidated into the model; iii) the data collected from additional questionnaires provided by AUSER can be used as groundthruth for final model validation. The collection of this data is still ongoing.

The present paper describes the first step among the three listed.

5. Data preprocessing

The AD dataset results from the interaction of the nine AUSER municipalities and the elderly that refer to them through the phone service Filo D'Argento. Specifically, the data provided by each municipality are contained in a spreadsheet where each row represents an interaction with a beneficiary. Each interaction, which can be a simple request for information or a service request, is characterised by data concerning the beneficiary, details about the service or information requested and specific data on the call. For reasons related to privacy, the beneficiary is represented by an identification code that replaces their name and surname. The data concerning them include non-specific physical or economic locations and characteristics. In detail, the most relevant data are the municipality of residence, date of birth, if there are contact persons, if the beneficiary lives alone, and if he is self-sufficient or retired. As for services, the data are more specific: there are all the possible details regarding the type, timing, places and any service problems. The entire dataset is characterised by a low quality of the data in terms of correctness and completeness, as they are the result of the manual entry of the volunteers and therefore contain numerous typos and missing data. Focusing solely on the data concerning the over 65s, we obtained a dataset composed of 52.939 services relating to 3.493 beneficiaries with a percentage of missing data of about 15% (1 958 743 data of which 298 500 are missing). For this reason, a cleanup and normalisation phase has been inserted in the pipeline described in Section 5.1. A sample of the **AD** dataset can be found in the Table 2.

Table 2
Sample of the AD dataset.

Center	Year	BeneficiaryID	Sex	PrivacyConsent	YearOfBirth	Age	CityOfBirth	CityOfResidence	...
Cantù	2019	56758	F	No	1931	88	URGNANO	CANTU'	...
Cantù	2019	228638	F	Not provided	1944	75	ARMENTO	CANTU'	...

To make the dataset more suitable for the application of the ML algorithm, we defined a pipeline consisting of three phases: i) Data cleaning and Normalisation; ii) Enrichment; and iii) Training.

5.1. Cleaning and Normalisation

In the data cleaning and normalisation phase, firstly, textual data are converted to integers. In detail, groups of values have been identified and each of them have been associated with a number (*e.g.*, sex: [M,F] $\longrightarrow$[1,2], Privacy Consent: [yes,no,missing] $\longrightarrow$[1,2,99]). The ID of the beneficiary (Beneficiary ID), the city of birth and residence, date and time of the service/information request have been excluded from the processed columns. In order to ease any possible additional data integration, the places of birth and residence ISTAT[4] codes, together with age, year of service and municipality where the data comes from, are stored in every line.

[4] Italian national statistics office.

Table 3
AD dataset sample after normalisation phase.

Center	Year	BeneficiaryID	PrivacyConsent	Sex	YearOfBirth	Age
cantu	2019	56758	99	1	1931	88
cantu	2019	228638	99	2	1944	75

CityOfBirth	CityOfBirthISTAT	CityOfResidance	CityOfResidenceISTAT	...
urgnano	16222	cantu	13041	...
armento	76005	cantu	13041	...

Going more in-depth with the cleaning procedure, the next steps are:

1. Removal of duplicate columns;
2. Removal of accents and apostrophes (*e.g.*, Cantù →Cantu; CANTU'→CANTU);
3. Convert text to lowercase (*e.g.*, Cantu →cantu; CANTU →cantu);
4. Edit column headings - no spaces, lowercase initials and typo fix (*e.g.*, year of birth →rptYearOfBirth; rptRet1red →rptRetired; "Year " →"Year")
5. There are two different columns representing a singular boolean value; this data is transformed into a single column: the new column stores the 0 value for service requests and 1 value for information requests;
6. Missing information for some columns can be determined by the text present in the note column, (*i.e.*, strings "partially self-sufficient", "wheelchair", "disabled", "guest", "lives alone" can resolve the column rptSelfsufficiency);
7. The columns that are not needed after this step are dropped (*e.g.*, 'rptNote');
8. Numeric columns wrongly identified as strings are converted to float, and other minor transformations are applied to ensure correct column classification.

A small subset example of the **AD** dataset after the cleaning and normalisation phase is shown in Table 3.

5.2. Enrichment

As soon as the original dataset **AD** is ready for ML algorithms, it can be enriched with new data (resulting in the **ADE** dataset). A first analysis brought us to the requirement to integrate also the province from the residency because some of the public data is available only on the province level and not on the municipality level. The integrated data include several areas such as mobility, health and job statistics.

