Measuring Selective Sustained Attention in Children with TrackIt and Eyetracking

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Introduction

- **Selective sustained attention (SSA):** the ability to maintain attention exclusively to one object or task for a period of time [1, 2]
  - important cognitive process that develops through childhood
- TrackIt is a recent visual object-tracking task for measuring SSA in young children. [3, 4, 5].
- Collecting eye-tracking data from children performing TrackIt creates unique opportunity for fine-grained measurement of SSA, but unclear how to analyze this data.
- We recently proposed a hidden Markov model (HMM) based eye-tracking analysis method for analyzing eye-tracking data collected during TrackIt [6].
- **Current study** used data from 3- to 6-year old children performing TrackIt to...

  1) validate this HMM method by comparing with human hand-coding (labeling).
  - human hand-coding has historically been used, but is extremely time- and labor-intensive

  2) explore potential uses of this HMM analysis for providing nuanced measures of SSA.

TrackIt

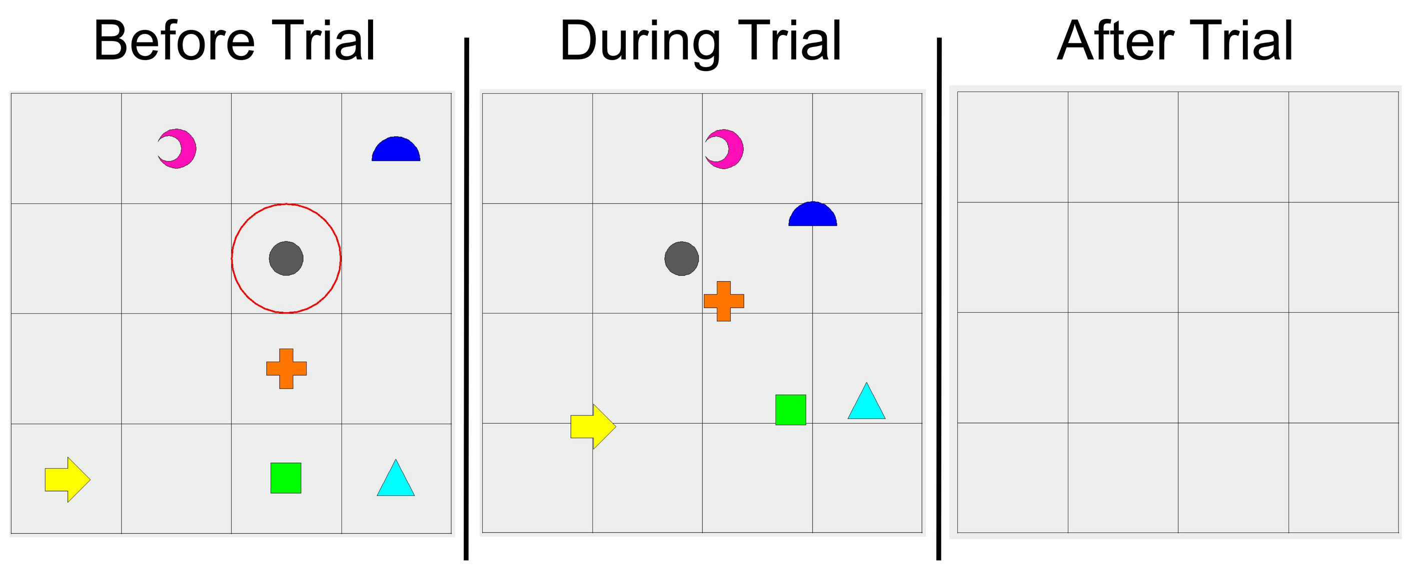

Figure 1: Example TrackIt trial (endogenous condition, 4 distractors). Target (grey circle) is circled before trial.

Hidden Markov Model (HMM)

- We know positions of participant's gaze and all objects on the screen.
- Single frame data is insufficient to infer which object is being tracked because:
  - (a) objects can overlap as they move
  - (b) eye-tracking (esp. in children) is noisy
- **HMM aggregates data across time to infer which object participant is tracking**
- Two main modeling assumptions:
  - At each timepoint, gaze is Gaussian around object being tracked
  - Between timepoints, stay on same object with high probability

