Modelling Right to Information Queries via Item Response Theory

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Abstract

The present work is an attempt to use models present in Item Response Theory, which are psychometric models, for modelling Right to Information (RTI) queries. A synthetic matrix resembling our RTI dataset (construction on-going) has been created and we have applied Graded Response Model (GRM) to the data. Outcomes of the experiment have helped us identify latent patterns regarding the RTI query-reply process. The model assigns values to the latent ability of each institution, which we shall call transparency of an institution, and showed us how each institution behaves differently to different topics of RTI queries. It also shows which institutions are good at replying to RTI queries and which institutions perform poorly. Such differences across different departments and institutions imply a possible scope for amendments to the ordinances of the institutions.

1. Introduction

The Right to Information (RTI) Act, 2005 (RTI) empowers any citizen of India to access information from any public body. The RTI Act came into force in October 12, 2005. Citizens can inspect documents and records, take notes and certified copies of documents or obtain information in any electronic form. There is a collection of RTI queries gathered in every public institution which forms a huge database of untapped resources from which we are likely to acquire knowledge about the interests of the citizens and the affairs of the society.

An amendment, in government and law, is any addition or alteration made to a constitution, statute, or legislative bill or resolution. The Indian law has seen a successful use of the RTI statistics for the introduction of amendments. Originally Indian Postal Orders (IPOs) were not an acceptable mode of RTI fee payment. Multiple applications where citizens used IPOs for payment were frequently rejected. Such repeated rejections ultimately caught the government's attention and IPOs were accepted as another mode of fee payment. On a similar note, many applications filed inquiring about funds received by political parties were rejected. Over time, a notice was issued stating political parties as not being public authorities. As observed from these two examples, repeated rejections of RTI queries served as a feedback or pointer for introduction of amendments into an existing law. This leads us to believe that the collection of RTI statistics should contain other pointers that can lead to tentative amendments. Finding such pointers in an automated way via learning algorithms is the aim of this work.

2. Related work

Attempts to model the legislative structure and outlook have been seen in the literature. Now and again, researchers have sought to apply mathematical models to represent affairs in the political domain. Such work opens up scope for understanding the political issues in depth. Gerrish and Blei (Gerrish & Blei, 2012) have developed a probabilistic model for legislative data to identify voting patterns in specific political issues. Such work has inspired us to undertake the task of analysing our RTI data.

Queries are the driving force in a process of thinking. From classrooms to commercial platforms and entertainment, queries are found everywhere and in all forms. Examples include customer service queries, product review queries, tourism queries, queries in medical diagnosis and of course RTI queries. Web queries (queries put to search engines for web search) are analysed to improve user experience and search

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engine performance. Research has been done to find user goals from queries (Lucchese et al., 2013). Q/A systems do not retrieve documents, but give brief, relevant answers in short text. Semantic information in questions and answers classification is studied in (Moschitti et al., 2007). Test questions are used to determine the qualification of individuals or behaviour of events. Typical examples are the survey questions under social or business context, tests for students, diagnosis of illness etc. Applications include understanding family relationships (Preston et al., 2015).

3. Item Response Theory

Since our data consists of queries as well, we have selected a method of analysis found in Test Questions to analyse the RTI queries collected from different public institutions. The method is known as Item Response Theory (IRT). It is a statistical method based on psychometrics. It deals with understanding how subjects behave to different items and questions. The data is modelled as a function of the trade-off between a) The respondent's abilities, attitudes or personality traits, and b) The item difficulty. For our data, we shall use an IRT model called the Graded Response Model (GRM). It models polytomous responses with two or more ordinal response categories. It has been used in problems like equating tests (Baker, 1992). For our initial experiment using GRM, analysis shall be done on the reply statistics of various institutions to RTI queries.

The GRM is an extension of the 2-Parameter Logistic Model. Let θ be the latent ability underlying the response to the test items. The probability of a candidate with ability θ responding to item i in a particular category c is:

$$P_{ic}(\theta) = P^*_{ic}(\theta) - P^*_{ic+1}(\theta)$$

where

$$P^*_{ic}(\theta) = \frac{1}{1 + exp(-\alpha_i(\theta - \beta_{ic}))}$$

α_i is the Item slope parameter (one per item), β_{ic} is the Category threshold parameters and P^*_{ic} is the Category Boundary Response Function for item i and category c. There is one set of β_{i1},..., β_{im} for each item and are ordered, where m+1 is the number of categories (Samejima, 1969).

4. Dataset

For the purpose of our study, we have decided to create an RTI database as part of our research. Our dataset consists of the RTI applications that have been posted to all public educational institutions by the citizens of India. The data collected consists of RTI applications (which include the RTI queries), date of reply of each query and the rejected applications with their grounds of rejection. This collection is going on and the database is not yet complete.

