Toddler mental development interventions: Can machine learning play a part?





28th June 2024 IDDDP Presentation Akshat Gautam

How is Physical Development Monitored?

- Physical parameters such as height, weight, and head circumference
- Standardized growth charts (WHO)
- z-scores calculated



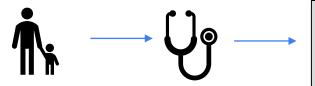
WHO WHITHY OUT VED PET 11

Mental development?



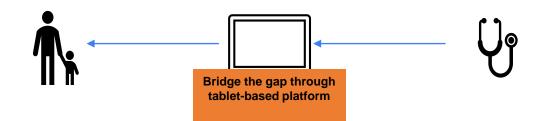
Gauging Mental Development

Goal : To measure mental development (ultimately for interventions) **Current Situation:** Parents observe atypical symptoms, visit hospital

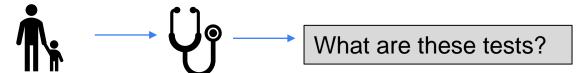


- Hospital conduct tests
- Too late? (symptoms already appeared)
- Results difficult to accept?

Long term goal: Bring hospital to children; generate developmental scores



Understanding Psychometric Tests



What are they:

 Standard and scientific method to measure mental capability

Why are they not used everywhere?

- Costly
- Trained professional; specific setting
- Not available in Low Income countries





Tablet Based Assessment

- Tablet contains set of tasks, each for different domain (social, motor, cognitive)
- Task generated raw data, not usable, needs to be processed One of the tasks is the **wheel task** (social domain)



Video recorded from front camera

Overview

- 1. Introduction (done)
- 2. Analysis Pipeline
- Understanding GMDS test (more detail)
- 4. Using features to predict GMDS scores
- 5. Using IRT (item response theory) to generate scores
- 6. Future Work
- 7. Understanding tasks and feature extraction

- Data collection done by STREAM team
- My work: Data analysis
- All contributions mentioned in purple colour.

Wheel Task

Feature description

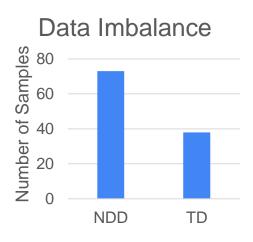
Get the distance of face from the camera given video

Involves Computer Vision (STAGE 1) Wheel Task Say to the child: "Look at this wheel moving. You can look at it for as long as you Frame Number want. If you want to stop it just press this red button. Shall we stop it?" Press the red Video recorded from Black and white wheel [3] Distance vs Frame no front camera

Classification

- Median and Std dev of distance signal
- 111 children, 2 input features, 2 classes
- 5-fold CV

Algorithm	Accuracy (%)	F1 Score
Random Forest	78.46	0.67
Logistic Regression	81.23	0.74
SVM	73.07	0.55



Classified children into NDD/TD using distance as feature

Overview

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- 6. Future Work
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Problem Statement

Generate
developmental
scores using tabletbased assessment

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What to do with these features?

Feature Tensor

Child 1	Coloring Task Feature	Wheel Task Feature	Button Task Feature	
Child 2	Coloring Task Feature	Wheel Task Feature	Button Task Feature	
Child 3	Coloring Task Feature	Wheel Task Feature	Button Task Feature	







Feature to scores supervised on psychometric tests (GMDS)

Features to scores but unsupervised using IRT (Item response theory) Features to classify NDD/TD (Done for wheel task)

For this, it's important to understand psychometric test GMDS

Griffith's Mental Development Scale (GMDS)

- Gold-standard tool
- o-6 years
- 321 items, 5 domains
 - Foundations of learning (63 items)
 - Language and communication (63 items)
 - Eye and hand coordination (67 items)
 - Personal-social-emotional (65 items)
 - Gross motor (63 items)
- Binary Items