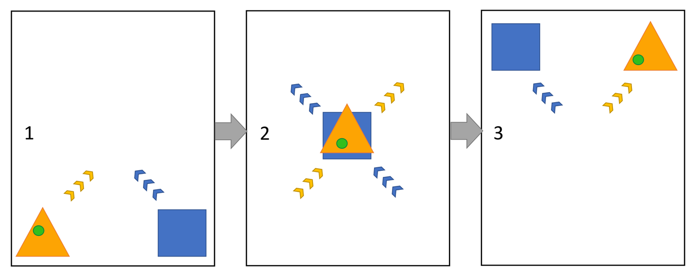

Figure 2: Example of two objects colliding

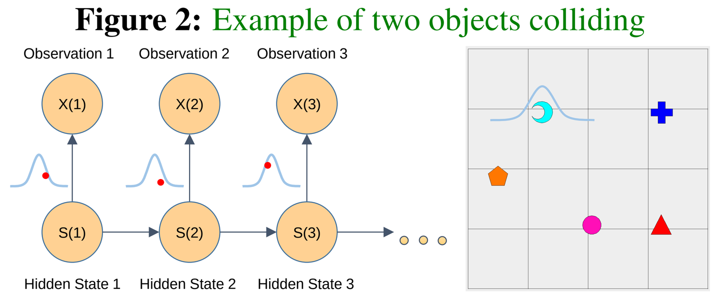

Figure 3: HMM (left) & gaze distribution (right)

Validating the HMM by Comparing with Human Coding

- Downsampled eye-tracking data from 60 Hz to 10 Hz
- Two human coders classified each gaze point as one of:

  {"Object 0", "Object 1", ..., "Object 6", "Off Screen", "Off Task"}.

- $>$500K judgments took $>$50 human hours

Data

- 50 typically-developing children, ages 3.5-6 years
- Eye-tracking collected at 60 Hz; downsampled to 10 Hz
- 11 trials (1 initial practice), in each of 2 conditions, "Endogenous" and "Exogenous" (distinction not relevant to current study)

Results

- Compared HMM to "Naive" model which simply assumes participant is attending to the object closest to their gaze
- Measured accuracy (agreement with human coder) of
  - Frame classification (which object is the participant tracking?)
    - HMM accuracy comparable with human coding reliability (up to 85% accuracy)
    - Naive model accuracy $\approx$ 66%
  - Switch detection (when does participant switch objects?)
    - For attention research, it is important to accurately identify *when* participant's attention switches from one object to another
    - Allowed 200 ms window between detected and true switches

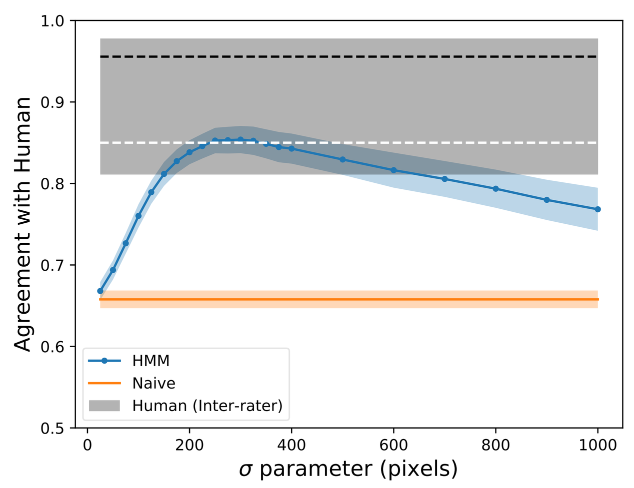

Figure 4: Accuracy (prop. frames agreeing with hand-coding) for HMM (as function of σ) and Naive models, as well as joint proportion of inter-rater agreement.

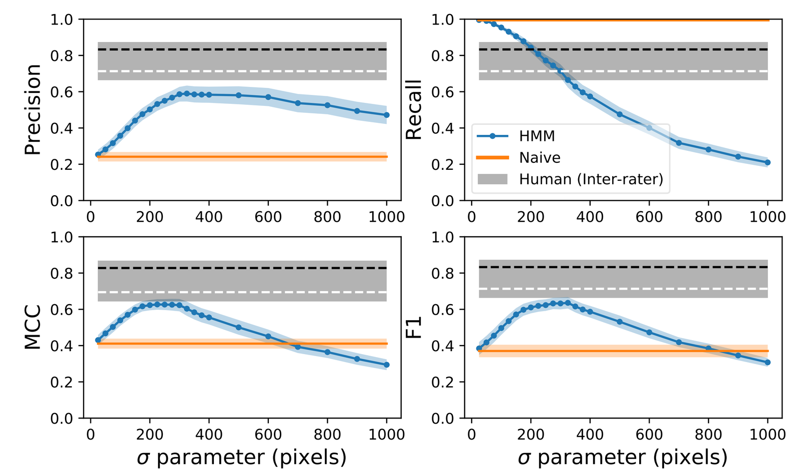

Figure 5: Precision, Recall, Matthews' correlation coefficient (MCC), and F1 score for attentional switch prediction, by HMM, naive model, and human coders.