Table 1. Synthetic Data containing response percentages of ten institutions and five items

Inst.No.	Finance	Academic	Employment	Alumni	Medical
1	75	10	26	28	45
2	35	49	70	15	11
3	62	89	6	38	50
4	48	78	52	95	71
5	51	64	53	30	74
6	84	70	94	69	97
7	52	49	47	45	55
8	24	29	27	22	34
9	2	32	28	8	49
10	30	57	65	7	86

Table 2. Percentage range of categories

Category	1	2	3	4	5
% Range	0-20	21-40	41-60	61-80	81-100

For our experiments, we have constructed a synthetic matrix of reply statistics that resembles our RTI dataset. An RTI application can have multiple queries. A survey of the data collected has shown that queries can be more or less classified into some fixed number of categories or topics, each independent of the other (for example Administration, Finance, Exams etc.). We have created matrices with topics of queries in one dimension (items) and various institutions on the other (persons). In order to carry out the experiments, we have created a matrix with ten institutions and five topics.

5. Experiment

Table 1 gives us the raw values of our RTI dataset. In order to fit this data into our IRT model, the matrix needs to be modified. We have divided the percentages into five buckets as shown in Table 2. The response categories follow the likert scale with 1 being the lowest and 5 representing the highest rating. Substituting the percentages with the above values results in the matrix shown in Table 3.

Once this substitution is done, we have a matrix of five query topics (items), five response categories (1-5) and ten institutions (persons). This data is now ready to be modelled by GRM. The experiments have been carried out in R. It has a few packages for IRT modelling, and we have chosen the 'ltm' package (ltm)

Table 3. Matrix created after substituting the percentages by assigned values

Inst.No.	Finance	Academic	Employment	Alumni	Medical
1	4	1	2	2	3
2	2	3	4	1	1
3	4	5	1	2	3
4	3	4	3	5	4
5	3	4	3	2	4
6	5	4	5	4	5
7	3	3	3	3	3
8	2	2	2	2	2
9	1	2	2	1	3
10	2	3	4	1	5

Table 4. Item Parameters after running the Graded Response Model on our data

Items	β_{i1}	β_{i2}	β_{i3}	β_{i4}	α_i
Finance	-1.451	-0.218	0.602	1.325	4.004
Academic	-2.559	-1.191	0.410	2.449	1.106
Employment	-5.197	-1.059	1.830	4.950	0.446
Alumni	-0.693	0.785	1.261	1.849	1.935
Medical	-2.424	-1.556	0.555	1.646	1.047

for implementing the GRM.

6. Results

The item parameters obtained are presented in the Table 4. For each and every item, a graph is drawn between ability (latent trait θ) and the probability of responding on a particular category. Such curves, called Item Response Category Characteristic Curves for each of the five items are shown in Figures 1, 2, 3, 4 and 5.

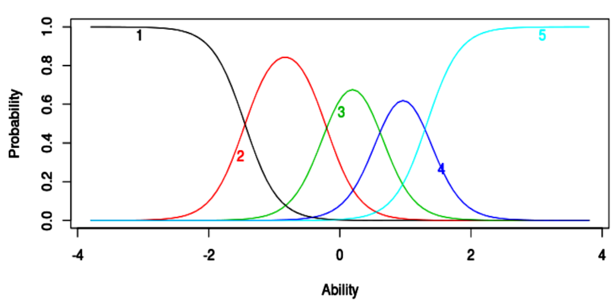

Figure 1. Item Response Category Characteristic Curve for item Finance

We have used Bayesian Estimate procedure for calculating the ability parameter for each and every institution. The results obtained are summarized in Table 5. Theta (θ) gives us the ability (transparency) of an institution. The higher the ability of an institution to respond to an item (query category), the more transparent an institution is. From Table 5, we can see

