Data Mining of Intervention for Children with Autism Spectrum Disorder

Pratibha Vellanki(✉), Thi Duong, Dinh Phung, and Svetha Venkatesh

Pattern Recognition and Data Analytics, Deakin University, Waurn Ponds, Australia
pratibha.vellanki@research.deakin.edu.au

Abstract. Studying progress in children with autism spectrum disorder (ASD) is invaluable to therapists and medical practitioners to further the understanding of learning styles and lay a foundation for building personalised intervention programs. We use data of 283 children from an iPad based comprehensive intervention program for children with ASD. *Entry profiles* - based on characteristics of the children before the onset of intervention, and *performance profiles* - based on performance of the children on the intervention, are crucial to understanding the progress of the child. We present a novel approach toward this data by using mixed-variate restricted Boltzmann machine to discover entry and performance profiles for children with ASD. We then use these profiles to map the progress of the children. Our study is an attempt to address the dataset size and problem of mining and analysis in the field of ASD. The novelty lies in its approach to analysis and findings relevant to ASD.

1 Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that onsets at an early age and limits the child's interaction with the world. It affects about 1% of the population globally [1]. The main areas that are affected due to ASD are cognition, sensory perception, language and communication, social relationships, and repetitive behaviors.

Children with ASD exhibit individual learning abilities and disabilities, resulting in a spectrum nature. This makes clustering children with ASD challenging. The conventional treatments are highly individualized, involve rigorous observation, data collection and analysis to determine and adapt the course of intervention. Moreover, for efficient intervention the children depend on the environmental setting with minimal distractions, and sensory profiles. Applied Behavioral Analysis (ABA) is the most popular conventional method that involves breaking single skills into smaller units and delivering the units in a structured manner till the skill is learnt [2]. While these methods are proven to be effective, they are time consuming and expensive: preparation of material and manual recording of data.

Of more importance are the opportunities wasted between diagnosis and the availability of therapists. It is suggested that the intervention for ASD shows desired effects when it is started at an early age [3]. Hence, there is a need

K. Giokas et al. (Eds.): eHealth 2016, LNICST 181, pp. 376–383, 2017.
DOI: 10.1007/978-3-319-49655-9_45

for alternate treatment methods that can both fill in the waiting gap between diagnosis and intervention, and later append the one-on-one intervention time with the therapist.

Research suggests that computers may preferably be used to deliver therapy due control on the environment and their data recording capabilities. It has also been observed that children with ASD are likely to prefer computers as social discomfort, often common in ASD, may be avoided [4]. Our research picks up from this path and aims to help analyze and build possible techniques toward personalized intervention for children with ASD.

Data from children with ASD can be used for profiling them before beginning intervention on a computer-based program. Using data from a computer based application, Vellanki *et al.* [5] proposed using the age, the sex, and the performance of the child on a few fundamental skills at the onset of the intervention to determine *entry profiles*. We expand on this by additionally determining their *performance profile* using data from the children once they have progressed along the syllabus of the intervention. We then analyze their progress by observing their performance profiles with respect to where they were before intervention, determined by entry profiles. This is done by mapping the entry profiles onto their performance profiles. Our study not only gives a deeper understanding of the learning profile of children by tracking progress, but also lays the foundation for tailoring personalized syllabus.

In this study, we use the data collected from TOBY Playpad, an iPad-based comprehensive intervention program [6]. Data comprises 283 children who navigated through its structured syllabus consisting of 34 skills in four skill areas. The highly correlated and mixed-variate data also contains missing elements where the child is on the path to completion, making it challenging to deal with. This calls for complex techniques such as the mixed-variate restricted Boltzmann machines to integrate and model the data leading to the discovery of *entry* and *performance* profiles. Our sample size of our dataset is significantly larger than traditional ASD datasets [7] and to the best of our knowledge, such a data-based research is only possible for the first time due to the availability of computer-based applications.

In summary, the aims of this study are: (1) To discover entry profiles of a cohort taking intervention on TOBY Playpad, (2) To discover performance profiles of this cohort after they have made some progress on the syllabus, and (3) To qualitatively analyze and map the progress of the children from entry profiles to performance profiles.