Urban Index[5], in Italy, there is a public portal with indicators for Urban Policies distributed as OpenData[6]. However, most of those indicators are pretty old, there are potentially valuable data in the dataset. More in detail, the Gini index[7] is a measure of statistical dispersion intended to represent income inequality or wealth inequality within a nation or a social group. This

[5]www.urbanindex.it
[6]www.urbanindex.it/opendata/DB_DIPE.zip
[7]www.urbanindex.it/indicatori/indice-di-gini

index was used as the first target example as a poverty measure and was integrated into the original dataset by the municipality of residence.

Open Data Lombardia[8], provides data related to indicators about population health and healthcare. Among these, it was decided to integrate:

- RSA (Nursing Home Residence) rate, the ratio between the number of beds in the nursing homes and the number of inhabitants over 65 per thousand;
- Rate of social offers for the elderly (sheltered accommodation and day centres), the ratio between the number of beds in social offers for the elderly and the number of inhabitants over 65 per thousand;
- Rate of social cooperatives for the elderly, ratio between the number of social cooperatives for the elderly and the number of inhabitants over 65 per 100 thousand.

All the rates listed above have been integrated through the municipality of residence.

Istat[9], instead, makes the information on demographic indicators accessible, those selected for integration were:

- Ageing index, rate between the number of inhabitants over 65 and the number of young people up to 14 years old per cent.
  Integrated through the municipality of residence and year.
- Turnover rate of the active population, rate between the population aged 60-64 and the population aged 15-19 per cent.
  Integrated through the municipality of residence and year.
- Masculinity index (complementary to the femininity index), rate between males over 65 and females over 65 per cent.
  Integrated through the municipality of residence and year.
- Retirment rate of over 65s, rate between the number of retirees over 65 and the population over 65 per thousand.
  Integrated through the province of residence and year.
- Elderly dependency index, rate between the population over 65 and the population aged 15-64 per cent.
  Integrated through the municipality of residence and year.
- Mortality rate.
  Integrated through the municipality of residence, year, gender and age of the beneficiary.

A sample for the ADE dataset is available in Table 4.

6. Bayesian Network

As for the prediction aspects of an individual's poverty index, Bayesian Networks have been chosen as they are self-explainable; namely, they allow to know which variables led to a

[8] dati.lombardia.it
[9] www.istat.it

Table 4
Sample of the ADE dataset.

Center	Year	...	GiniIndex	RSA rate	social Cooperatives rate	Eldery dependency	retirement rate	population	...
cantu	2019	...	0,2045	38,89807163	22,04	35,86	811,88	8973	...

specific result and to what extent each single data contributed to the final result. Regarding the implementation, there is a wrapper class which allows the configuration of the parameters of the pyAgrum[10] library. This library has been selected among the many available (*e.g.*, Pgmpy, bnlearn, sklearn, Pythin, pomegranate, PyBNesian) for the remarkable possibilities of rapid prototyping and production of charts.

Recalling that we have not yet the final data of the ongoing data collection that will provide the groundtruth label in terms of poverty, we decided to adopt the Gini Index as the target to analyse the feasibility of the proposed framework. Even if this index represents only income inequality and does not consider multidimensional variables of deprivation, it shares common ground with poverty indexes, permitting a first validation of the proposed Bayesian Network.

To obtain a preliminary version of our model, the **ED** dataset has been used. The training is carried out using 80% of the data, while the remainder is used as a test set. This data split has been performed randomly. Using the Gini index as target index, the BN automatically identifies 4 classes. The pipeline was developed with a Python Jupyther Notebook instance. The data cannot be shared due to privacy and GDPR concerns. In Table 5 available statistics about the dataset are reported.

Table 5
ED Dataset statistics

	#	**Notes**
Total Instances	3493	Train: 2794 Test: 699
# Features	29	AD: 19 CD: 10
Target class	4	0: 83 1: 1533 2: 1698 3: 179

Background knowledge integration The manual addition of arcs (called 'mandatory_arcs') allows the integration of the initial data with the domain knowledge acquired from the literature or directly from experts. In the same way, it is possible to remove arcs with the 'tabu_arc' list to avoid incidental correlations. In Figure 1 the initial BN is reported. In Figure 2 instead, we can see the correlation between representative variables of the initial model. It is possible to

[10]https://pyagrum.readthedocs.io/

notice that the link between column "rptAnnoNascita" (birthYear) and the target Gini index is an incidental strict correlation because there is no demonstrated reason to say that older people are poorer even if the data of this dataset may suggest so. For this reason, we can identify this as a 'tabu_arc'. As a representative example of integration of knowledge from domain experts, it was established to force the arch between the rate of available beds (RSA rate) with the target Gini Index.

Figure 1: Initial BN.