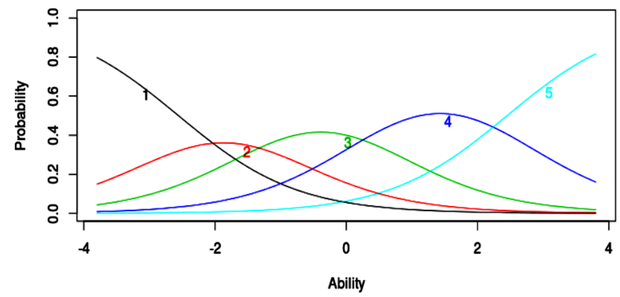

Figure 2. Item Response Category Characteristic Curve for item Academic

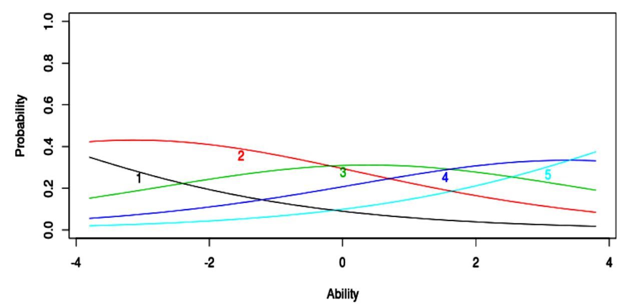

Figure 3. Item Response Category Characteristic Curve for item Employment

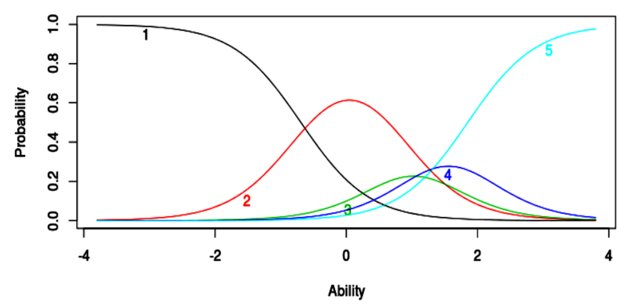

Figure 4. Item Response Category Characteristic Curve for item Alumni

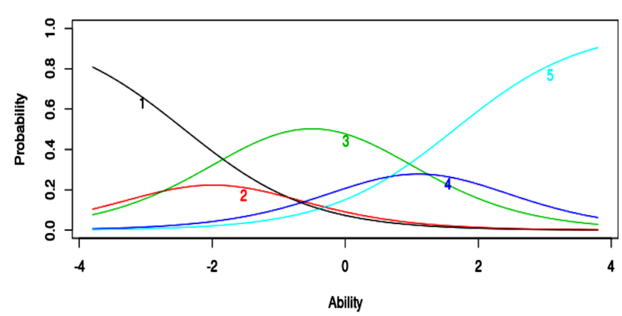

Figure 5. Item Response Category Characteristic Curve for item Medical

Table 5. Ability Parameters (θ) for ten institutions

Inst.	1	2	3	4	5	6	7	8	9	10
θ	0.426	-0.906	0.690	0.589	0.276	1.623	0.260	-0.720	-1.590	-0.542

that institute number 6 with the scores (5,4,5,4,5) has the highest ability (1.623). Institute number 9 with the scores (1,2,2,1,3) has the lowest ability (-1.590). It means that institutions with higher abilities will respond well to RTI queries and institutions with lower abilities will respond poorly to RTI queries.

Each and every item has a discrimination parameter. An item with high discrimination parameter can discriminate well between institutions with high ability and low ability as opposed to an item with low discrimination parameter. From our results, Finance has the highest discrimination parameter and Employment has the lowest discrimination parameter. These can be reflected from the Item Characteristic Curves of Employment and Finance. Even institutions with high abilities have less probability of responding to category 5 in the Employment item.

7. Conclusion

In this paper we have modelled the RTI query-reply process via Item Response Theory. We have created a synthetic dataset that resembles our collected RTI data, and tried to model it in terms of inputs to an IRT model. We have selected GRM as the preferred model, and successfully run it with promising results. The novelty of our approach lies in two main points.

Firstly, such an analysis of RTI data has never been undertaken. We are collecting RTI data related to each individual, from each public educational institution and shall span multiple locations across India. Most RTI studies are limited to specific regions or specific issues in that their surveys are based to explore a fixed set of problems. Our present work of applying learning algorithms to uncover hidden traits in the RTI query-reply process is the first of its kind. The application of GRM has been limited to the examination domain. This work is a successful attempt to extend its application scope. Secondly, the implications from the outcomes of this experiment are enormous. With this attempt, we have assigned a transparency value to the institutions with respect to the reply patterns of each and every institution. A closer look into Tables 4 and 5 can help us extract further information. For example, certain institutions (for example, institution 6) are very good in responding to the finance category questions (Figure 1), but not so well in responding to employment category questions (Figure 3). This reveals that there is inconsistency in RTI replies across departments of the same institution, and leads us to question as to why such inconsistencies are present. This is an indication of same rules being implemented in different ways for different institutions as well as different departments within the same institution. A solution for this may be to bring some changes to the ordinances of the institution. Hence, this work of analysing RTI queries and reply statistics shall also give us strong basis for proposing amendments to the law of an institution. Once the data collection part is over, we shall be able to apply this model to our actual RTI dataset, and the conclusions from the results shall give us a clear picture of the laws and policies that govern our public institutions.

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