

# Play with Me - Measuring a Child's Engagement in a Social Interaction

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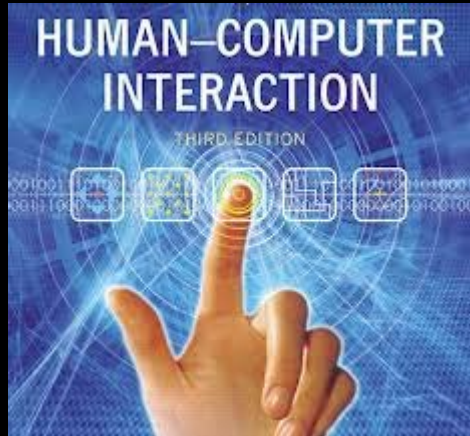
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# Computational Behaviour Analysis in Social Interactions - Challenges

1. Human behaviours expressed using subtle verbal and non-verbal cues are often contextual and social.
2. Analysis of interaction dynamics using multimodal signals.
3. Hard to obtain non-invasive high-level features such as body and head poses in semi-structured social interactions.

# Applications



# Autism Spectrum Disorders (ASD)

## What

social, communication and  
cognitive deficits

## Statistics

Fastest growing  
1 in 88

## Treatment

Early Intervention

## Diagnosis

No single genetic/ biological  
marker  
Behaviour study  
Detection > 18-24 months

**Red flags by 14 months**

Low social responsiveness and reciprocity

Infrequent initiation of joint attention and response to social cues

Infrequent playful imitation

Language delay

Repetitive and stereotyped interests and play

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# Joint Attention

Development psychology – JA is used to encompass behaviours young children use to actively coordinate their attention and interest in shared objects and events with their social partner. [Chris Moore and Philip J Dunham [1]]



(a) Initiate joint attention by alternating gaze - child looking at the toy and person



(b) Respond to joint attention

Source : ESCS

## Joint Engagement

Development psychology - More extended periods of shared attention between a child and (typically) their caregiver in which both partners are focused on their social partner and on the shared activity. [Roger Bakeman and Lauren B. Adamson [2]]

Developing computational model of engagement result in determining child's JA in a social interaction. This will provide metrics for early diagnosis of ASD.



# Related Work

1. Human-Robot Interactions
  - Head and hand poses
2. Adult-Child Interactions
  - Object, head trajectories and audio features
  - Body gestures from depth images
  - Electrodermal activity (EDA) of the children from wearable sensors
3. Virtual Humans

# Computational Approach to Engagement Prediction

1. An investigation of the feasibility of using low-level features in the absence of robust, accurate high-level non-verbal features.
2. A two-stage HCRF + SVM model for engagement prediction using the learned hidden structures of the behaviours.

# Multimodal Dyadic Behaviour Dataset (MMDB) [7]



1. 160 sessions
2. 3-5 min semi-structured play between adult and examiner
3. 5 stages

0 = Easy to Engage,

1 = Requires Some Effort to Engage

2 = Requires Extensive Effort to Engage

## Example from MMDB dataset - Challenges in automatic extraction of high-level features (head pose)

| Child actions |  |
|---------------|--|
| 1             | Child looking down                                 |
| 2             | Child turning towards other parts of the room      |
| 3             | Child climbing up on the mother and looking at her |
| 4             | Child walking away and coming back after some time |
| 5             | Child's head hair occluding the face               |
| 6             | Child's hand occluding the face                    |
| 7             | Child looking down at the book                     |
| 8             | Child's drinking from a glass occluding the face   |

These challenges warrant exploring low-level features

## Investigation of low-level features

1. When a child dominates in a social interaction, the motion cues reflect the child's behaviour.
2. The sub-actions leading to a behaviour can be learnt using Hidden Conditional Random Fields (HCRF).

# Investigation of low-level features using MMDB

- The released ground truth annotations are used for baseline comparison.
- Compute Behaviour Words using STIP-HOG-HOF features. These are used as low-level features.
- Detect manually guided head pose orientations for each frame. These are used as high-level features.
- Learn a discriminative model using Hidden Conditional Random Fields (HCRF).

| Engagement prediction   | Ground Truth | Manually guided high-level features | Behaviour words based low-level features |
|-------------------------|--------------|-------------------------------------|--|
| Classification Accuracy | 71.2%        | 69.3%                               | 70.3%                                    |

# Proposed two-stage algorithm for engagement prediction

**Stage 1 – Learning the hidden structures of a behaviour**

**Input : Behaviour Words**

**Output : Estimated hidden state probabilities**

**Behaviour words used as node observations to train a HCRF model**

**Stage 2 – Training a model using the learnt hidden structures**

**Input : Estimated hidden state probabilities**

**Output : Classification Accuracy**

**Train a SVM using estimated hidden state probabilities as a feature vector**

## Computing Behaviour Words

1. Detect child's upper body region
2. Construct a visual vocabulary using Histogram of Optical Flow (HOF) features of all frames using clustering. The cluster centres represent visual words.
3. Map HOFs of each frame to nearest visual word and choose the visual word containing maximum HOF as the frame descriptor.
4. Perform clustering on the frame descriptors and the cluster centres are referred as "Behaviour Words".

