Measuring Data Collection Quality for Community Healthcare

Ramesha Karunasena¹, Mohammad Sarparajul Ambiya², Arunesh Sinha¹, Ruchit Nagar², Saachi Dalal², Divy Thakkar³, Milind Tambe³

¹Singapore Management University, Singapore, {rameshkarunasena}@smu.edu.sg
²Khushi Baby, India, {sarfraz,ruchit,saachi}@khushibaby.org
³Google Research, India, {dtthakkar,milindtambe}@google.com

Abstract

Machine learning has tremendous potential to provide targeted interventions in low-resource communities, however the availability of high-quality public health data is a significant challenge. In this work, we partner with field experts at a non-governmental organization (NGO) in India to define and test a data collection quality score for each health worker who collects data. This challenging unlabeled data problem is handled by building upon domain-expert’s guidance to design a useful data representation that is then clustered to infer a data quality score. We also provide a more interpretable version of the score. These scores already provide for a measurement of data collection quality; in addition, we also predict the quality for future time steps and find our results to be very accurate. Our work was successfully field tested and is in the final stages of deployment in Rajasthan, India.

1 Introduction

Machine learning provides healthcare planners with a powerful tool for optimized health care delivery benefiting large populations, especially in under resourced communities. Data collection is enabled through frontline health workers in the public health system, that provide last mile connectivity to reach rural communities. There is extensive human infrastructure to enable data collection in India. However, due to various social and organization reasons, some frontline health workers (Dinesh Songara, Akanksha Goyal, Pankaj Suthar) are not able to deliver expected data quality. Data quality challenges have prevented the use of such data for downstream applications and when used, occasionally led to incorrect inferences. Poor data quality can be attributed (Pal et al. 2017) [Ismail and Kumar 2019] to various factors such as overburdened healthcare workers, lack of training on technology-mediated data collection tools, conflicting organizational incentives, low pay. We recognize the importance and challenges of frontline health workers [Ismail and Kumar 2019] [Kumar et al. 2015] [Yadav et al. 2017] in providing access to medical care and health outreach to rural and marginalized communities. Field experts (including our NGO partners) struggle with fundamental design techniques to effectively measure the quality of health data in terms of accurate data collection and reporting, to provide feedback to the health worker and to design targeted interventions for the community. In this paper, we study pregnancy related health data collection in the state of Rajasthan, India and propose a data collection quality score to measure the veracity of the data collected under consideration. We collaborate with the India-based NGO Khushi Baby.

We find that the data collection quality score problem is in itself a learning problem. There are two main challenges in this problem: (1) absence of labeled data for indicators of poor and high quality data and (2) the data collected by one health worker is not expected to be of the same quality over time, which brings in a temporal aspect to the problem. While at first the problem may seem solvable by an unsupervised anomaly detection approach, we found (and know from our NGO partners) that more than 50% of the reported data is suspected to be of poor quality, which rules out unsupervised anomaly detection techniques. As far as we know, there is no general method of quantifying the quality of data collection and methods in literature are mostly simple rule-based or unsupervised anomaly detection based techniques (Eskin 2000) [Chandola, Banerjee, and Kumar 2009].

Our first technical contribution is to build upon rules provided by domain experts and transform them to probabilities of non-diligence for each health worker. The domain experts (Khushi Baby employees) use a set of 18 rules that measures non-diligence along 18 dimensions. All these rules measure percentages in a time window, for example, one rule (BP rule) tracks the percentage of number of blood pressure readings in a health camp (over a month) that are all same, where 0% is fully diligent and 100% is fully non-diligent for this rule. Then, for each rule, by considering the distribution of percentages over all health workers and all time windows, we obtain a probability of non-diligence for a health worker for that rule in any given time window. Overall, for all rules we obtain a 18-dimensional probability of non-diligence for any given time window. We call these health-worker specific probability vectors as their behavior and this forms a vector valued measure of the health worker behavior in a given time window.

Our second technical contribution is to infer non-
diligence labels (or scalar scores) for these behavior vectors across all health workers and time windows (in training data) by clustering into two clusters. We find that k-means works best in case of binary \( \{0,1\} \) labels and fuzzy c-means (Bezdek, Ehrlich, and Full 1984) works best when we aim for a soft \([0,1]\) non-diligence score. Given the natural interpretation of probabilities of non-diligence we are able to readily identify which cluster is non-diligent by looking at the probability values of the cluster centers. We also perform an explainability analysis of the clustering and propose another more explainable scalar non-diligence score.

Our final technical contribution is a classifier that takes in as input the past six time windows of a health worker’s behavior and predicts the next window’s non-diligence score. We have two types of prediction: \( \{0,1\} \) classification or \([0,1]\) regression score. We obtain very good accuracies of over 90% in classification with reasonable precision and recall. Our main highlight of this work is the field test of our prediction on fresh data that came in from the field, which was successful and obtain similar results as we did on our test data. Based on this field test, we have started the deployment process of this software in the state government controlled server for use by Khushi Baby. We firmly believe that our data collection quality score and prediction of the same coupled with well-designed apriori and post-hoc intervention, such as more informed training or nudges and auditing, will over time result in improved data quality in the setting we are concerned with, leading to positive health outcome for millions of people.

