Initial report on analysis of the Anganwadi 2010 dataset

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1 Abstract

This report summarises the results of exploration of the Anganwadi dataset provided by the Akshara Foundation. The analysis aims to characterise the structure of the data, and reveal trends (which would otherwise be obscured by the format of the source data) which may inform strategy through subsequent prediction and/or classification procedures.

2 Methodology

2.1 CRISP-DM

CRISP-DM is a process model distilled from the most common approaches used in data mining procedures. It stands for Cross Industry Standard Process for Data Mining. Not so much a prescription as a collection of 'good practices' follwed by data mining professionals, **CRISP-DM** has the following characteristics.

- Domain-neutral
- Tool-neutral
- Provides a structural approach to the data mining process

CRISP-DM segregates data mining endeavours into the following phases.

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment

2.2 Relevance of CRISP-DM to this report

As far as this report is concerned, the relevant or most significant phases we focus on are:

- Data Understanding
- Data Preparation
- Modeling

Work on the Evaluation step is still preliminary, and will probably be the subject of another report. In a full-fledged project, the rest of the activities upstream and downstream to the above list will assume more importance, and require corresponding investment.

3 Data Preparation

3.1 Nature of the source data

The dataset comes from the education domain. The source data is a file, with each line corresponding to a single student evaluation record. Roughly, there are 29000 records, prior to any data sanitisation. Each line is pipe(|)-delimited into multiple fields. The fields salient to this analysis are listed below:

- Location of the student's school
- Language of the student
- Student's score before intervention
- Student's score after intervention

The score is not a single number, it is a set of 56 responses marked as 0/1. Generally, a 1 may be treated as a favourable answer, therefore, adding them up to get a single aggregate score has natural ordering: a sense of who did better. We reproduce two such records below, with the original formatting.

30915|YALLAMMANADODDI|KANNADA|1231468|Girl||1NoSection|Aug 2010 Assessment
|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1
|Anganwadi Post Test|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|

29607|BADAMAKAAN I|KANNADA|1445172|Girl|URDU|1NoSection|Aug 2010 Assessment |1|0|1|1|0|1|0|1|1|1|1|1|1|1|1|0|1|1|1|1|1|0|1|1|1|1|1|0|1|1|1|0|1|1|1|1|1|1|0|1|1|0|1|1|1|1|1|1|1|1|1|1|1|1|1|0
|Anganwadi Post Test|1|0|1|1|1|0|1|1|0|1|1|0|1|1|1|1|0|1|1|1|0|0|1|1|0|1|0|0|1|1|1|0|1|1|0|0|1|1|1|0|0|1|1|1|1|1|1|1|1|1|1|1|1|1|1|1|
...

Looking at the second row, we see that the location of the Anganwadi is BADAMAKAAN I, the student is female and speaks Urdu. The first contiguous set of 0s and 1s is the pre-intervention score, and the next set is the post-intervention one.

3.2 Data representation

3.2.1 Data store

Before any sort of sanitisation or analysis may be performed, it is important to ensure that the source data is stored in a format/datastore which makes querying and modifying the data relatively painless. This decision is largely driven by technological considerations, like:

- Scale of data (centralised/distributed store?)
- Sophistication of queries (OLAP/OLTP?)
- Structure of data, or lack thereof (SQL/NoSQL?)

We were dealing with only about 29000 records, and most of the analysis would probably be performed outside the database. Thus, we opted to use MySQL as our datastore.

3.2.2 Schema

The decisions when creating the database schema affect the ease of querying for relevant information. Apart from the attributes of interest, we wanted to store the individual binary responses as well. One way is to create one column for each response, giving us a total of 112 columns for storing these responses (56 for pre-intervention, 56 for post-intervention). The other way, and that is the one that we chose was to store this information as a 64-bit integer (bigint for MySQL). When required, we could unpack the individual response bits from this number.
A `desc responses;` command on the table reveals the schema we ended up with.

```
+------------------+------------+------+-----+---------+----------------+
| Field            | Type       | Null | Key | Default | Extra          |
+------------------+------------+------+-----+---------+----------------+
| student_id       | int(11)    | YES  |     | NULL    |                |
| area             | char(50)   | YES  |     | NULL    |                |
| pre_performance  | bigint(20) | YES  |     | NULL    |                |
| post_performance | bigint(20) | YES  |     | NULL    |                |
| language         | char(50)   | YES  |     | NULL    |                |
| gender           | char(20)   | YES  |     | NULL    |                |
| pre_total        | int(11)    | YES  |     | NULL    |                |
| post_total       | int(11)    | YES  |     | NULL    |                |
| id               | int(11)    | NO   | PRI | NULL    | auto_increment |
| school_id        | int(11)    | YES  |     | NULL    |                |
| year             | int(11)    | YES  |     | NULL    |                |
+------------------+------------+------+-----+---------+----------------+
```

The most important use of the reference data is to locate the schools geographically. Given that geocoding the school from its name, we used the cluster to locate schools in 2D space. We deal with geographical analysis in a later section. The schema of the master data mostly mirrors the CSV master data file format, with the addition of latitude and longitude, like so:

```
+-------------+----------------+------+-----+---------+----------------+
| Field       | Type           | Null | Key | Default | Extra          |
+-------------+----------------+------+-----+---------+----------------+
| district    | char(50)       | YES  |     | NULL    |                |
| block       | char(50)       | YES  |     | NULL    |                |
| cluster     | char(50)       | YES  |     | NULL    |                |
| school_id   | int(11)        | YES  |     | NULL    |                |
| school_code | char(20)       | YES  |     | NULL    |                |
| school_name | char(50)       | YES  |     | NULL    |                |
| id          | int(11)        | NO   | PRI | NULL    | auto_increment |
| latitude    | decimal(20,10) | YES  |     | NULL    |                |
| longitude   | decimal(20,10) | YES  |     | NULL    |                |
```

+------------+---------------+------+-----+---------+---------------+

To identify latitude and longitude, we used Google's Map API to geocode the cluster information. It is to be noted that there may be some clusters which weren't located by the Map API, and some more work is needed to cross-validate the coordinate information taken from the Map API.

3.3 Data migration: Identifying invalid data

It is natural to expect missing or corrupted data. The most crucial attribute are the score data, as any misinterpretation of that data may adversely bias the quality of our analysis. Thus, specific checks were put in place to ensure that none of the binary responses was null or some string other than 0 or 1.

Using this check, we found 1067 responses which violated it. All of them had either empty pre- or post-intervention scores. We did not migrate these response records, though it may be possible to do Monte Carlo simulations to predict the missing data.
As a result, out of a total of 28535 records in the original source, 27468 were migrated to the database.
We also found a large fraction of records which did not have a LANGUAGE attribute, i.e., that field was empty. Nevertheless, they were included in the migration.

4 Bias

Analysis is most suscpetible to bias in the data collection stage. Sampling is one such activity. If, for a statistical study, participating individuals are not equally likely to have been selected, it may be difficult to distinguish between the actual phenomenon and this biased sampling. This sort of bias is called sampling bias.

4.1 Sampling bias

To find evidence for bias, we looked at a few parameters. Here is the breakdown of the population by language, with the biggest language bucket highlighted.