2 Related Background

Patient profiling based on individual characteristics and the diagnosis is crucial in determining the course of medical intervention, especially for children with ASD. Each child with ASD exhibits highly individualised learning patterns and may show different results for standard procedures. It is hence of importance to (a) determine the entry profile for children with ASD and (b) to track their progress so a personalised course of intervention can be recommended. Research on discovering profiles among children with ASD and using them for administering interventions that cater to individual needs is contemporary [8]. We are driven by this novel problem and employ data from TOBY Playpad - an iPad application in implementing our ideas.

One of the main challenges with our data is that it is in a mixed-variate space and does not naturally integrate with traditional techniques for clustering. For example, sex, age, and performance on the skills of TOBY syllabus measured in terms of *Learn Units* (LU). Learn units are similar to count data in a document, thus enabling us to use a topic modelling based approach for discovering latent profiles. Tran *et al.* [9] propose a mixed variate restricted Boltzmann machine (MV.RBM) that integrates this type of data, which was successfully used to model chronic health data, in a similar setting [10].

Replicated Softmax is an undirected, two-layered, generative model of word counts that can be trained using Contrastive Divergence and is modelled using RBM [11]. Replicated Softmax smoothly integrates with the modelling of age and sex and can be modelled together using the mixed-variate RBM model.

3 Data Source and Dataset

TOBY Playpad [6] is a comprehensive iPad program that facilitates intervention for children with ASD, developed by a team of computer scientists and autism experts. It integrates independent learning and caregiver assistance in a regulated environment that allows recording data seamlessly on a structured syllabus. The hierarchical construction of the TOBY syllabus places fundamental skills at the top of the tree and releases complex skills one by one as the child masters skills along the syllabus tree. TOBY follows a predefined algorithmic criteria for prompting, reinforcement and mastering [6]. The structure of TOBY allows us to record learning in a controlled manner by keeping the ways in which the syllabus can be navigated and mastered fixed.

The simple units of teaching in TOBY are stimuli, response, prompt and reinforcement. Within each skill these four units are repeated until the skill is mastered. The TOBY iPad syllabus is divided into four categories: Imitation, Sensory, Expressive Language and Receptive language. Imitation (13 skills) involves video stimuli, and the child responds by emulating the action presented in the video. Sensory (3 skills) involves matching tasks with a visual stimulus (image) and response is selected from a set of three images presented. Expressive Language (9 skills) - learning how to speak words, involves visual stimulus and the child responds by vocalizing the label of the object. Receptive Language (9 skills) - learning the connection between words and visual representations in a reverse manner.

To quantify learning via TOBY, we use a measure called the Learn Unit (LU). A LU indicates number of stimulus - response pairs that the child requires to master each skill; higher number of LUs indicating increased difficulty faced by the child in the skill [5].

Users download TOBY onto their personal iPads and the learning occurs in the child's natural environment. The caretaker uploads the data recorded by TOBY onto a server[1]. This data is accessed and de-identified in a secure manner by the developers. The data consists of 283 children using TOBY for intervention. Children start using TOBY at random entry times and show progress based on their ability, and time spent on intervention. As a result, each child is at a different place in the intervention. The children who are a part of our study have undergone some progress - the child must have mastered at least one entry skill and another skill within the same category as the entry skill. Our data contains information on the age, sex and performance across the syllabus attempted for the child. The inter-quartile range of age of the children in this study is 1.58 to 9.75 years. Our dataset studies performance of 152 male and 44 female children; the caretakers of 87 children chose to withhold information about the child's sex.

We divide our data into two subsets: (1) entry profile data - contains the performance of the child on the entry skills of TOBY (first skill in each of the 4 skill categories) in terms of LU required to master, and the sex and the age of the child; (2) performance data - contains the LUs required to master all the skills in the syllabus attempted so far by the children.

4 Framework

We first discover entry profiles by modeling the sex, age and LUs required to master entry skills of the syllabus using MV.RBM [9]. We then model the LUs required to master all the skills attempted in the syllabus to discover performance profiles. For this study, we identify three data types to the multivariate visible units used in our research: *binary* for sex, *continuous* for age, and *Replicated Softmax* for LUs required to master skills [5].