2 Related Work

There is a long history of dealing with data quality issues in machine learning. Many of these approaches focus on scenarios where the data is noisy or adversarial corrupted but the amount of such noise or corruption is small. This low perturbation assumption naturally leads to unsupervised anomaly detection based techniques (Eskin 2000; Chandola, Banerjee, and Kumar 2009; Xiong et al. 2011; McCarthy et al. 2013; Xiong, Póczos, and Schneider 2011; Yu, He, and Liu 2015; Naidoo and Marivate 2020). However, as stated earlier, poor quality data is not an anomaly in our problem; in fact, majority of the data is poor quality due to non-diligence in collecting data. Also, with no label, supervised anomaly detection (Görnitz et al. 2013) cannot be used. Further, distinct from these prior work, our goal is not to measure the data quality in aggregate but to measure the data quality collected per health worker.

More closely related to our work is a work that directly focuses on measuring anomalous data collection by health workers (McCarthy et al. 2013). However, this work also treats poor data collected by a health worker as an outlier, which is not true in our problem. In experiments, we perform a baseline comparison with anomaly detection for sake of scientific completeness. In not so closely related work, detecting human behavior in context of fabrication (Birnbaum et al. 2013) has been studied using behavior data from a controlled user study: we do not possess behavior data of health workers and it is quite infeasible to collect such data.

Even though unsupervised anomaly detection does not directly apply, it has been observed that an anomaly has to be often defined using human provided inputs (Kuo, Li, and Kifer 2018). Similarly, we utilize domain experts’ guidance to determine what type of behavior could constitute non-diligence. Then, inspired by a common technique in semi-supervised learning (Goldberg 2010) we use clustering to infer labels of behavior data. However, unlike semi-supervised setting, we possess no labels at all, but our definition of behavior provides a natural interpretation of which cluster maps to non-diligent behavior.

Clustering has been used in past work to detect fraud in social networks (Cao et al. 2014), in internet advertising (Tian et al. 2015), in healthcare billing (Massi, Ieva, and Lettieri 2020; Liu and Vasarhelyi 2013). However, as far as we know, clustering has not been used in a problem context as ours. Moreover, our problem is not one of fraud, which is easier to define, but, one where we rely on human input to define non-diligence. Further, we use fuzzy clustering and explain the clustering result to yield better outcomes overall.

There are other kinds of data quality issues in machine learning. These include data missing over a large part of the feature space (Lakkaraju et al. 2017), adversarially corrupted data (Papernot et al. 2016), and imputation for missing data in healthcare (Hu et al. 2017). Our concern in this work is orthogonal to all these other issues.

3 Problem Description

In this work we collaborate with the NGO Khushi Baby (http://khushibaby.org), whose main mission is to motivate and monitor the health care of mothers and children to the last mile. Using human-centered-design, they have developed a technology platform for longitudinal tracking of maternal and child health using a combination of a mobile application for health workers, a Near Field Communication enabled smart health card and automated local-dialect voice reminders for beneficiaries, and automated high-risk and dropout reports over WhatsApp for health officials and teams. They have deployed their platform to track the health of over 40,000 mothers and infants at the last mile in Rajasthan in India in partnership with the district government.

Khushi Baby has made available datasets that correspond to health camps that have been conducted in the past, including data about the health workers. These health workers, called ANMs (Auxiliary Nurse Midwives), are employed by the state government and are responsible for screening pregnant women and infants at these village-based maternal and child health camps. Each ANM provides antenatal care checkups and infant checkups (including immunizations) on four to five fixed camp sessions, each in a separate village, typically on each Thursday of the month. On average, an ANM caters to approximately 200 beneficiaries across these villages. An ANM also provides a set of 18 heuristic rules to readily identify which cluster is non-diligent by looking at the probability values of the cluster centers. We also perform an explainability analysis of the clustering and propose another more explainable scalar non-diligence score.

In experiments, we perform a baseline comparison with anomaly detection for sake of scientific completeness. In not so closely related work, detecting human behavior in context of fabrication (Birnbaum et al. 2013) has been studied using behavior data from a controlled user study: we do not possess behavior data of health workers and it is quite infeasible to collect such data.

Even though unsupervised anomaly detection does not directly apply, it has been observed that an anomaly has to be often defined using human provided inputs (Kuo, Li, and Kifer 2018). Similarly, we utilize domain experts’ guidance to determine what type of behavior could constitute non-diligence. Then, inspired by a common technique in semi-supervised learning (Goldberg 2010) we use clustering to infer labels of behavior data. However, unlike semi-supervised setting, we possess no labels at all, but our definition of behavior provides a natural interpretation of which cluster maps to non-diligent behavior.