Unspecified=869
URDU=3564
KANNADA=18685
TELUGU=1688
TAMIL=2051
MARATHI=91
OTHER=239
HINDI=243
KONKANI=18
GUJARATHI=12
NOT KNOWN=3
ORIYA=2
MULTI LNG=1
BENGALI=1
NEPALI=1

There is an overwhelming proportion of students who speak Kannada as their mother tongue (leading by an order of magnitude), a fact that is very likely to bias any sort of analysis where language is involved. We must remain cognizant of such biases, and interpret the results accordingly.

Here is the breakdown of the population by gender.

Girl=14822
Boy=12646

There is not a huge disparity between the two sexes, which indicates that any analysis/prediction based on gender may be less biased.

5 Shape of the data

Before embarking on any deep analysis of data, it behooves us to look at the shape of the raw data. There are a few reasons why we want to do this.

- **Evident trends/outliers**: Visualisation of the raw data set is always a quick way to spot trends without doing too much analysis. Of course, visualisation is best suited for 1,2 and 3-dimensional data: data of higher dimensionality must usually be either sliced prior to visualisation, or have its dimensionality reduced, before projecting it onto the 2D plane.
  Having said that, there are other ways of visualising the data without sacrificing any dimensions at all, such as Parallel Coordinates, though it is more suited to data exploration.
- **Evidence of conformance to well-known distributions**: There exist many probability distributions, some of whose properties are well-studied and well-known, like the Normal distribution. If the data approximates one of these distributions, there are several mature statistical methods which may be applied to test different hypotheses and properties of the data.
  Indeed, many of the classical statistical analyses make the assumption that the underlying data is (approximately) normally distributed.

In the following sections, we shall explore the shape of the Anganwadi 2010 dataset, and record our observations on it.

5.1 Univariate distributions

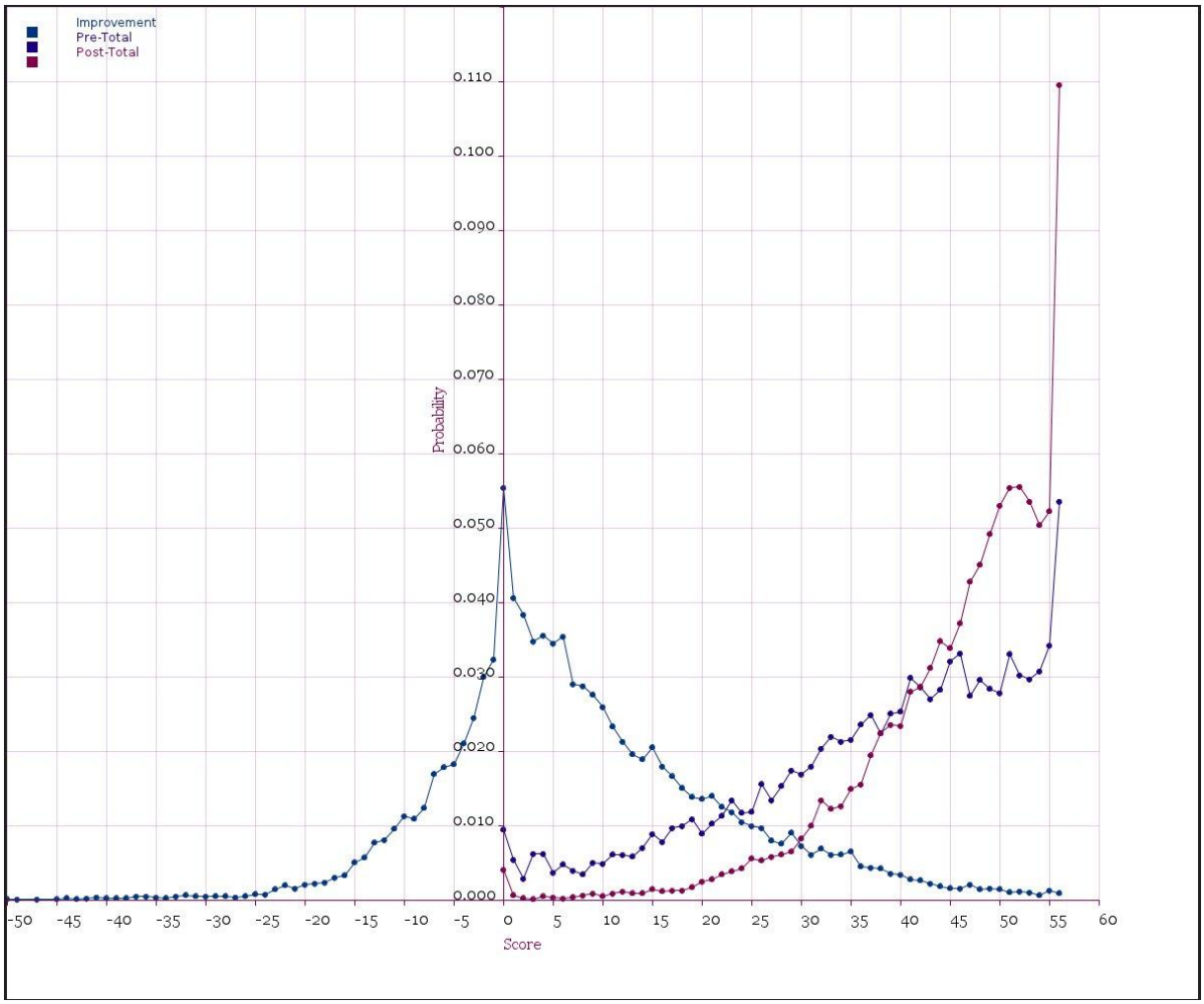
Figure 1 shows 3 distributions: the pre-intervention scores, the post-intervention scores, and the improvements.

5.1.1 Observations/Notes

- The pre-intervention score with the highest number of students is 56, which is the highest score possible. This implies that, even prior to intervention, a sizeable fraction of the students have scored very high on the test.
- The post-intervention score also follows the same trend, albeit with a steeper curve, which implies that many students have scored better in the post-test than in the pre-test.
- The improvement distribution is peaked, the peak being near zero. This makes sense, because if a large fraction of students answered all 56 questions as 1 in the pre-intervention score, there really is no way for them to improve. This is assuming that their performance did not worsen in the post-test. In fact, the calculated mean is around 7.
- There is a significant fraction of students whose performance has worsened in the post-test. This number is 7081. Out of those, we noticed that the worsening was dramatic for a small set. We have listed down the records which had a regression of 40 or more, below.

student_id	area	pre_total	post_total	language
1506619	VABASANDRA	52	0	KANNADA
1444355	KITTAGANA COLONY	56	0	KANNADA
1426910	PRIYA DARSHINI	53	0	KANNADA
1445387	KYALASANAHALLI	51	1	TELUGU
1445382	KOTHANUR	44	0	TAMIL
1445383	KOTHANUR	41	0	KANNADA
1442911	BETTANA PALYA	55	12	KANNADA
1445160	KODIGEHALLI	52	0	KANNADA
1457095	KAVERI NAGARA	41	0	KANNADA
1457090	KAVERI NAGARA	44	0	TELUGU
1457092	KAVERI NAGARA	41	0	TELUGU
1507686	REHMATH NAGAR	44	0	URDU
1448385	MALSANDRA	50	0	KANNADA
1455798	KANTEERAVA COLONY	55	15	KANNADA
1444466	PRIYA DARSHINI	52	0	KANNADA
1444467	PRIYA DARSHINI	44	0	KANNADA
1445337	RACHENAHALLI	52	0	KANNADA