Convert these "raw scores" into normalized scores

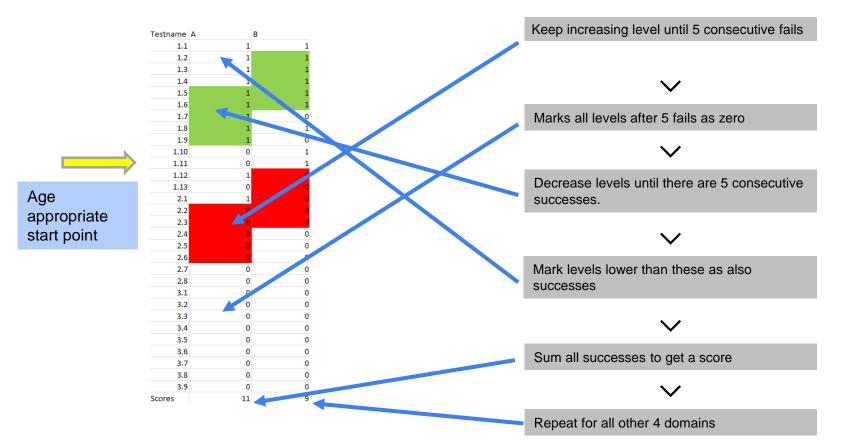


Photo of GMDS test kit [4]

Sample GMDS Results					
ChildID	Α	В	С	D	E
MW-0113	33	43	44	53	47
IN-1653	49	51	52	56	60
IN-1682	31	43	46	45	46

Short demo of GMDS test

This is done so a child doesn't have to sit through all 321 items



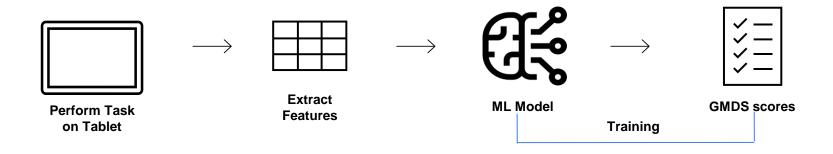
How do we use these raw scores?

Motivation

- Want psychometric test to be administered easily
- Want to show features actually capture development

Features to developmental scores based on psychometric test

Pipeline



Setup

Training

384 data points (i.e. features and scores for 384 children) 56 features (54 features from 6 different tasks + Age,Gender) Target label is GMDS scores across 5 domains

Training Setup

5-fold cross-validation (due to less data)

What is model choice?

Regression Models

Metrics

R2 Score Mean absolute percentage error (MAPE) Mean square error (MSE)

Models

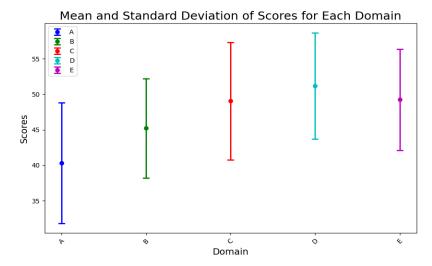
- Linear Regression
- Ridge Regression
- Random Forest
- Gradient Boosting
- AdaBoost
- Decision Tree
- Support Vector Regression
- KNN regressor
- XGBoost

Results [1/3]

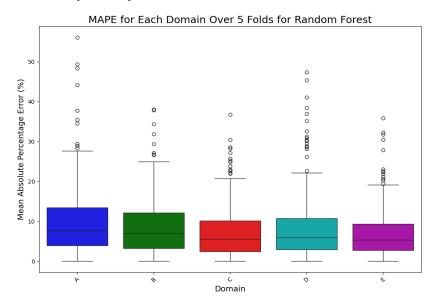
Best Model

Model	R2 Score	MAPE	MSE
Random Forest	0.64	7.88%	20.12

Ground truth GMDS score distribution

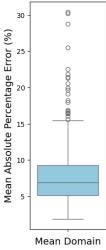


Results (2/3)