One of the complexities of real data is that it consists of missing elements. Our data is complete in age but in the cases where the caretakers withheld information about the sex of the child, there are missing instances. Missing data also occurs when a child has not yet mastered certain skills in the syllabus. We deal with data missing in LUs by substituting zero for simplicity. We represent sex by two binary variables, one denoting if the child is male and the another variable denoting if a child female and when the sex of the child is unknown, the both these values take on zero. The latent posterior equation of RBM consists of the product term involving v_n, which results in the model to account for no statistics from the missing elements.

We use CD with a batch size of 100 children for learning the parameters. After 100 data sweeps posterior hidden units are extracted and clustered for similar profiles using K-means. In this manner, we obtain both entry profiles and performance profiles. We then use t-SNE, a dimensionality reduction technique, for visualizing the results in a two-dimensional space.

[1] This study is approved by the university ethics committee.

5 Results

We present the results of our experiment in three parts: entry profiles, performance profiles and their description, and mapping of entry profiles to performance. Mapping enables us to study how the members of the cohort diverge after progress on syllabus.

5.1 Entry Profiles

Figure 1 shows the discovered 5 *entry profiles* (EP). We describe the shared characteristics of the entry profiles before listing their specific properties.

Regarding the diversity in skills attempted, children in EP 1 and EP 2 mastered entry skills across most categories: at least 2 and at most from all 4 categories, followed by children in EP 4: at least 1 and at most 4. While children in EP 3 and EP 5 managed to master entry skills up to 3 categories.

With respect to the difficulties among entry skill from all categories, most children found Receptive most challenging (EP 1, EP 2, and EP 4) evident from the highest medians, followed by Sensory (EP 1 and EP 2) or Expressive (EP 4). Children from EP 3 and EP 5 did not master the Receptive and among the remaining 3 categories mastered, they found Sensory most difficult. It is interesting to observe that the discrepancy in the amount of work required (e.g. LUs) to master Sensory is most significant for all groups involved, followed by Receptive.

EP 1 (85 males) and EP 4 (44 females) found Imitation to be the least challenging - lowest LU accumulation. Within EP 4 the entry skills in all categories were found to be mastered by around uniform number of children.

EP 2 (58 children, sex unknown) and EP 3 (29 children, sex unknown) mastered Imitation and Expressive Language entry skills with the equally least efforts (lowest LUs). Within EP 3, the ability to master skills in these two categories is more uniform (evident by small interquartile in their LUs). Compared to EP 1, EP 2 achieved mastery in Receptive with lesser LUs. Distribution of LUs for EP 5 (67 males) bears similarity with that of EP3, however, the medians and the variances are much higher for EP 5, especially for Sensory.

5.2 Performance Profiles

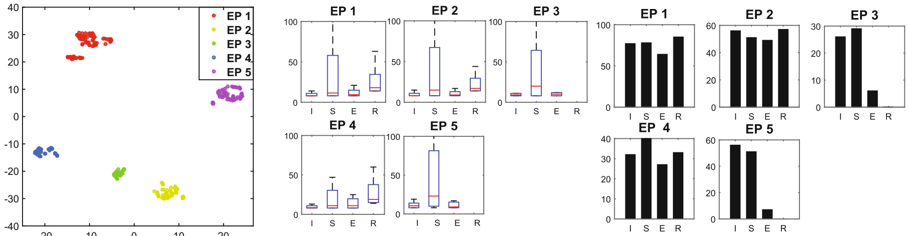
Figure 2 shows the discovered 9 *performance profiles*. We observe that with an increase in complexity of the data the clusters are not well defined and they overlap often. We expect this behavior because ASD is a spectrum and well-defined clustering of the children is challenging. We describe the characteristics of the *performance profiles* (PP).

In a broader view, we observe that the children belonging to PP 1, PP 2, PP 7 and PP 8 have mastered 10 or fewer skills on the entire syllabus; children from PP 4 and PP 5 have mastered almost 20 skills; and children from PP 6 and PP 9 have mastered mostly 20 skills or more.