Figure 1: Probability distributions of pre-, post-intervention, and improvement



1425269	VINYAKNAGAR	41	0	KANNADA	
552534	KYALASANAHALLI	52	1	TELUGU	
1448976	KRISHNA SAGARA COLONY	54	14	KANNADA	
1507157	BELTHURU	52	7	KANNADA	
1444897	MUNESHWARA NAGAR	45	0	TAMIL	
1444890	MUNESHWARA NAGAR	40	0	KANNADA	
1542861	VERABADRA NAGAR 1	56	1	KANNADA	
1358415	KOTHANUR	48	8		
1445437	THRIVENINAGARA	40	0	TELUGU	
1442907	BETTANA PALYA	55	8	KANNADA	
1457106	KAVERI NAGARA	40	0	TELUGU	
1445444	THRIVENINAGARA	41	0	TELUGU	
1444474	PRIYA DARSHINI	54	0	KANNADA	
1445159	KODIGEHALLI	41	0	KANNADA	
511998	KODIGEHALLI	55	0	KANNADA	
1356274	KAVERI NAGARA	56	0		
1358429	KOTHANUR	42	0		
1497510	JALAHALLI 1	42	0	KANNADA	
1443914	BIDARAHALLI	56	12	KANNADA	
1366955	PRIYA DARSHINI	53	0	KANNADA	
1366956	PRIYA DARSHINI	53	0	KANNADA	
1447019	MADAPPANA HALLI	42	0	TELUGU	
1355112	BYRATHI BANDE	55	14		
1504259	MAYASANDRA A	56	0	KANNADA	
1457120	KAVERI NAGARA	43	0	TAMIL	
1457089	KAVERI NAGARA	43	0	TAMIL	
1445171	KODIGEHALLI	44	0	KANNADA	
1457203	SARAIPALYA	51	0	URDU	
1457179	BYRATHI BANDE	55	14	KANNADA	
1504538	KEMPEGOWDA NAGAR	51	7	KANNADA	
1444486	PRIYA DARSHINI	49	0	KANNADA	
1444488	PRIYA DARSHINI	42	0	KANNADA	
1451831	AMBED NAGAR	50	9	TAMIL	

- The post-intervention score distribution seems to follow a power law. We shall consider modeling this attribute further on.

5.2 Outlier analysis

5.3 Bivariate distribution

So far, we've been looking at single variables in isolation. Figure 2 shows a bivariate histogram of pre- vs. post-intervention scores. The lighter a cell, the more the number of records in that 'bucket'.

y = 0.224.x + 37.134

5.3.1 Observations/Notes

- Many of the scores seem to be clustered near the top right. To further highlight this, we have draw a linear regression line as a rough indicator of a trend (To model the trend in more detail, we could use LOESS). What is somewhat puzzling is that there are not a few students whose performance has dropped after the intervention. This is evident even without doing a linear regression.
- The immediate outliers which are visible are the ones on the extreme left (pre 0, post 56) and at the origin (pre=0, post=0). The latter outlier(s) may be an artifact of corrupted data collection; we cannot say.

Figure 2: Bivariate probability distribution of pre- vs. post-intervention scores

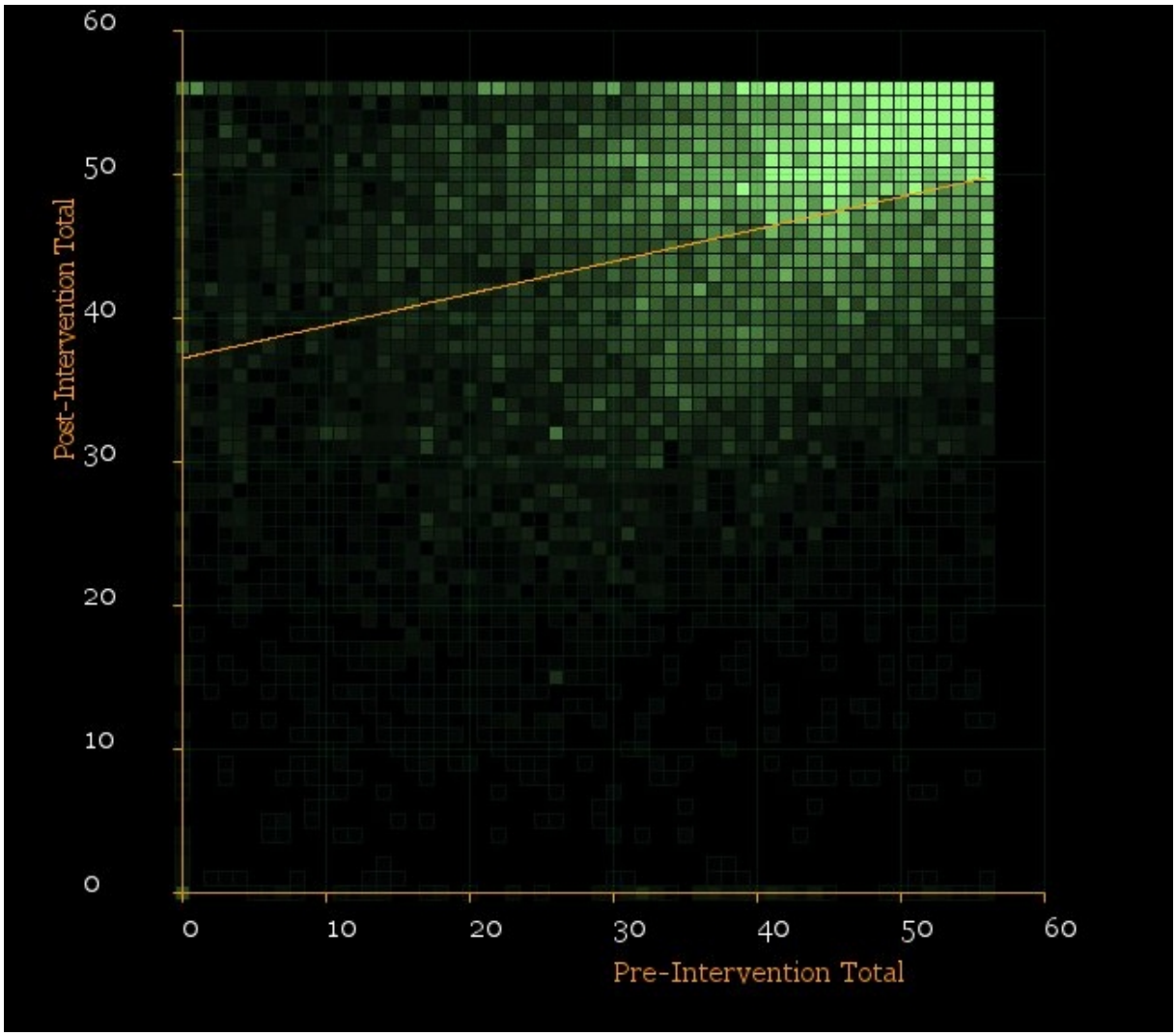
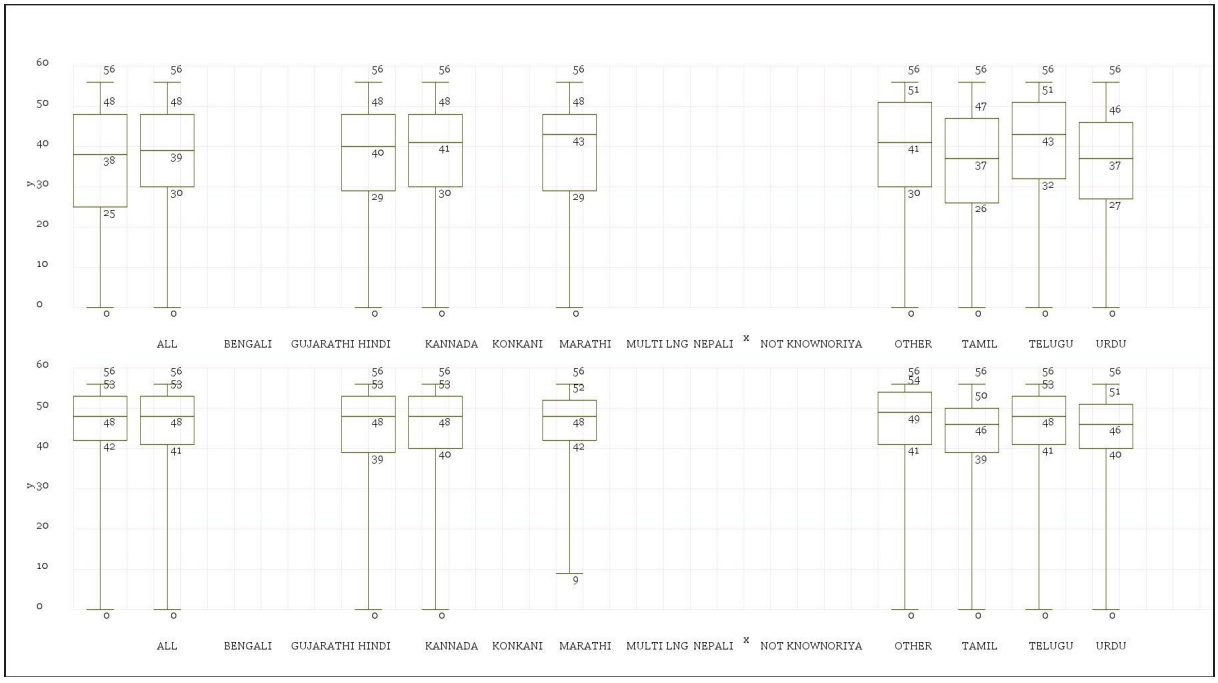