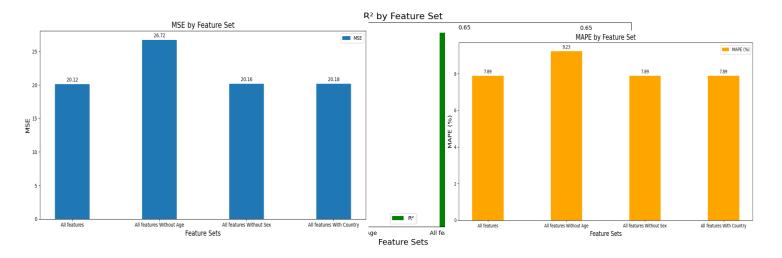


- 1st plot: MAPE across 5 domains
- 2nd plot: Average MAPE
- 5-10% error for half of the samples

Average MAPE Across All Domains for Random Forest



Results (3/3)



- Removing Age reduces performances, GMDS highly correlated with Age
- Sex and Country don't show any effect
- Same trend in MAPE and MSE

Overview

- 1. Introduction (done)
- 2. Analysis Pipeline
- 3. Understanding GMDS test (more detail)
- 4. Using features to predict GMDS scores
- 5. Using IRT (item response theory) to generate scores
- 6. Future Work
- 7. Understanding tasks and feature extraction

Problem Statement

Generate
developmental
scores using tabletbased assessment

Where are we now?



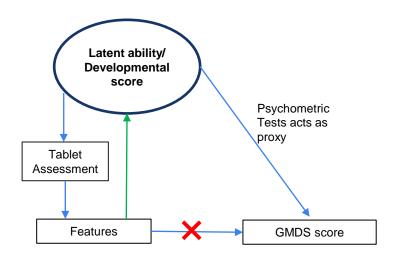
Features extracted can be used to generate scores like GMDS



Developmental scores could be generated independently

Not depend on GMDS

- Costly
- Will need to administer again for a new country



What's Next?

To generate developmental scores without relying on psychometric test

Item Response Theory (IRT)

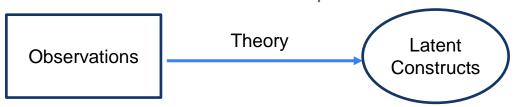
What is IRT?

- Theory of measurement
- Family of statistical models

What does it do?

IRT maps observations onto internal traits / states :-

- Test scores responses into knowledge / intelligence
- Questionnaire items into attitude / beliefs



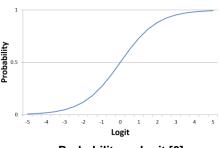
IRT equation

$$Y_{ij} = \theta_j - b_i$$
 Where, Y_{ij} = Logit of Response by person j for item i,
$$\theta_j$$
= **Trait** of person j,
$$b_i$$
= Difficulty of item I

Thus, for mapping values to [0,1],

$$Logit = \ln(\frac{Pr}{1 - Pr})$$

So, we have probability value between [0,1] and binary responses (0/1) to items. We can optimize the two parameters (θ , b)



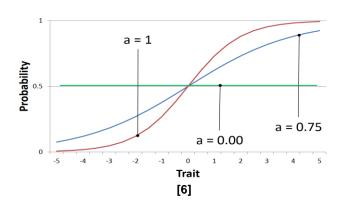
Probability vs logit [6]

Some other models

2 Parameter Model

 $Y_{ij} = a_i \theta_j - b_i$ $Y_{ij} = ext{Logit of Response by person j for item i,}$ $a_i = ext{Discrimination of item I,}$ $\theta_j = ext{Trait of person j,}$ $b_i = ext{Difficulty of item i}$

Same difficulty, different discriminations



In STREAM, if we consider tasks metric as "items" in questionnaire, responses are not in binary. e.g., for coloring tasks

Task metric / Items	Features / Responses
Points Inside	636
Points Outside	1595
Crossovers	63
Time Taken	88216