PP 1, PP 2, PP 7, and PP 8 consist of 30, 35, 47 and 40 children respectively. Sensory skills were mastered by most. The accumulated LU statistics shows a similar distribution for PP1, PP 2 and PP 7, Sensory being the most difficult to master, followed by Receptive Language when attempted. Compared to the other profiles, PP 7 and PP 8 have found Imitation difficult to master.

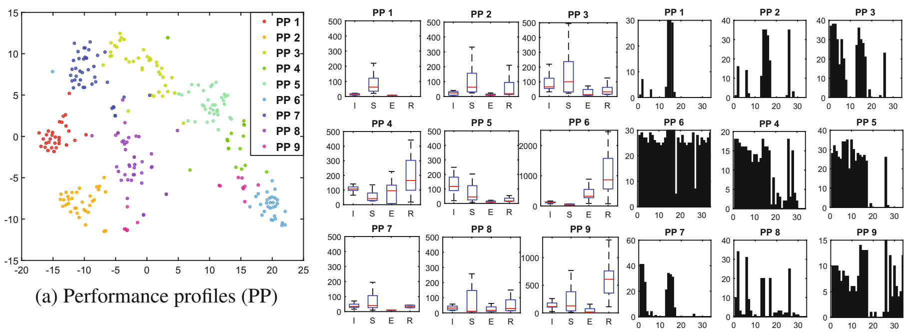
PP 4 and PP 5 consist of 18 and 35 children. They preferred Imitation and Sensory categories. PP 4 struggled and show little progress in the language skills - comparatively higher LUs in language areas than other skills.

PP 6 and PP 9 consist of 31 and 15 children and have mastered most skills. PP 6 found Receptive most difficult, followed by the Expressive. PP 9, on the other hand, found Receptive and Sensory most difficult. It is also observed that PP 9 struggled with the later skills of Imitation, which consist of learning oral



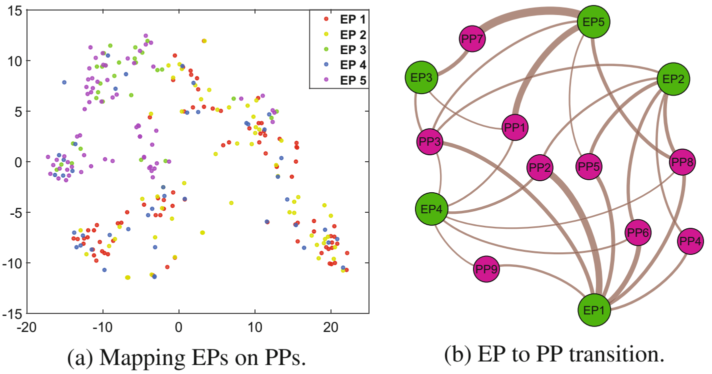
(a) Entry profiles (EP). (b) LU statistics. (c) Histogram of skills mastered.

Fig. 1. Entry Profiles and their group characteristics. Here, I - Imitation, S - Sensory, E - Expressive Language and R - Receptive Language are the skill categories. In the sub-figures (b) and (c) the y-axis shows LUs. Sub-fig (b) shows the boxplot of LUs acquired by children in each entry skill. Sub-fig (c) shows the number of children who mastered each entry skill.



(a) Performance profiles (PP) (b) Accumulated LUs (c) Histogram of skills mastered

Fig. 2. Performance profiles and their group characteristics. Sub-fig (b) shows the boxplot of LUs acquired by children in skill category. Here the LUs under each category are accumulated for a category level analysis. Sub-fig (c) shows the number of children who mastered each of the 34 skills (x-axis).



(a) Mapping EPs on PPs.

(b) EP to PP transition.

Fig. 3. Progress tracking using entry profiles (EP) and performance profiles (PP).

imitation, as compared to PP 6. A person struggling with oral imitation (sounds of vowels and consonants) subsequently may find vocalizing entire words difficult (Expressive Language).

5.3 Mapping Entry Profiles to Study Progress

We map the entry profiles to the performance profiles in Fig. 3a and observe how groups diverge after progress. Figure 3b shows the network highlighting the relationship between entry and performance profiles. Here the thickness of the connection denotes the probability of migration between a pair of entry and performance profiles.