Figure 3: Box plots of pre- and post-intervention scores, broken down by language



5.4 Summary plots

Summary plots are so called for their ability to summarise up a data set as a set of numbers, which can be easily interpreted. We used Box Plots to summarise the data, broken down by language. Figure 3 shows that breakdown. The top row represents the box plots for the pre-intervention assessment, the bottom one for the post-intervention assessment.

5.4.1 Observations/Notes

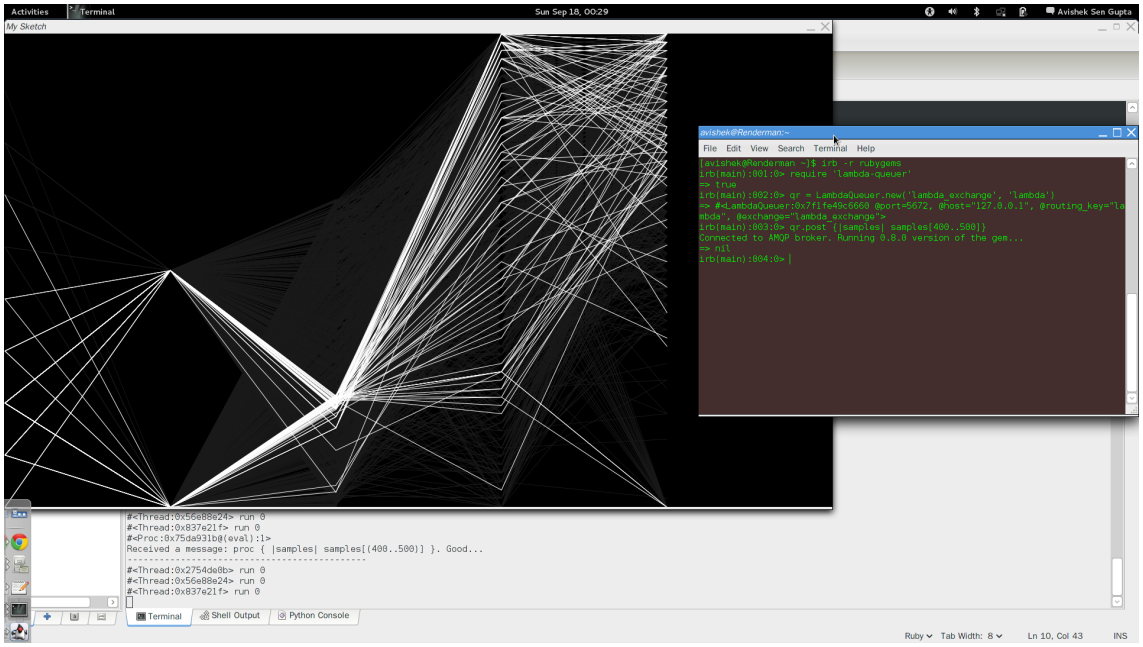
- Out of all the languages, we were not able to create box plots because the corresponding samples were too few in number to differentiate between the different quartiles. These languages are Bengali, MultiLng, Not Known and Oriya.
- There are no dramatic differences between the plots in each set. The medians, 1st and the 2nd quartiles are rather close to each other.

5.5 Rank Order Charts: Cluster

6 Data exploration

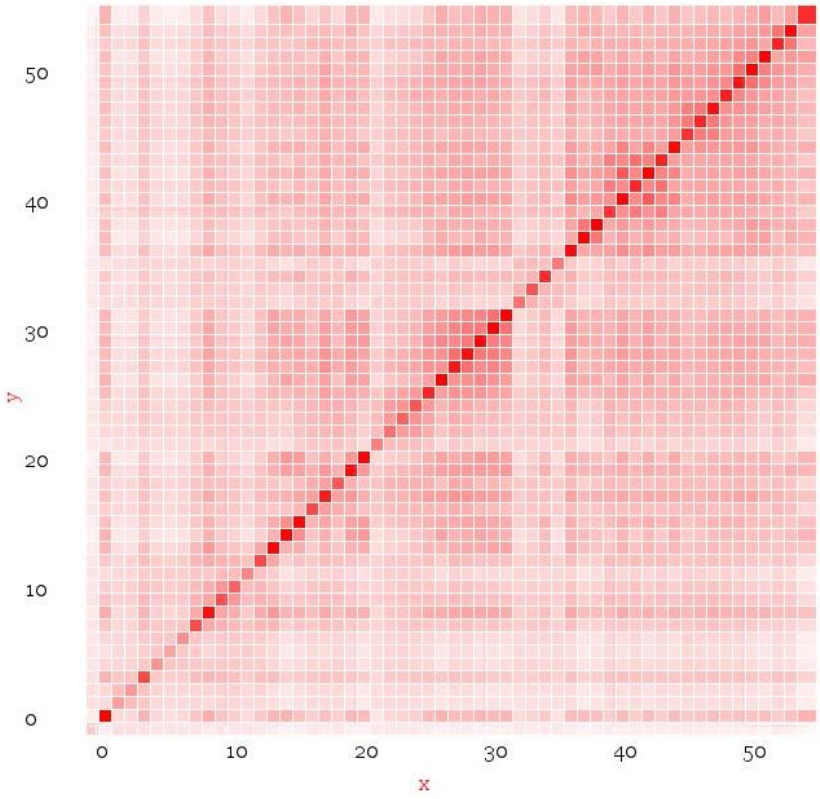
There are multiple ways of exploring datasets when simple visual inspection is tedious and unintuitive. Many of them are standard, but some of them may reveal more about the nature of the data. Often, they are motivated by specific business drivers and questions, and some exploration may be custom to the dataset under analysis. Data exploration is also commonly done through queries to an OLAP database.