Clustering has been used in past work to detect fraud in social networks (Cao et al. 2014), in internet advertising (Tian et al. 2015), in healthcare billing (Massi, Ieva, and Lettieri 2020; Liu and Vasarhelyi 2013). However, as far as we know, clustering has not been used in a problem context as ours. Moreover, our problem is not one of fraud, which is easier to define, but, one where we rely on human input to define non-diligence. Further, we use fuzzy clustering and explain the clustering result to yield better outcomes overall.

There are other kinds of data quality issues in machine learning. These include data missing over a large part of the feature space (Lakkaraju et al. 2017), adversarially corrupted data (Papernot et al. 2016), and imputation for missing data in healthcare (Hu et al. 2017). Our concern in this work is orthogonal to all these other issues.

3 Problem Description

In this work we collaborate with the NGO Khushi Baby (http://khushibaby.org), whose main mission is to motivate and monitor the health care of mothers and children to the last mile. Using human-centered-design, they have developed a technology platform for longitudinal tracking of maternal and child health using a combination of a mobile application for health workers, a Near Field Communication enabled smart health card and automated local-dialect voice reminders for beneficiaries, and automated high-risk and dropout reports over WhatsApp for health officials and teams. They have deployed their platform to track the health of over 40,000 mothers and infants at the last mile in Rajasthan in India in partnership with the district government.

Khushi Baby has made available datasets that correspond to health camps that have been conducted in the past, including data about the health workers. These health workers, called ANMs (Auxiliary Nurse Midwives), are employed by the state government and are responsible for screening pregnant women and infants at these village-based maternal and child health camps. Each ANM provides antenatal care checkups and infant checkups (including immunizations) on four to five fixed camp sessions, each in a separate village, typically on each Thursday of the month. On average, an ANM caters to approximately 200 beneficiaries across these villages. An ANM also provides a set of 18 heuristic rules to readily identify which cluster is non-diligent by looking at the probability values of the cluster centers. We also perform an explainability analysis of the clustering and propose another more explainable scalar non-diligence score.

In experiments, we perform a baseline comparison with anomaly detection for sake of scientific completeness. In not so closely related work, detecting human behavior in context of fabrication (Birnbaum et al. 2013) has been studied using behavior data from a controlled user study: we do not possess behavior data of health workers and it is quite infeasible to collect such data.
the part of the ANM when screening a patient. Examples of non-diligence include: filling in test results in the absence of conducting the test, rounding results when more precise data is available, failing to record data fields that are non-mandatory, and recording test results for certain patients but reporting that the same test equipment is not available for other patients in the same camp. Analysis of the state’s data set and observations from the field have shown major gaps in data fidelity. Less than 50 percent of expected maternal and child deaths are reported in the state’s digital portal. Frequencies of normal urine studies are reported as high, when in many cases, due to lack of a private bathroom at the health camp, women are not asked to produce a urine sample for the test. Frequencies of blood pressure values in the state database show evidence of rounding, with low reporting of hypertension, which is expected at a certain baseline frequency during pregnancy. Even the number of actual blood pressure examinations done has been called into question (Dinesh Songara, Akanksha Goyal, Pankaj Suthar).

**Dataset description:** The data from Khushi Baby is for 85 ANMs. Every ANM conducts health camps at particular locations at regular intervals in her (ANMs are females) jurisdiction. Pregnant women are advised to get at least four check-ups in the course of the pregnancy and they visit the nearest camp, when due for a check-up, for the same. The data recorded is quite extensive ranging from basic health parameters such as blood pressure and sugar levels to pregnancy-specific parameters such as fundal height and baby position. All data about the beneficiaries who visit the health camp was de-identified and anonymized. Some health test happen at every camp and others (like HIV status) are conducted once in the pregnancy in a primary health center. Other population wide statistics, such as new-born child mortality rate, are also recorded. The data provided was initially from 09 February 2017 to 17 March 2020. Maternal and child health camps were suspended between March and May 2020 due to the COVID-19 outbreak. A data drop from after this period was used for field test.

**Problem statement:** The long term goal of Khushi Baby is to use the data collected for AI based support for better health care. However, the NGO knows from experience as well as confirmation from other NGOs that the data collected by ANMs is often not accurate. Thus, there is a need to identify non-diligent ANMs. Concretely, this requires solving two problems: (1) how to quantitatively measure non-diligence per ANM and (2) how to predict non-diligence per ANM in order to enable apriori intervention.

4 Methodology

We describe our approach in three distinct parts: first is a definition and multi-dimensional score of non-diligence per ANM, second is clustering and a scalar non-diligence score for each ANM, and finally a prediction of non-diligence.