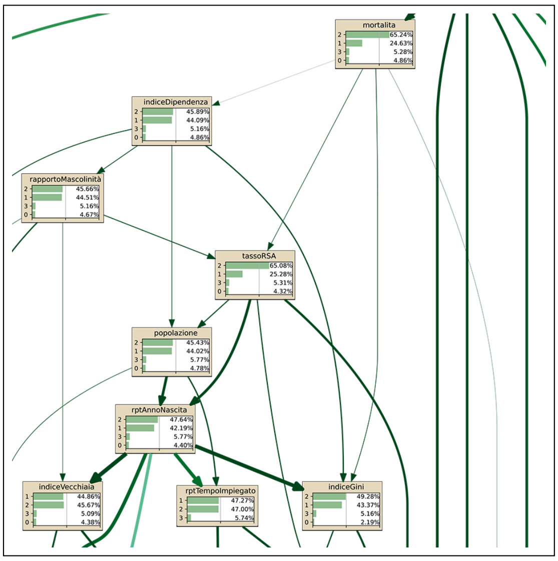

Figure 2: Initial Inference diagram.

In Figure 3 it's possible to see the BN with a first attempt to integrate domain knowledge. At the same time Figure 4 shows the updated inference diagram.

The model described in this section will be further improved with the **RD** dataset and will be completed and optimised once the **ND** dataset is available.

6.1. Validation

The validation was executed against the **ED** dataset, which was divided as described above (the 20% of the 3493 beneficiaries have been selected as a test set). For the Gini Index, the Bayesian Network automatically identifies 4 classes as the target, so this experiment is carried on with this aggregated index with 4 classes. The results of our experiment show a performance of 0.49 of accuracy with a weighted f1-score of 0.46 (accuracy of the random baseline is 0.25). Since data acquisition is still ongoing, and we have not yet fully integrated the domain knowledge, these preliminary results can be considered promising. As described in Section 1, we plan to use a three-level semaphore classifier as the target in the future, integrating further data.

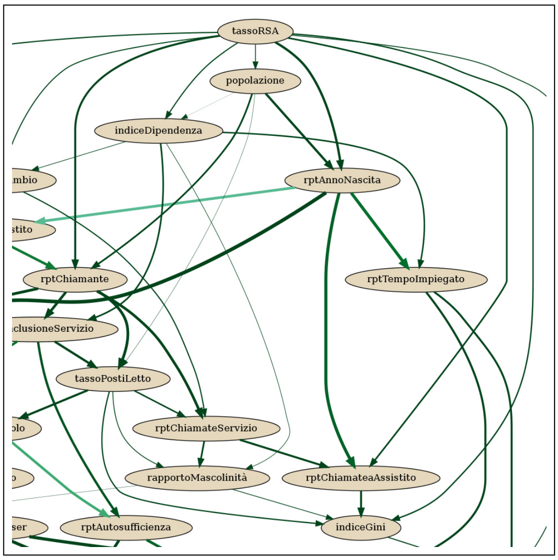

Figure 3: BN with domain knowledge.

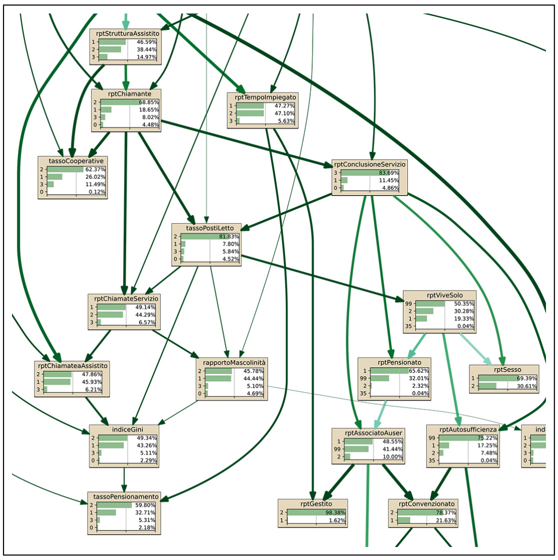

Figure 4: Diagram with domain knowledge.

7. Conclusion and future work

In this paper, we present a framework to analyse unconventional and heterogeneous data to define a three-level risk of poverty index for elderly people and, at the same time, identify novel indicators of multidimensional poverty. A Bayesian Network approach is proposed to encode background and domain expert information and underline mutual interference among all the considered variables. Further subsequent tests are planned to identify any under-represented variables. Preliminary results, validated with a state-of-the-art inequality index, confirm the power of the proposed solution. In the future, knowledge from the analysis of already concluded projects and ongoing questionnaire collection will be integrated into the model to answer the research questions better.

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