Figure 4: Parallel Coordinates showing language, gender, school, pre- and post-intervention scores



6.1 Parallel Coordinates

Figure 5: Covariance plot of pre-intervention responses



6.2 Covariance plot

Figure 6: Covariance plot of post-intervention responses

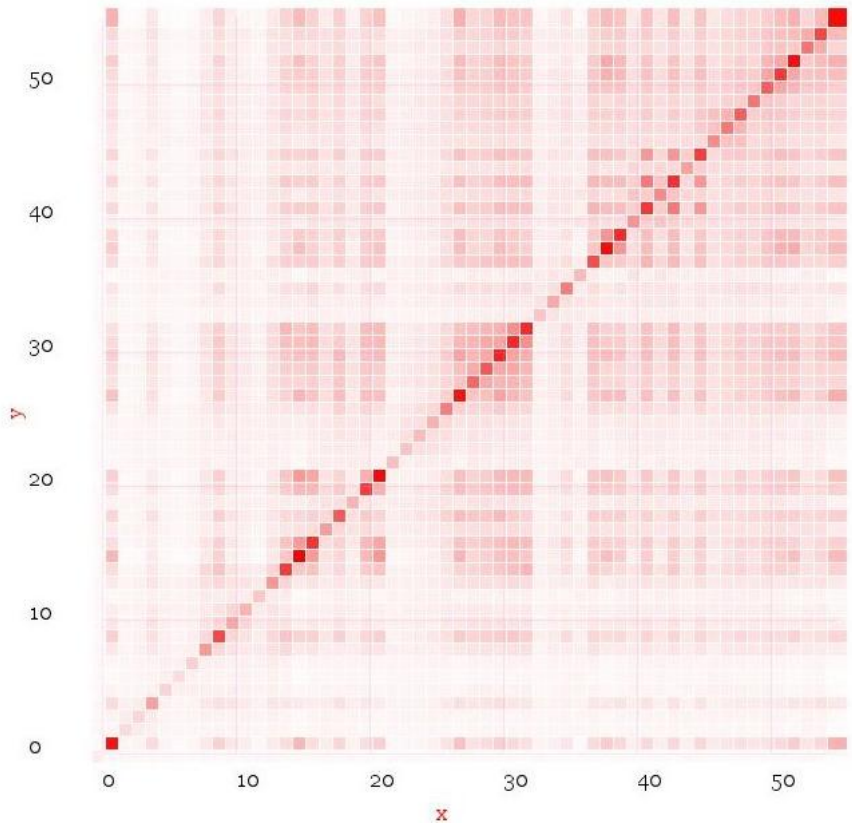
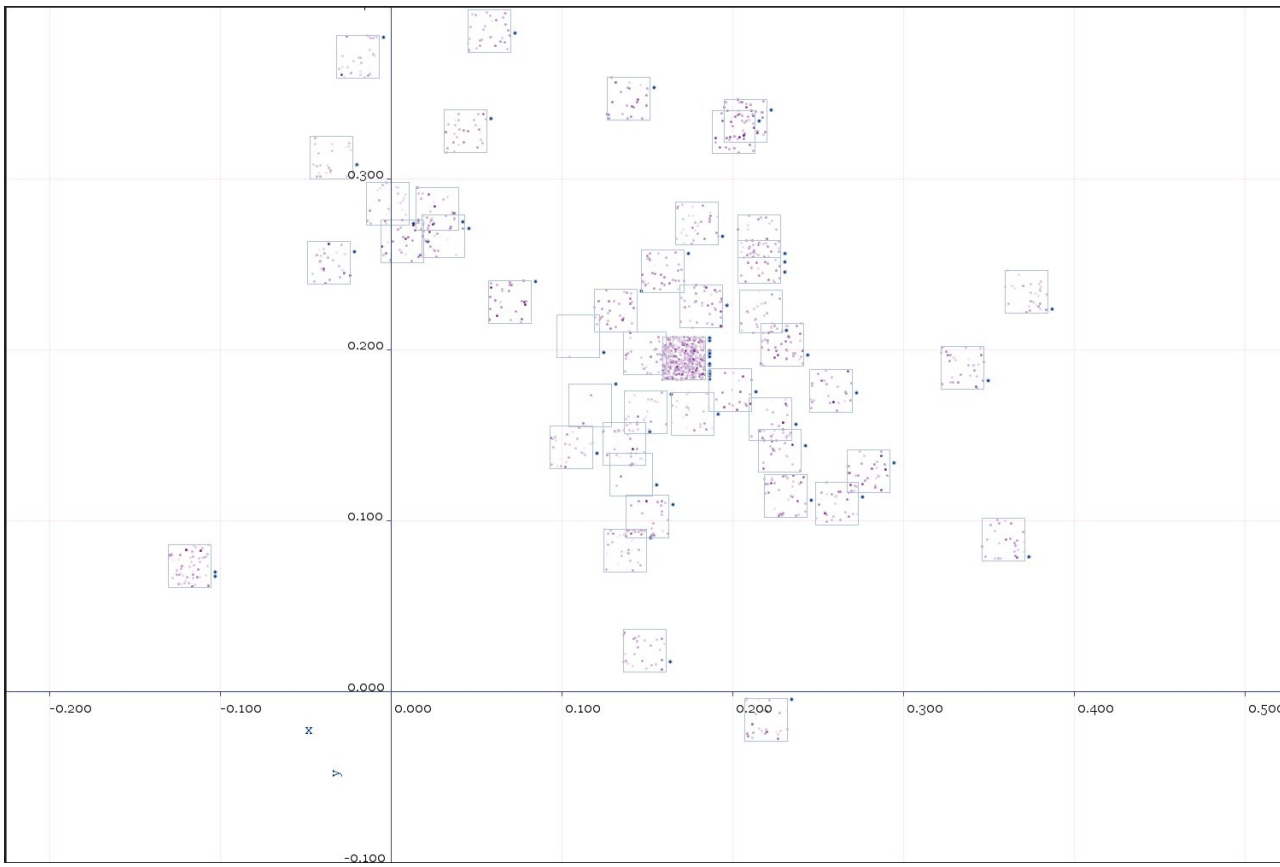