We observed groups based on the patterns of migration: group 1 (EP 1 and EP 2), group 2 (EP 4) and group 3 (EP 3 and EP 5). The members of these groups also bore similarity in entry profiles. Group 1 transgressed toward PP 2, PP 3, PP 4, PP 5, PP 6, PP 8 and PP 9. Group 3 transitioned toward PP 1 and PP 7. EP 4, which is an all-female group, is the only one to have highly dispersed after the progress. These observations may be critical to determine the weakness and strengths of the children and adapt the intervention course based on their mapping. Medical practitioners might find this kind of analysis invaluable for gaining a deeper understanding of how different children with ASD behave on a standard structured syllabus.

6 Conclusion

Profiling and tracking the progress of children with ASD is crucial personalized intervention. The nuance in this study is possible due to the dataset we present, but at the same time dealing with heterogeneous, mix-variate, and highly correlated data with missing elements needs complex models. We present entry and performance profiles discovered using MV.RBM on a dataset of 283 children and map their progress after administering intervention. This helps us to observe how groups that are similar at the onset of the intervention react differently to the same syllabus. Our study of progress mediated by the discovery of entry profiles and performance profiles is, to the best of our knowledge, first of its kind. Followed up with predictive analysis, it can help recommend suitable intervention paths for children with ASD. Such an analysis might be invaluable to medical practitioners to furthering the understanding of learning patterns of children with ASD.

References

1. American Psychiatric Association. Diagnostic and statistical manual of mental disorders (DSM-5®). American Psychiatric Pub (2013)
2. Lovaas, O.: Behavioral treatment and normal educational and intellectual functioning in young autistic children. J. Consult. Clin. Psychol. **55**(1), 3–9 (1987)
3. Dawson, G., et al.: Early behavioral intervention, brain plasticity, and the prevention of autism spectrum disorder. Dev. Psychopathol. **20**(3), 775 (2008)
4. Hetzroni, O., Tannous, J.: Effects of a computer-based intervention program on the communicative functions of children with autism. J. Autism Dev. Disord. **34**(2), 95–113 (2004)
5. Vellanki, P., Phung, D., Duong, T., Venkatesh, S.: Learning entry profiles of children with autism from multivariate treatment information using restricted Boltzmann machines. In: Li, X.-L., Cao, T., Lim, E.-P., Zhou, Z.-H., Ho, T.-B., Cheung, D., Motoda, H. (eds.) PAKDD 2015. LNCS (LNAI), vol. 9441, pp. 245–257. Springer, Heidelberg (2015). doi:10.1007/978-3-319-25660-3_21
6. Venkatesh, S., Phung, D., Duong, T., Greenhill, S., Adams, B.: TOBY: early intervention in autism through technology. In: Proceedings of the SIGCHI, pp. 3187–3196. ACM (2013)
7. Peters-Scheffer, N., Didden, R., Korzilius, H., Sturmey, P.: A meta-analytic study on the effectiveness of comprehensive aba-based early intervention programs for children with autism spectrum disorders. Res. Autism Spectr. Disord. **5**(1), 60–69 (2011)
8. Garnett, M.S., Attwood, T., Peterson, C., Kelly, A.B.: Autism spectrum conditions among children and adolescents: a new profiling tool. Aust. J. Psychol. **65**(4), 206–213 (2013)
9. Tran, T., Phung, D., Venkatesh, S.: Mixed-variate restricted Boltzmann machines. In: Proceedings of the 3rd ACML, pp. 213–229 (2011)
10. Nguyen, T.D., Tran, T., Phung, D., Venkatesh, S.: Latent patient profile modelling and applications with mixed-variate restricted Boltzmann machine. In: Pei, J., Tseng, V.S., Cao, L., Motoda, H., Xu, G. (eds.) PAKDD 2013. LNCS (LNAI), vol. 7818, pp. 123–135. Springer, Heidelberg (2013). doi:10.1007/978-3-642-37453-1_11
11. Hinton, G.E., Salakhutdinov, R.: Replicated softmax: an undirected topic model. In: NIPS, pp. 1607–1614 (2009)