Prediction of neonatal mortality in Sub-Saharan African countries using data-level linkage of multiple surveys

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Abstract

Existing datasets available to address crucial problems, such as child mortality and family planning discontinuation in developing countries, are not ample for data-driven approaches. This is partly due to disjoint data collection efforts employed across locations, times, and variations of modalities. On the other hand, state-of-the-art methods for small data problem are confined to image modalities. In this work, we proposed a data-level linkage of disjoint surveys across Sub-Saharan African countries to improve prediction performance of neonatal death and provide cross-domain explainability.

1. Introduction

Different surveying efforts were conducted to understand the global health challenges in developing countries, which include Demographic and Health Surveys (DHS) Program (dhs, 2004-2017), Knowledge Integration (KI) Data (ki), and Performance Monitoring for Action (PMA2020) (pma). However, these surveys are often utilised in silos with minimal intra- and inter-country integration. Thus, effective utilisation of small but multi-domain data is beneficial to address problem domains known for data scarcity, or when more data collection is not economically feasible.

State-of-the-art methods for small data challenges use data-augmentation (Salamon & Bello, 2017), generation (Douzas & Bacao, 2018) and transfer learning (Sung et al., 2018) techniques. Though augmentation and generation help to create artificial samples, the intelligibility of these samples is still limited by the small data size in order to generate samples with enough variance. Transfer learning is the most extensively explored solution for small data problems in the existing literature, and its common strategies include multitask learning (Tschandl et al., 2018), few-shot learning (Guo et al., 2019), domain adaptation (Pan & Yang, 2009). These existing methods are often applied during or after modelling, and data-level linkage is not well exploited. The critical limitation of existing solutions is their confinement to image modality and the assumed availability of data-rich source domain, which may not be the case in addressing pressing global health challenges, e.g. neonatal death using survey data.

In this work, we propose a principled approach to link disjoint datasets, which do not have overlapping of either their samples (rows) or features (columns) but related to the same outcome of interest. Examples of such datasets include PMA collected in Ethiopia in 2016 and DHS collected in Ghana in 2014, which both can be used to understand neonatal death.

2. Methods

The proposed framework (see Fig. 1) involves the linkage of samples across two disjoint datasets: \( D_1 = (S_1^n)_{n=1}^N \) and \( D_2 = (S_2^m)_{m=1}^M \), where \( S_1^n = (f_{j1}^n, f_{j2}^n, \ldots, f_{jK}^n) \) and \( S_2^m = (f_{j1}^m, f_{j2}^m, \ldots, f_{jL}^m) \), and \( N \) and \( M \) represent the numbers of samples; \( K \) and \( L \) represent the number of features in \( D_1 \) and \( D_2 \), respectively. Since the datasets are disjoint and have different feature spaces, we, first, apply dimension reduction to project \( D_1 \) and \( D_2 \) into equal-dimensional feature spaces. To do so, three techniques are employed that use: feature-importance, principal component analysis (PCA), and autoencoder (AE).

Feature-importance-based linkage utilises the t-score of a feature in each dataset after domain-specific modelling. We obtain the minimum number of positive \( (p_{min}) \) and negative \( (n_{min}) \) features across the two datasets, and represent the samples \( D_1 \) and \( D_2 \), using the top \( p_{min} \) and \( n_{min} \) features sorted in descending order. PCA-based linkage applies principal component analysis of \( D_1 \) and \( D_2 \) followed by projections using the top \( R \) Eigen vectors. Similarly, autoencoder-based linkage employs dense encoders and decoders trained on each dataset separately, and the output of the encoder part \( (E(\cdot)) \) is treated as a latent space with reduced dimen-
sion. The layer size of the encoder outputs in these two autoencoders is set to be $R$-dimensional. Any of the dimension reduction techniques results in $R$-dimensional $\hat{D}_1$ and $\hat{D}_2$ from $D_1$ and $D_2$, respectively. The linkage matrix is obtained by applying Euclidean based distance computation for every pair of samples in $D_1$ and $D_2$. Close neighbours for a sample are then identified in the other dataset from the distance metric, and the feature values of the neighbors are the median-aggregated and concatenated with the original feature space of a sample, resulting linked datasets $D_{12}$ and $D_{21}$.

3. Experiments

We focus on the problem of neonatal death across Sub-Saharan African countries, and hence use datasets collected across two different efforts (DHS (dhs, 2004-2017) and PMA (pma)) in the following countries: Burkina Faso (BF), Ethiopia (ET), Ghana (GH), Kenya (KE) and Nigeria (NG). Due to the high imbalance between neonatal death and not (often 2-4%), we employed area under receiver operating characteristics (AUROC) as our performance metric.

Results shown in Table 1 demonstrate that the linkage mechanism helps to alleviate the prediction performance of neonatal death on PMA data of Ethiopia when linked with DHS data of other African countries. Random linkage of samples is used as a baseline.

| Linking method              | Linked with DHS of: |   |   |   |
|-----------------------------|---------------------|---|---|---|
| Random                      | ET  | BF   | GH  | KE  | NG |
| Feature importance          | 66.6 | 59.9 | 69.3 | 57.3 | 66.6 |
| Principal component analysis| 64.3 | 64.8 | 64.7 | 56.3 | 66.7 |
| Autoencoder                 | 90.0 | 90.0 | 94.1 | 84.6 | 86.1 |

Table 1. Increase in the neonatal death prediction on PMA data of Ethiopia when linked with DHS data of other African countries. Random linkage of samples is used as a baseline.

Figure 2. PCA projections of PMA data from Ethiopia (ET) before linkage is applied followed by the projections after PMA ET is linked with DHS of other African countries.

and unified data collection is often difficult and expensive. The proposed data-level linkage of these datasets helps to achieve that, and importantly, can be extended to other sectors beyond healthcare. Example includes understanding and monitoring of multiple sustainable development goals by exploiting data collected across different streams.
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