Figure 7: Geocoded populations by cluster

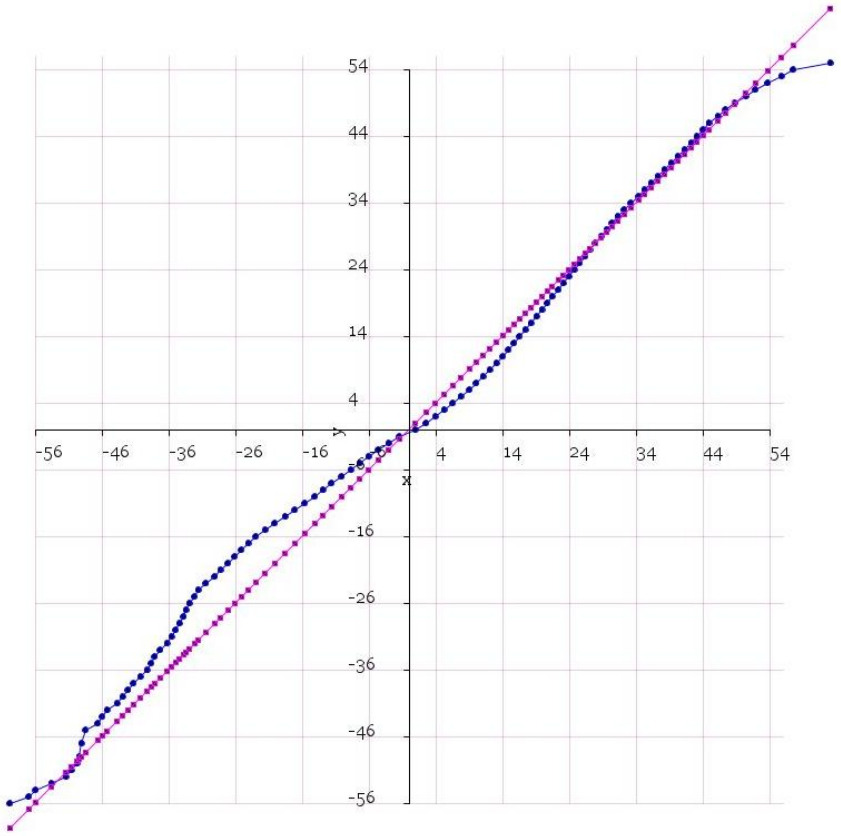


6.3 Geographical distribution

7 Models of probability distribution

7.1 Tests for conformance to distributions

Figure 8: Quantile-Quantile plot of score improvement vs. theoretical Gaussian



7.1.1 Jarque-Bera test

7.1.2 Quantile-Quantile plots

7.2 Answer distribution

lolol

Figure 9: Curve-fitted theoretical exponential for reflected post-intervention probability distribution

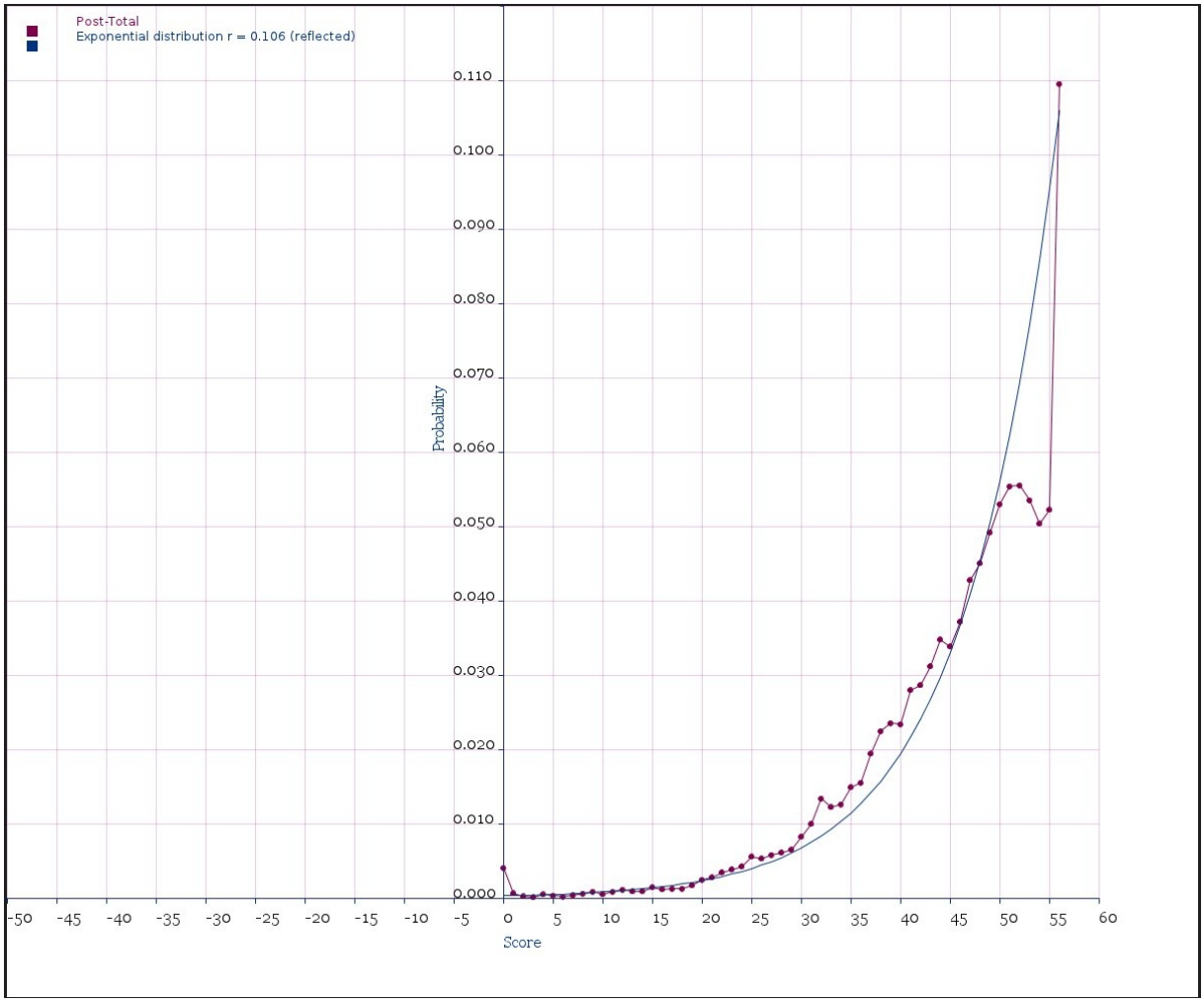


Figure 10: Quantile-Quantile plot of post-intervention score (reflected) vs. theoretical exponential