Human performance was computed using each coder as ground truth for the other, and then averaging over coders, and is plotted with (dashed white) and without (dashed black) frames either coder coded as "Off Task".

- For reasonable σ, **HMM performs much better under balanced metrics (MCC and F1 score)**
- For example, naive model exhibits high recall, but very low precision
  - classifies over 27% of frames as switches ($\approx$ 2.7 switches/second)

Sustained Attention in Children

- Not obvious how best translate rich HMM output into measure of attention
- We explore 2 HMM-based attentional measures:
  - Total proportion of time on target ("PropT")
  - Decrement over trial time (10-20 s)

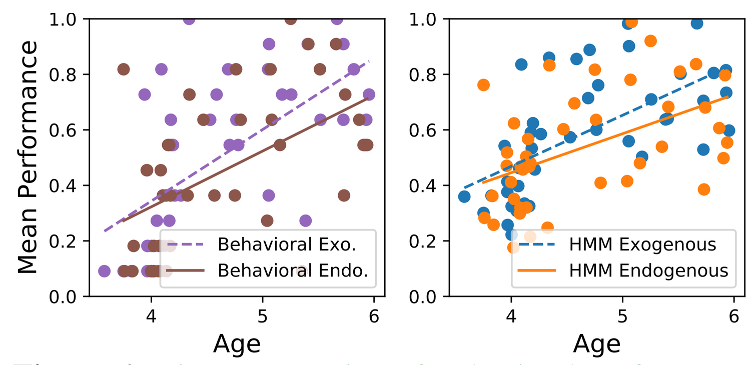

Figure 6: Linear regression of Behavioral Performance and HMM PropT both improve strongly with age.

Measure	Condition	β_{age}	R^2	95% CI
Behavior	Exo.	25.8	0.40	(15.7, 35.9)
Behavior	Endo.	20.1	0.28	(9.9, 30.3)
HMM	Exo.	18.4	0.39	(11.1, 25.7)
HMM	Endo.	14.1	0.24	(6.1, 22.0)

Table 1: Regression of performance measures over age. All β_{age} coefficients were significantly positive according to a two-sided t-test for the null hypothesis $\beta_{age} = 0$ ($ps < 10^{-3}$).

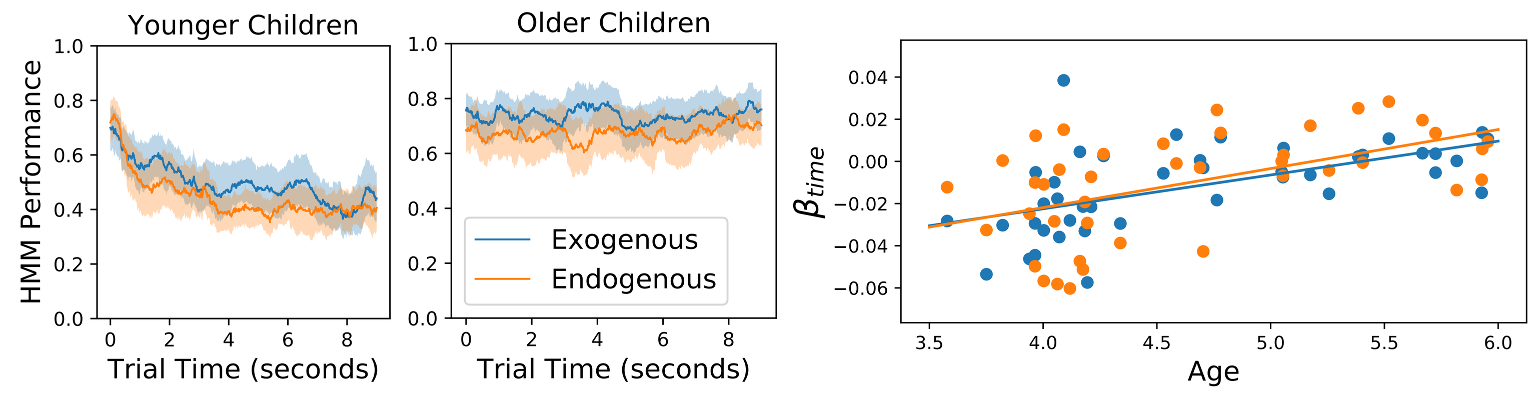

Figure 7: Decrement over trial time (slope) decreases with age.

Conclusions

- HMM classifies TrackIt eye-tracking data with near-human accuracy and temporal precision.
- Potential to
  - Eliminate need for hundreds of hours of manual coding of eye-tracking data in dynamic visual scenes
  - Accelerate rate of eye-tracking research
  - Enable studies that were previously constrained by data annotation
- May help to allow HMM to abstain from classifying difficult "Off-Task" frames

References

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