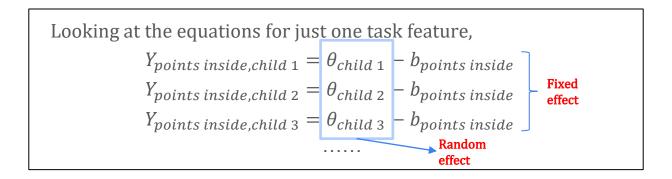
Adapting for STREAM data

What if we remove the logit link from the equation earlier :-

$$Y_{ij} = \theta_j - b_i$$
 Where, Y_{ij} =Feature of child j for the task metric i, θ_j = Ability of the child j, b_i = Difficulty of task metric j

- Known as LME (linear mixed effect) model
- Ime4 package in R [7]

Setup for START data



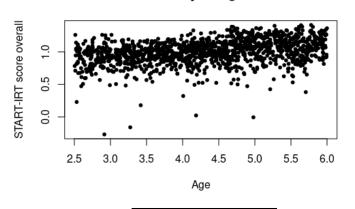
Final equation

$$Feature_{task,child} = \theta_{child} - b_{task}$$

- Higher ability should lead to higher feature value
- Not true, higher ability child should have lower crossover counts

Results (1)





r = 0.34

Correlation of IRT score with	r
GMDS domain A	0.27
GMDS domain B	0.22
GMDS domain C	0.24
GMDS domain D	0.24
GMDS domain E	0.25

Correlating IRT scores with GMDS

Relatively low correlation with age and GMDS scores, the scores need to be improved

Improvements/Future Work

Why is correlation not good?

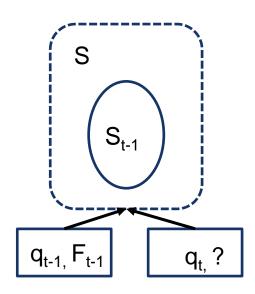
- IRT assumes monotonicity, ability increases, task feature should also increase
 - Not necessarily true since they are hand crafted features, e.g. number of crossovers increases as age of children increases which is not expected
- IRT assumes local independence: responses given to the separate items in a test are mutually independent given a certain level of ability (multiple features are extracted from same task)
- We are using all features to predict a single score, could bin features into different domains and generate multiple scores like -> social, motor ...

Future Work Motivation

- We are not including the fact that the child is performing tasks in a particular order, and in a single sitting
- Each feature may require mastery in multiple areas (social, motor, fine motor etc.), however we may not know the areas corresponding to each feature
- We are fitting a linear mixed effect regression model

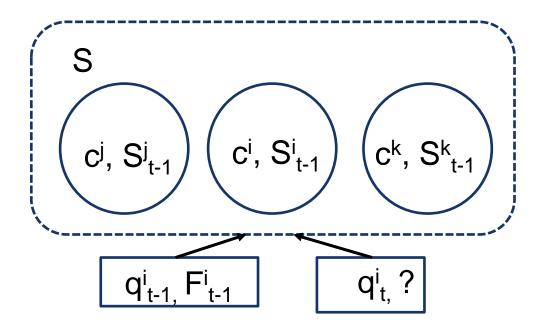
Knowledge State

- Given a child's previous task attempts X= {x1,x2, ... xt-1}, our goal is to predict the feature (say number of crossovers) that child will achieve in the current task
 - Fach input $x_t = (q_t, F_t)$ is a tuple containing task q_t , and its feature F_t which is computed from the tablet data
- The information of previous attempted tasks is condensed into a latent knowledge state S={s1,s2, ... st-1}
 - For example, if our previous method incorrectly predicts a feature F_t , our goal is to update the model and the knowledge state, thus improving our understanding of the child as she attempts task over time



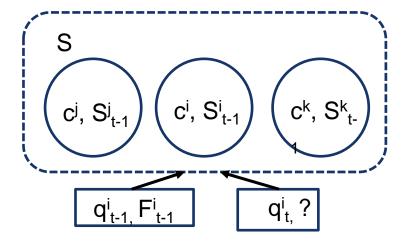
Concepts

We want to have multiple concepts for each state i.e c1,c2....cn



States and concepts

- Combine knowledge state and concept in a memory augmented neural net paradigm
- Training
 - Learn static matrix (key) for storing concepts associated with each task independent of child
 - Learn matrix (value) for storing student's knowledge state in each concept
- Inference
 - Update the value matrix as child completes task
 - Final score after all tasks are completed