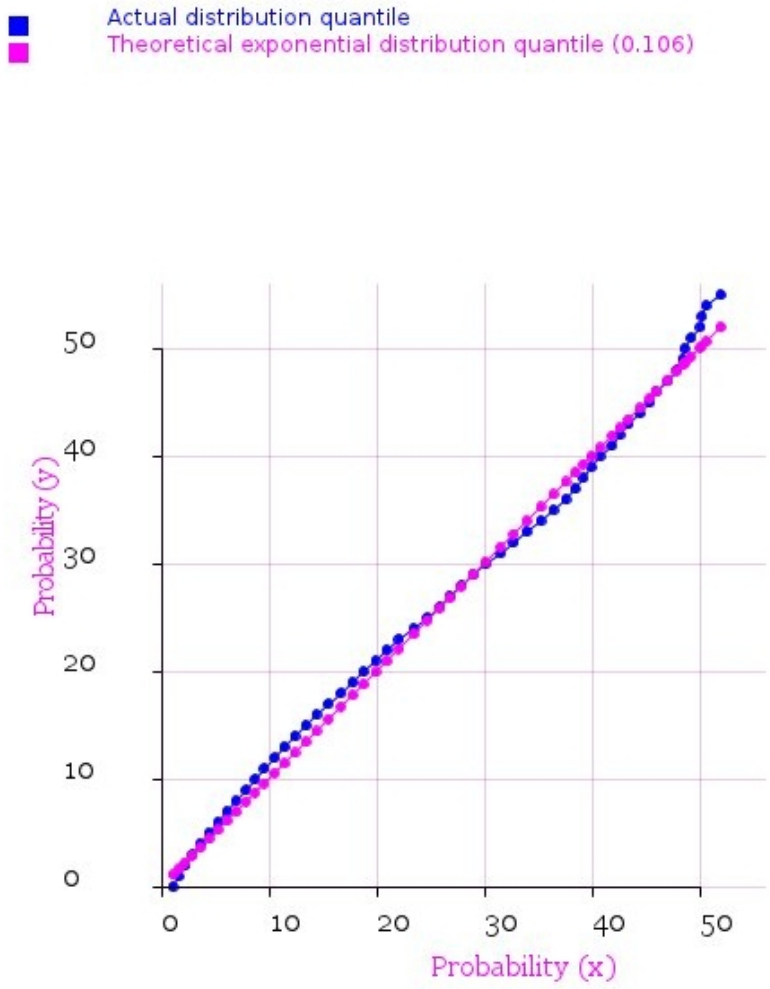
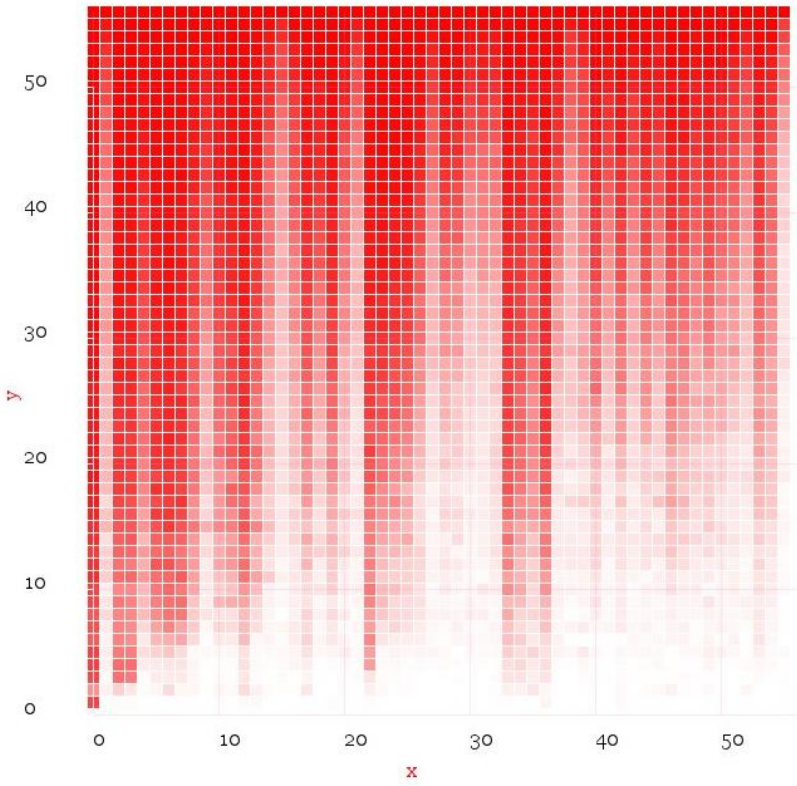


Figure 11: Answer distribution vs. question number



7.3 Modeling responses as Bernoulli trials

7.3.1 The Binomial Distribution

7.3.2 Typical questions

8 Tests for variable independence

8.1 Chi-square test

Null hypothesis: Area and Improvement are NOT related.
For **area vs. improvement**
Chi-Square statistic = 56499.4692602837
X2 = 9652.9739
Degrees of freedom = 9426
Null hypothesis rejected
c
Null hypothesis: Area and Pre-Score are NOT related.
For **area vs. pre-score**
Chi-Square statistic = 58665.7089390644
X2 = 8062.2959
Degrees of freedom = 7855
Null hypothesis rejected

Null hypothesis: Area and Post-Score are NOT related.
For **area vs. post-score**
Chi-Square statistic = 38567.0016158761
X2 = 8062.2959
Degrees of freedom = 7855
Null hypothesis rejected

Null hypothesis: Language and Post-Score are NOT related.
For **language vs. post-score**
Chi-Square statistic = 280.234448946825
X2 = 96.2166
Degrees of freedom = 75
Null hypothesis rejected

Null hypothesis: Language and Improvement are NOT related.
For **language vs. improvement**
Chi-Square statistic = 232.464548410971
X2 = 113.1452
Degrees of freedom = 90
Null hypothesis rejected

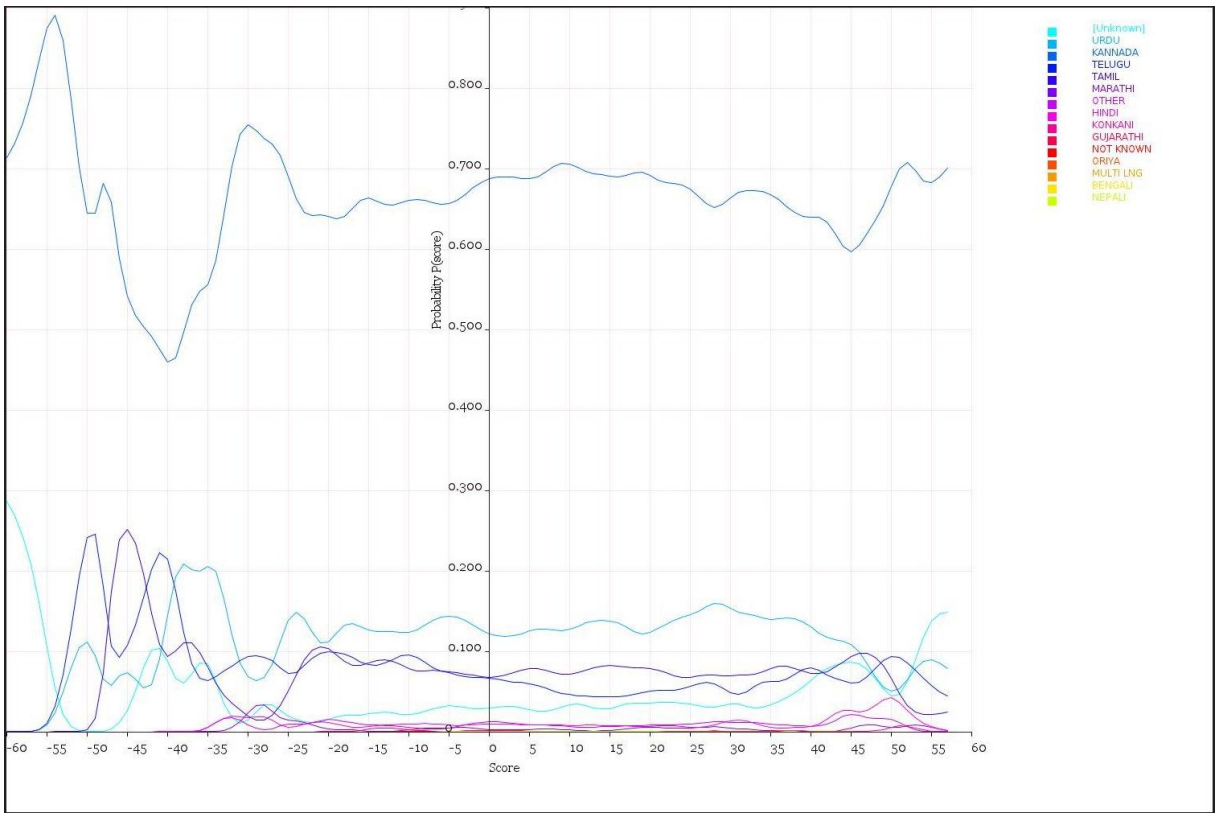
Null hypothesis: Language and Pre-Score are NOT related.
For **language vs. pre-score**
Chi-Square statistic = 277.85501653079
X2 = 96.2166
Degrees of freedom = 75
Null hypothesis rejected