4.1 Defining Non-diligence

Our first main idea is to obtain a probability of non-diligence per ANM corresponding to each of the 18 rules provided by the NGO using the data generated by each ANM. These 18 rules are of two types (1) rules that apply to data within one health camp (12 in number) and (2) rules that track longer term phenomenon (6 in number). All rules specify a percentage of something and we know which extreme (0% or 100%) corresponds to non-diligence. For reasons of required confidentiality of these rules, we do not list all the actual rules used in the work. As a running example we will use two rules throughout this paper:

**Running examples:** Short-term rule: percentage of blood pressure readings that are 120/80 or 110/70. We know that higher percentage corresponds to non-diligence. We call this the BP rule. Long-term rule: child mortality rate. We know that towards 0% is non-diligence and higher values are diligent readings (higher value in the data are typically low for this rule and does not reach anywhere close to 100%). We call this the child mortality rule.

**Handling Short-term Rules** We describe our approach here using the BP rule stated in the running example; rest of the short term rules are similar or flipped where 0% is diligent. In the BP rule we view 100% as non-diligent with probability 1 w.r.t. this rule. We compute the percentages as stated in the BP rule for each ANM for each health camp over all the training data. We filter out the percentages that are exactly 0% or 100% - as these extremes are for sure diligent or not. We treat the left over computed percentages as samples from a probability distribution and plot a density distribution using Kernel Density Estimation (KDE). Then, given the percentage computed for the BP rule, say $x$, for a health camp for an ANM, the probability of non-diligence $p$ is the probability mass between $(0, x)$. Clearly as $x$ increases, the probability of fraud is increasing and is exactly 1 when percentage is 100. See Figure 2 for an example KDE plot for the BP rule.

For other rules, where non-diligence with probability 1 is at the 0% extreme, the probability of non-diligence $p$ is the probability mass between $(x, 100)$.

**Aggregate over one month:** The ANM behavior varies a lot from one health camp to another so instead of considering the non-diligence probability for a short-term rule at one health camp we consider the average of non-diligence probability over all health camps conducted in a time window of four weeks. Applied over all the twelve short-term rules this yields twelve non-diligence probability values for each time window of four weeks.

**Handling Long-term Rules** The long term are evaluated on data for past 6 months (1 month = 4 weeks) since these rules track events that happen in sufficient numbers only over a longer term. We describe our approach here using the child mortality rate rule here; rest of the long term rules are very similar or the non-diligence percentage extremes are flipped. We use six months of data for each ANM to get the percentages for any long term rule. Then, the processing is similar to that of health camp level rules. We filter out percentage that are exactly 0% or 100%. For the left over percentages we plot a density distribution using KDE estimate. Then, given the percentage for the child mortality rate, say $x$, for the six months for an ANM – the probability of non-diligence $p$ is the probability mass between $(x, 100)$. Clearly
Figure 1: Data processing of an ANM’s data. Overall training/test data is from such processing for all 85 ANMs.

Figure 2: Kernel Density Estimation plot for the blood pressure rule after removing extremes

as \( x \) increases, the probability of fraud is decreasing and is exactly 0 when percentage is 100 (actually for child mortality rate rule it is zero much before 100 as the maximum percentage is low).

**Vector valued score of ANM behavior** The above approach provides 18 non-diligence probability values (vector of probabilities \( \vec{b} \)) to measure each ANM’s behavior at any given point in time by using past one month of data for short term rules and past six months of data for long term rules. Later in Section 4.2, we describe our approach to obtain a scalar valued non-diligence score.

**Behavior of ANM over Time** Using our training data, we compute the vector of non-diligence probabilities for an ANM at multiple time points that are separated by one month (using a sliding window of one month). In the training data, for each ANM we get 19 such vectors of non-diligence probabilities. There are 85 ANMS. So, we should ideally obtain 19x85=1615 vectors of probabilities, where each probability vector is 18-dimensional. However, because of some missing data, we actually obtain 1455 such vectors. Each probability vector is a data point. Observe that compared to the dimension of the problem (18) the number of data points are relatively few. The whole sliding window set-up is shown is Figure 1.

### 4.2 Clustering and Scalar Scores

After obtaining the non-diligence probability vectors (using training data) we cluster them into two clusters. Note that we do not have labels for ANM’s behavior, but the nature of our constructed features (non-diligence probabilities) readily allows us to identify which of the two cluster contains non-diligent behaviors. More precisely, we compare the 18-dimensional cluster centers after clustering and find that the average probabilities indicated by one of the cluster centers is clearly greater than that of the other cluster center, which enables us to tag the clusters as non-diligent and diligent. We denote the non-diligent cluster center as \( \vec{c}_n \) and diligent cluster center as \( \vec{c}_d \).

Observe that we obtained the probabilities of non-diligence for each of the 18 rule using single dimensional probability density estimates, which by themselves can be viewed as a soft clustering along the 18 dimensions of non-diligence. Thus, overall we have two levels of clustering, one at the level of each rule (each dimension) and then another clustering at an aggregate level.