Maintains a knowledge state for each concept simultaneously and all states constitute the "knowledge" of a child

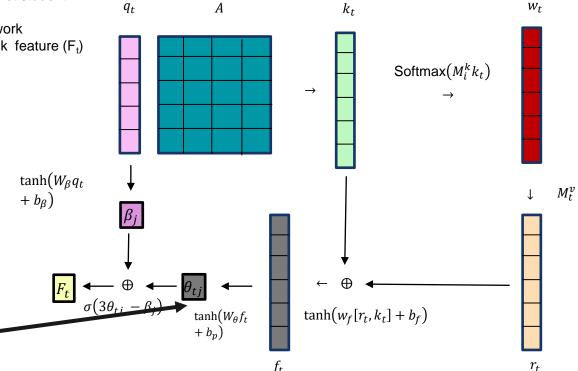
Method 3: Deep IRT

- IRT Module is built on top of key-value network
 - Instead of predicting probability, we predict student ability using f,
- Task difficulty is calculated using another network
- Ability and difficulty is combined to predict task feature (F_t)
 [reminiscent of Item Response Theory]

M^v ∈ ℝ^{N×d_v}: Value memory matrix (skill states)
 M^k ∈ ℝ^{N×d_k}: Key memory matrix (latent abilities)
 A ∈ ℝ^{d_k×Q}: Ability Components Embedding matrix

 $\begin{array}{ll} - & k_t \in \mathbb{R}^{d_k} & : \text{ Embedding vector (key)} \\ - & v_t \in \mathbb{R}^{d_v} & : \text{ Response Embedding vector} \\ - & e_t \in \mathbb{R}^{d_v} & : \text{ Response erase vector} \end{array}$

 $\mathbf{B} \in \mathbb{R}^{Q \times d_v}$: Ability Components response embedding matrix



Ability is our developmental score

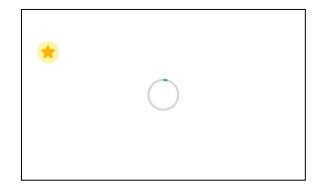
Delayed Gratification Task

Task Description

A star appears on screen. Child is told to wait for some time to get all three stars.

Feature Description

- 1. Proportion time spent delaying gratification
- 2. Proportion of frames child's face visible



Start time and end time are read through the excel files. Total task time is 180 s

Proportion Time =
$$\frac{End\ Time-Start\ Time}{180}$$

Medipipe face mesh is used to detect if a face is present or not in the frame. If more than one faces are present, then that frame is ignored.

Proportion face =
$$\frac{No \ of \ frames \ with \ a \ face}{Total \ No \ of \ frames}$$

Summary

 The data stored as raw data from tablet assessments can be converted into relevant features.

These features can be used for classification into NDD/TD.

- These features used to generate scores under the supervision of GMDS scores.
- Item Response Theory used to generate developmental scores in an unsupervised setting.

Acknowledgements

- My advisor: Prof. Sharat Chandran
- STREAM team
- Shubham (especially for distance work, experiments ..)

Thank You!

References

- [1] https://www.who.int/tools/child-growth-standards/standards/weight-for-length-height
- [2] https://www.who.int/tools/child-growth-standards/software
- [3] https://journals.sagepub.com/doi/full/10.1177/13623613231182801
- [4] https://www.aricd.ac.uk/about-the-griffiths-scales/griffiths-iii/griffiths-iii-kit/
- [5] https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1000273
- [6] https://hummedia.manchester.ac.uk/institutes/methods-manchester/docs/irt.pdf
- [7] https://www.jstatsoft.org/article/view/vo39i12
- [8] https://www.mdpi.com/2624-8611/5/3/50
- [9] https://arxiv.org/abs/1904.11738