9 Prediction

9.1 Decision Trees

9.2 Bayes classifier

Figure 12: Bayes posterior distribution of language from score improvement



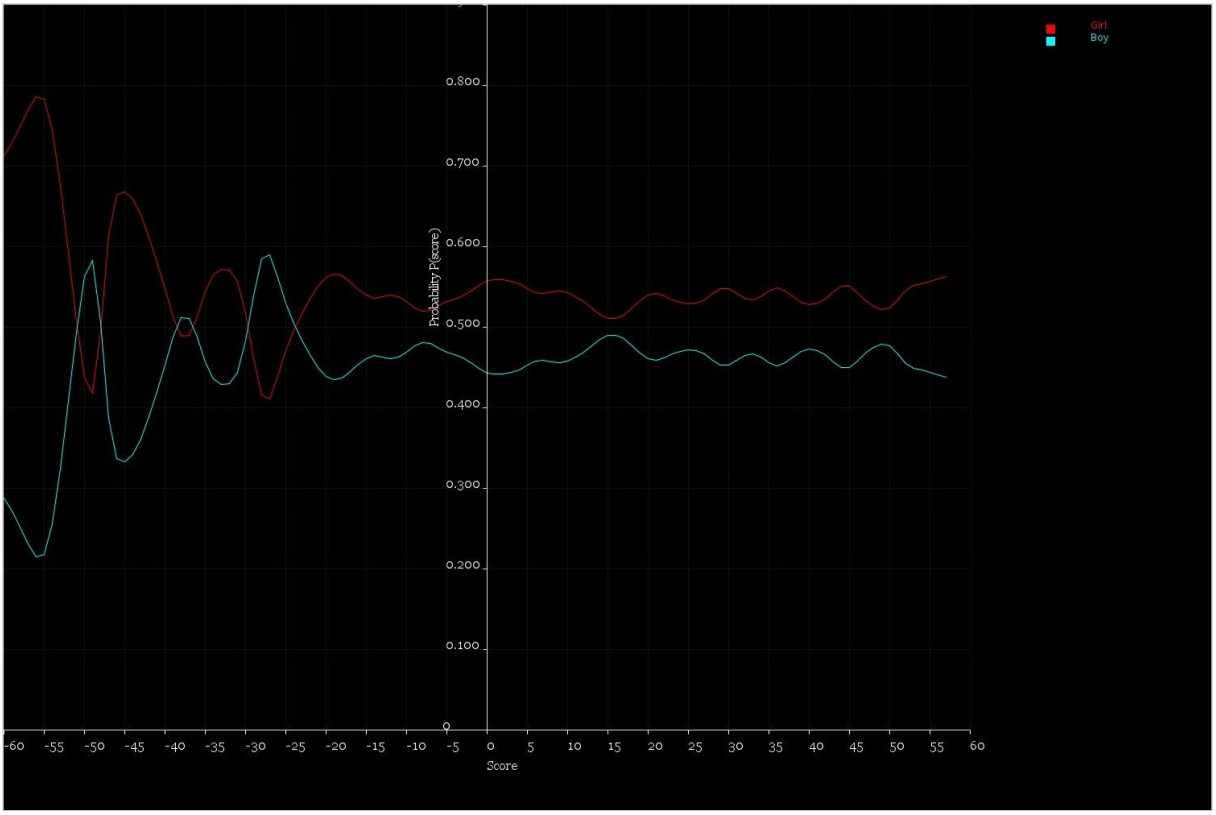
9.3 Density estimators

9.3.1 Naive Bayes density

9.3.2 Kernel density estimation

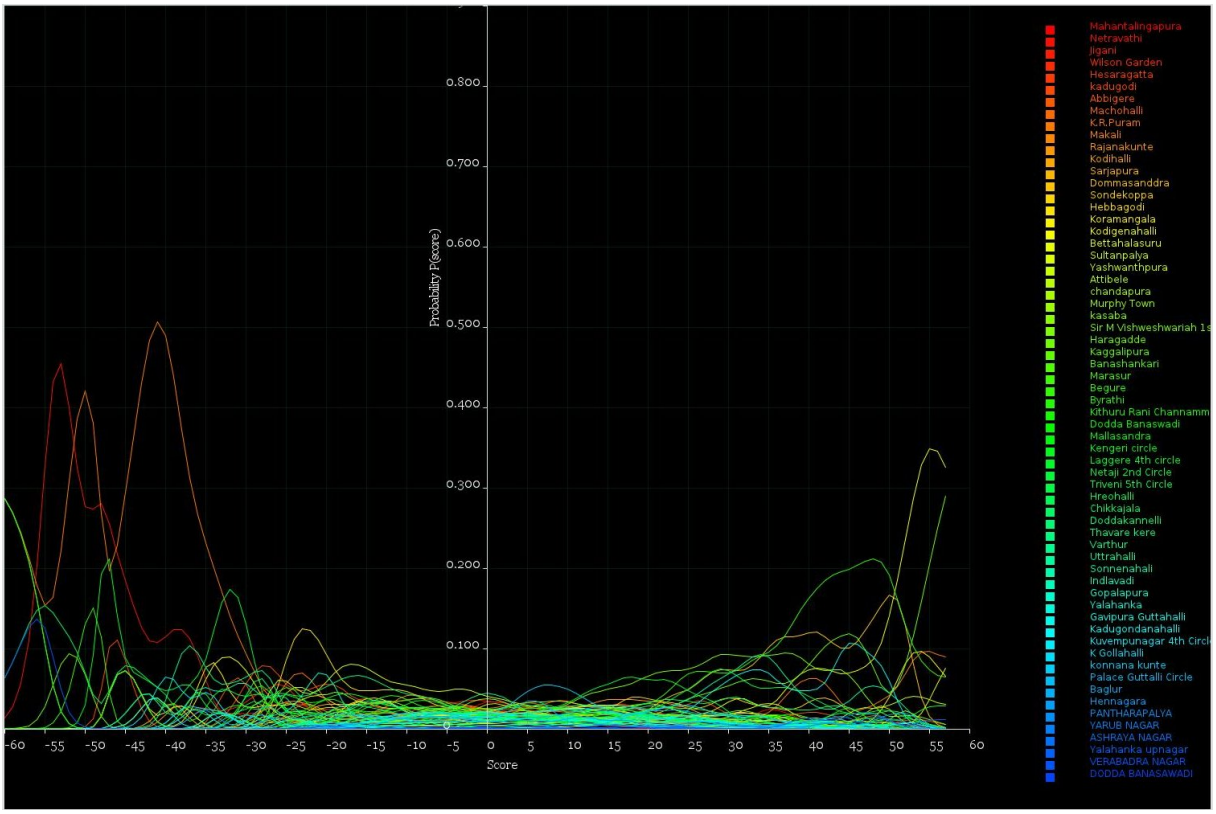
9.3.3 Results

Figure 13: Bayes posterior distribution of gender from score improvement



10 Dimension reduction/Factor analysis

Figure 14: Bayes posterior distribution of geocluster from score improvement



10.1 Principal Component Analysis

11 Technical notes