We perform two types of clustering at the aggregate level, k-means and fuzzy c-means (Bezdek, Ehrlich, and Full 1984). Both these clustering techniques are standard and well-known, we also tried variations such as kernel k-means (Dhillon, Guan, and Kulis 2004) but that did not change the results at all. The difference between these methods are that k-means assigns every data point to one cluster whereas for every data point fuzzy c-means (FCM) assigns a probability of belonging to one or other cluster. Once the clusters are determined using the training data, the clusters are fixed for any future evaluation, that is, no future data is used to update the clusters. This is to ensure that we measure the future behavior vectors within a static frame.
Data collection quality score based on clustering: For any given ANM behavior \( \vec{b} \) (which may not be one of the vectors used in clustering), FCM assigns a probability for belong to the non-diligent cluster. We treat this probability of belonging to the non-diligent cluster as the data collection quality score for that ANM at that time point.

Interpreting Clustering  The clustering we used by itself provides little insight into why some data points belong to one cluster over other (in case of FCM, why are some probabilities higher). Since, we have only two clusters, we performed a simple explainablility analysis by calculating the hyperplane \((y = \sum_{i=1}^{18} w_i x_i + c)\) between the two cluster centers \(c_n, c_d\) and checking the weights assigned to each of the 18 dimension. We found that three rules have much higher weights than other rules, pointing to the fact that these rules provide the most distinguishing dimensions for the formation of clusters. In consultation with the NGO, we performed further analysis that provides confidence that the clustering outcome is expected (details in experiments).

However, there are some rules for which almost all ANMs have low probability of non-diligence, which are not considered important in clustering as the mostly low probabilities do not provide any distinction in behavior. This motivated us to define another simple scalar score metric that also captures overall behavior, as described next.

Simple norm score: The ideal behavior vector for an ANM is \(\vec{0}\), meaning zero probability of non-diligence for every rule. Thus, given a vector \(\vec{b}\), a natural score is its distance from \(\vec{0}\), that is, \(||\vec{b}||_2\). This score is interpretable and by definition explicitly gives equal importance to all rules. In our final deployment, we use both the scores together as described in experiments.

4.3 Prediction

We aim to predict the scalar score (both clustering based and norm score) of an ANM’s behavior in the test dataset. We also perform a binary prediction (interpreted as belonging to one of the clusters) using labels derived from k-means. Accordingly, while training the labels are \(\{0, 1\}\) using k-means or \(a [0, 1]\) using FCM or a number \(\geq 0\) using the simple norm score. The inputs to the predictor neural network are the past six months of non-diligence vectors of the ANM under consideration. We also tried other inputs such as estimated number of health camps, estimated frequency of health camps, and estimated number of free days for the next month. However, these additional features did not change the result much, hence in our final product we choose the simpler input of the past six month history of the ANM only. The neural network uses an initial LSTM layer to compress the history. Our code for the network is available publicly at (Karunasena 2020).

Finally, the NGO Khushi Baby finds scalar scores to be more useful in order to design targeted intervention (such as ANM training) for a limited number of ANMs. The scores allow us to extract top-K non-diligent ANMs, whereas classification just provides a coarse output in which more than 50% ANMs are not diligent. Thus, our proposed deployment will use the regression based prediction of non-diligence scores (both clustering based and simple norm score).

5 Results

We present our experimental results in this section. The data-set was already described earlier in Section 3. An additional detail is that after our initial data till March 17, 2020, the health camps stopped running due to the COVID caused lockdown in India. Thus, the next data drop we obtained for field test only had reliable data for July and August, 2020. Even in the new data, not all ANMs were conducting camps so our results shown for the field test are only for those ANMs that conducted the camp.

We process the data as we described earlier. We split the data set we have into training and test data, where the split was according to time due to the sequential (time series) nature of data. Our training data was from 27 December 2017 to 11 June 2019 and test data from 25 December 2019 to 17 March 2020. The gap between this data sets is because the probability vectors computed for test data uses data from last six months and the gap was deliberately introduced to avoid any overlap of test and train data (see Figure 1).

For KDE, we use the kde1d library in R (invoked from python) with an adaptive Gaussian kernel bandwidth (Sheather and Jones 1991). The FCM clustering uses a hyper-parameter \(m\) that controls the fuzziness; we choose this to be 2 based on experimental tuning. We used scikit-fuzzy library (Warner et al. 2019) for FCM. All our code is written in python and ran on Google cloud infrastructure. We start by presenting results from two baseline methods.

5.1 Baseline Methods Results

We tried two baselines. The first is a simple heuristic baseline that uses the 18 rules provided by Khushi Baby with fixed thresholds percentage. For example, for the BP rule a threshold of 70% of all blood pressure readings in a health camp being exactly same was used to tag ANMs as diligent or not. Note that these rules do not provide a score, so are not very desirable to start with. Moreover, these rules performed very poorly—the outcome we obtained was that either (1) no ANM was tagged as non-diligent when the rules were used in an AND manner and (2) all ANMs were tagged as non-diligent when the rules were used in an OR manner.
Table 3: Accuracy, recall, precision for test data over three months in 2020

| Metric                  | Jan. | Feb. | Mar. |
|-------------------------|------|------|------|
| Accuracy                | 0.96 | 0.96 | 0.86 |
| Class 0 Recall          | 0.90 | 0.88 | 0.82 |
| Class 0 Precision       | 1.00 | 1.00 | 0.82 |
| Class 1 Recall          | 1.00 | 1.00 | 0.88 |
| Class 1 Precision       | 0.95 | 0.94 | 0.88 |

Table 4: MSE and R2 for test data over three months in 2020

| Metric                  | Jan.      | Feb.     | Mar.     |
|-------------------------|-----------|----------|----------|
| MSE (cluster score)     | 0.0112    | 0.0080   | 0.0152   |
| R2 (cluster score)      | 0.7644    | 0.8355   | 0.6359   |
| MSE (norm score)        | 0.0102    | 0.0113   | 0.0118   |
| R2 (norm score)         | 0.8228    | 0.7747   | 0.7970   |

Table 5: Accuracy, recall, precision for field test over two months data in 2020

| Metric                  | July | Aug. |
|-------------------------|------|------|
| Accuracy                | 0.95 | 0.91 |
| Class 0 Recall          | 0.87 | 0.78 |
| Class 0 Precision       | 0.93 | 0.78 |
| Class 1 Recall          | 0.98 | 0.95 |
| Class 1 Precision       | 0.96 | 0.95 |

Table 6: MSE and R2 for field test over two months in 2020

| Metric                  | July  | Aug.  |
|-------------------------|-------|-------|
| MSE (cluster score)     | 0.0111| 0.0115|
| R2 (cluster score)      | 0.7048| 0.5836|
| MSE (norm score)        | 0.0202| 0.0255|
| R2 (norm score)         | 0.5346| 0.5479|

The second baseline that we try is anomaly detection. We used a popular variational auto-encoder based anomaly detector \cite{An and Cho 2015}. We pre-processed our training data over time similarly as for clustering by using one month sliding window and processing short term and long term rules as percentages. We did not convert the raw percentage to probabilities. We trained the anomaly detector on the training data and then tested how the simple norm score differs for the set of ANMs tagged non-diligent vs the set of ANMs tagged diligent by the anomaly detector in the test data. We use the norm score to compare these two sets as the norm score is interpretable. The results for the three months in test data is shown in Table 1, which indicates that the anomaly detector is unable to capture non-diligence as the mean norm score is almost same in the two sets of ANMs. As stated earlier, this is likely because non-diligence is not an outlier and unsupervised anomaly detection is based on the outlier assumption.

5.2 Clustering Results

As described earlier our clustering provided two clusters, for which we present the difference in the two cluster centers in Table 2. We present the average, minimum, and maximum difference across the 18 dimensions of the cluster center. Also, in total 15/18 dimensions have higher probability of one cluster over another in k-means and that number is 11/18 for FCM. As these numbers show, the FCM clusters are less separated than that of k-means, which is potentially due to the soft clustering nature of FCM. This result allows us to label the cluster with higher average probability of non-diligence as the non-diligent behavior cluster.

5.3 Explaining Scalar Scores

As explained earlier, the cluster formation and hence the scalar score based on FCM clustering was found to heavily rely on three rules (or three dimensions out of 18 dimensions). These three dimensions were all found to be corresponding to behavior where the ANM is supposed to follow up with the patient on whether they got a test done at a primary health center (not health camp) and record the results. Clearly, less diligent ANMs, on average, shirk this more arduous task and hence the clear distinction for these rules is likely a meaningful indicator of diligence.

However, some ANM could still be scoring good for these three rules while being non-diligent with respect to other rules. This is precisely why we also defined our simple norm score rule. We find that the norm score and the clustering based score have a Pearson correlation coefficient between 0.8 and 0.84 for the three months in test data, showing strong correlation with just one or two ANMs who score high on the norm score and lower on the cluster based score. Thus, we propose to use predictions of these scores in an OR fashion where a union of the top-K worst performing ANMs for each score are chosen for intervention.

5.4 Prediction on Test Data

The clustering was done using the training data and fixed, meaning future test data does not change the clusters. For classification, the data points in the test set were assigned to clusters using nearest cluster center to obtain test data labels. For regression, when using FCM the probability of a test data point belonging to a cluster was determined using fuzzy assignment \cite{Ross 2004}. Table 3 and 4 show the results for classification and regression respectively. The results show an average accuracy of over 90% with high precision and recall and low MSE in case of regression.

5.5 Field Test Results

After the encouraging results on test data, we performed a field test. However, due to the unprecedented situation arising from COVID we had to make some adjustments. First, there were very few health camps held from April 2020 to about mid-May 2020, after which the numbers stabilized to pre-COVID levels. Thus, six weeks of data was essentially missing. We choose July and August 2020 for the field test in
order to further allow the data to be stabilized. For calculating the probability for the long term rules for field test data we had to go back six months and six weeks in order to account for the missing six weeks of data in between. The prediction was done with exactly the same model learned using our training data. Table 5 and 6 show the results for classification and regression respectively. The results are very similar in quality to the results on test data. We also show in Figure 3 that the predicted scores are spread over the range and the two scores are strongly correlated. Hence, predicting scores provides a ranking of the ANMs that allows choosing top-K non-diligent ANMs for intervention.

5.6 Robustness Check

Our good accuracy might appear to be in part due to our prediction of ANM behavior over four weeks (averaging four weeks of short term rule probabilities). However, four weeks averaging is a very practical choice. Indeed, our NGO partner also believes that the ANM behavior must be analyzed over a period and not a very short duration due to spurious reasons of non-diligence in the short run. For academic completeness, we perform predictions for a shorter one week duration over the weeks in Jan to March 2020. We observed a small variance of accuracy and MSE; details of this result are in the appendix.

5.7 Sensitivity Analysis

We tested the variance of the cluster centers using 30 random seeds for initializing the two clustering approaches. Table 7 shows the variance of average, minimum, and maximum differences of cluster centers; the very low values mean that practically the clusters do not change with random seeds. We also tested the variance of the regression and classification models trained with 30 different random seeds and the results are shown in Table 8. The low numbers here also indicate the prediction outputs are quite robust to different random initialization. Additional results on sensitivity are in the appendix.

6 Summary and Future Work

Our work is in final stages of deployment and will continuously predict scores every month for the ANMs as well as measure their performance in hindsight. Moreover, the data format for tracking pregnancy health used in Rajasthan is consistent with National Health Mission Guidelines followed across India. Thus, this work has the potential to be broadly applied across a health workforce of 250,000 ANMs who care for 25M pregnant women annually.

Listing a few limitations, we identify that the model itself will need to be tuned to new data and new health workers. New domain specific insights from the field such as deviation in GPS points, match rate of entries with beneficiary records, distribution of time stamps during which the app was used on the camp day may all further improve the clustering.

A future work topic is design of intelligent interventions that are effective in nudging the ANMs to be more diligent in data collection. The design of interventions is a complex social science issue with ethical considerations. Our data collection quality scores provide a quantitative measure of the effect of such interventions. In the longer term, this work has implications for using pregnancy health data to predict adverse maternal and child health outcomes. By having a diligence score available, data from community health workers can be quantitatively weighted to ensure fidelity of these models.

| Month     | Var. in MSE of cluster score reg. | Var. in MSE of simple score reg. | Var. in Acc. of classifi. model |
|-----------|----------------------------------|----------------------------------|-------------------------------|
| Jan       | 1.96 × 10^{-4}                  | 4.90 × 10^{-4}                  | 5.89 × 10^{-2}                |
| Feb       | 2.23 × 10^{-4}                  | 3.84 × 10^{-4}                  | 6.73 × 10^{-2}                |
| Mar       | 9.23 × 10^{-5}                  | 4.43 × 10^{-4}                  | 4.67 × 10^{-2}                |
| Jul       | 1.27 × 10^{-4}                  | 1.10 × 10^{-4}                  | 8.32 × 10^{-2}                |
| Aug       | 9.78 × 10^{-5}                  | 2.29 × 10^{-4}                  | 9.30 × 10^{-2}                |

| Method    | Var. in Avg. Diff. | Var. in Min. Diff. | Var. in Max Diff. |
|-----------|-------------------|--------------------|-------------------|
| k-means   | 5.26 × 10^{-10}   | 3.04 × 10^{-9}     | 1.78 × 10^{-9}    |
| FCM       | 3.38 × 10^{-11}   | 4.95 × 10^{-12}    | 1.65 × 10^{-9}    |

Figure 3: Non-diligence scores per ANM distribution in July and August 2020 (x-axis are anonymized ANM ids)
health workers through peer learning in rural india. In Proceedings of the 26th International Conference on World Wide Web, 499–508.

[Yu, He, and Liu 2015] Yu, R.; He, X.; and Liu, Y. 2015. Glad: group anomaly detection in social media analysis. ACM Transactions on Knowledge Discovery from Data (TKDD) 10(2):1–22.
A Baselines

As stated, we used a variational auto-encoder based anomaly detector as our second baseline to detect non-diligent ANMs. Log reconstruction plots for the three months in test data set are available in Figure 4. The ANMs with lower reconstruction log probabilities correspond to anomalies. We chose 30 as the threshold to separate the diligent and non-diligent ANMs. Table 9 shows the percentages of ANMs tagged as non-diligent by the anomaly detector in the test set. These percentages are considered small by our NGO partners.

B Additional Results

We observed the correlation among the 18 dimensions of the non diligence probability vectors in each month in both the test set and field test set and we found that most of these dimensions (each corresponding to a short term or long term rule) show a weak correlation, except for three prominent rules which show a strong positive correlation with each other. The results are shown in Figure 5 for the month January and the heat maps for the other months do not deviate significantly from this. These three prominent rules are the rules that contributes most towards our cluster score, as explained in Section 5.2.

The results for the robustness check are shown in Figure 6 and 7. The movement of accuracy (or MSE) is still in somewhat of a narrow band (clearly with a small variance).

We analyzed the sensitivity of the cluster centers and noted that they show very low variance in both clustering methods. Tables 10 and 11 show the results of the variance of cluster centers across 30 random seeds for FCM and k-means respectively.

Table 9: Percentages of non-diligent ANMs tagged using variational auto-encoder based anomaly detector

|       | Jan. | Feb. | Mar. |
|-------|------|------|------|
| Percentage | 28.57 | 19.15 | 17.86 |

Table 10: Variance of c-means cluster centers across 30 seeds

| Rule | Non-diligent cluster center variation | Diligent cluster center variation |
|------|-------------------------------------|----------------------------------|
| 0    | $2.06 \times 10^{-14}$              | $5.61 \times 10^{-12}$          |
| 1    | $7.70 \times 10^{-14}$              | $1.91 \times 10^{-11}$          |
| 2    | $5.29 \times 10^{-14}$              | $2.28 \times 10^{-16}$          |
| 3    | $1.85 \times 10^{-12}$              | $4.15 \times 10^{-12}$          |
| 4    | $3.06 \times 10^{-16}$              | $8.50 \times 10^{-15}$          |
| 5    | $3.51 \times 10^{-17}$              | $8.67 \times 10^{-14}$          |
| 6    | $8.95 \times 10^{-17}$              | $1.19 \times 10^{-14}$          |
| 7    | $9.49 \times 10^{-15}$              | $1.38 \times 10^{-14}$          |
| 8    | $4.16 \times 10^{-15}$              | $4.59 \times 10^{-13}$          |
| 9    | $1.10 \times 10^{-15}$              | $4.67 \times 10^{-16}$          |
| 10   | $5.63 \times 10^{-14}$              | $1.70 \times 10^{-13}$          |
| 11   | $5.67 \times 10^{-14}$              | $1.70 \times 10^{-13}$          |
| 12   | $1.55 \times 10^{-10}$              | $7.92 \times 10^{-10}$          |
| 13   | $5.71 \times 10^{-11}$              | $2.68 \times 10^{-10}$          |
| 14   | $1.37 \times 10^{-10}$              | $7.47 \times 10^{-10}$          |
| 15   | $2.05 \times 10^{-16}$              | $2.62 \times 10^{-13}$          |
| 16   | $2.59 \times 10^{-13}$              | $3.58 \times 10^{-12}$          |
| 17   | $4.00 \times 10^{-13}$              | $1.34 \times 10^{-12}$          |

Table 11: Variance of k-means cluster centers across 30 seeds

| Rule | Non-diligent cluster center variation | Diligent cluster center variation |
|------|-------------------------------------|----------------------------------|
| 0    | $1.43 \times 10^{-9}$               | $6.62 \times 10^{-9}$            |
| 1    | $9.22 \times 10^{-10}$              | $6.14 \times 10^{-10}$           |
| 2    | $2.50 \times 10^{-11}$              | $1.14 \times 10^{-10}$           |
| 3    | $7.73 \times 10^{-10}$              | $7.08 \times 10^{-9}$            |
| 4    | $1.16 \times 10^{-12}$              | $7.42 \times 10^{-12}$           |
| 5    | $9.28 \times 10^{-12}$              | $2.52 \times 10^{-11}$           |
| 6    | $8.36 \times 10^{-13}$              | $1.51 \times 10^{-12}$           |
| 7    | $4.99 \times 10^{-12}$              | $1.20 \times 10^{-11}$           |
| 8    | $9.26 \times 10^{-11}$              | $2.10 \times 10^{-10}$           |
| 9    | $2.11 \times 10^{-12}$              | $8.87 \times 10^{-12}$           |
| 10   | $5.75 \times 10^{-11}$              | $1.85 \times 10^{-10}$           |
| 11   | $5.76 \times 10^{-11}$              | $1.86 \times 10^{-10}$           |
| 12   | $1.01 \times 10^{-8}$               | $3.37 \times 10^{-9}$            |
| 13   | $1.58 \times 10^{-10}$              | $2.61 \times 10^{-8}$            |
| 14   | $1.67 \times 10^{-9}$               | $2.85 \times 10^{-8}$            |
| 15   | $1.11 \times 10^{-11}$              | $3.33 \times 10^{-12}$           |
| 16   | $5.22 \times 10^{-10}$              | $2.21 \times 10^{-9}$            |
| 17   | $9.95 \times 10^{-10}$              | $5.76 \times 10^{-9}$            |
Figure 4: Log reconstruction plots using the variational autoencoder

Figure 5: Heatmap of the correlation between the 18 dimensions of the non-diligence probability vectors of ANMs in January 2020

Figure 6: One week classification predictions

Figure 7: One week regression predictions