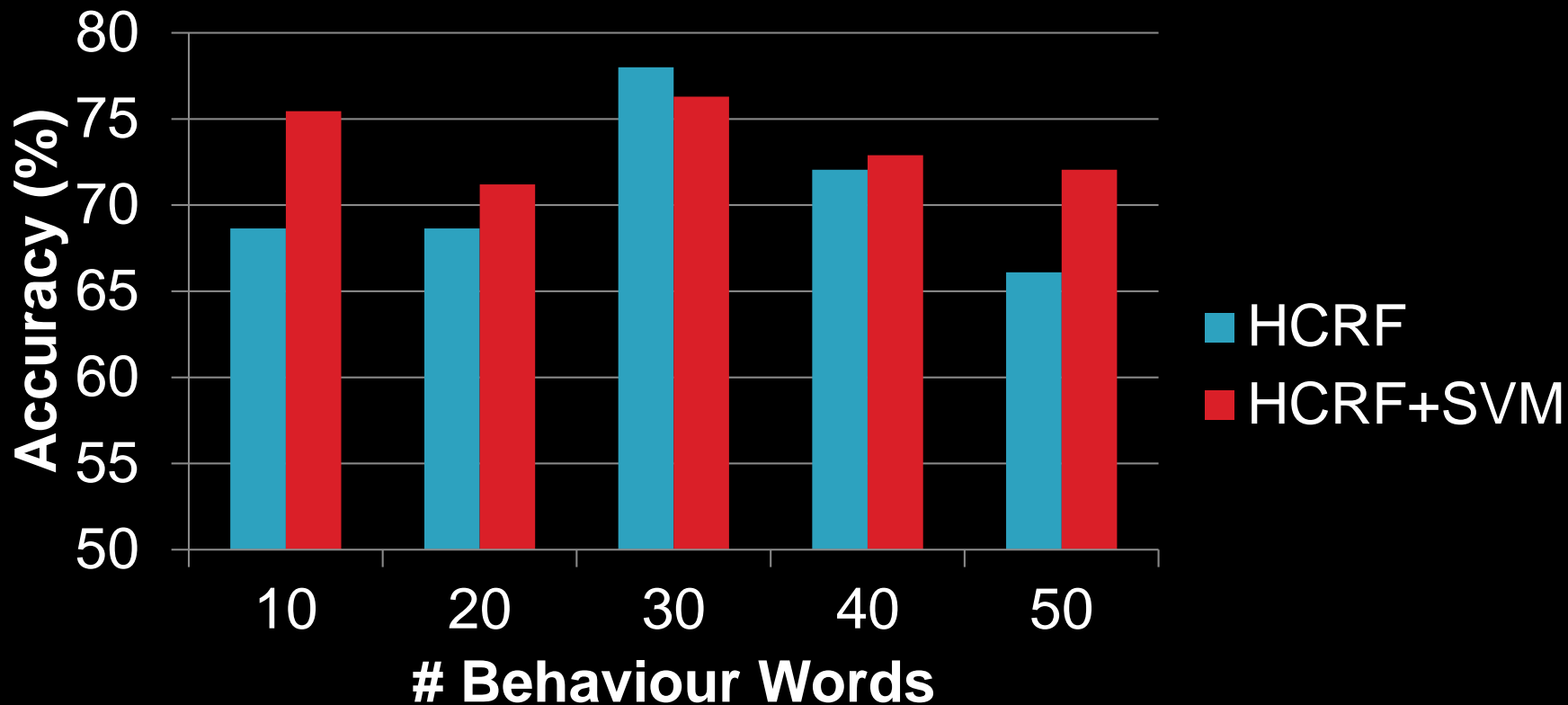


## SVM feature computation

1. The probabilities of each hidden state for each class and each node is available at the end of the training procedure from stage 1.
2. In stage 2, for each hidden state, compute the marginal probability across all classes.
3. The marginal probability of all the hidden states are fused together to form a feature vector.
4. Use this feature vector for training the SVM

# Experiments and Results - MMDB

## Optical Flow - Hidden States - 6



# Experiments and Results – J-HMDB

| Hidden States             | HCRF (A) | A + SVM      | A + FV |
|---------------------------|----------|--------------|--------|
| 4                         | 25.0%    | 28.0%        | 65.3%  |
| 7                         | 30.8%    | 35.7%        | 65.5%  |
| 10                        | 36.1%    | 39.0%        | 66.4%  |
| 12                        | 37.5%    | 42.1%        | 66.1%  |
| 15                        | 35.7%    | 37.0%        | 65.0%  |
| <b>Jhuang et al. [10]</b> |          | <b>57.6%</b> |        |
| Fisher Vector (FV) [11]   |          | 62.8%        |        |

Given that high-level features are difficult to obtain, the low-level features are good substitute for engagement prediction. Two-stage approach results in providing additional complimentary information.

## Summary

1. When a child dominates in a social interaction, the motion cues reflect the child's behaviour
2. The motion based low-level features can be a good substitute for hard to obtain high-level features
3. The learned hidden structures are used in two-stage framework for better recognition performance
4. Future work involve using multi-view learning to exploit the relationship between multimodal signals.

Thank You

# References

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# BACKUP



## Effectiveness of the two-stage approach

Hidden states  $<$  optimal hidden states – 2-stage is useful

Hidden states  $>$  optimal hidden states – 2-stage is useful under certain conditions

Hidden states = optimal hidden states – 2-stage is not needed

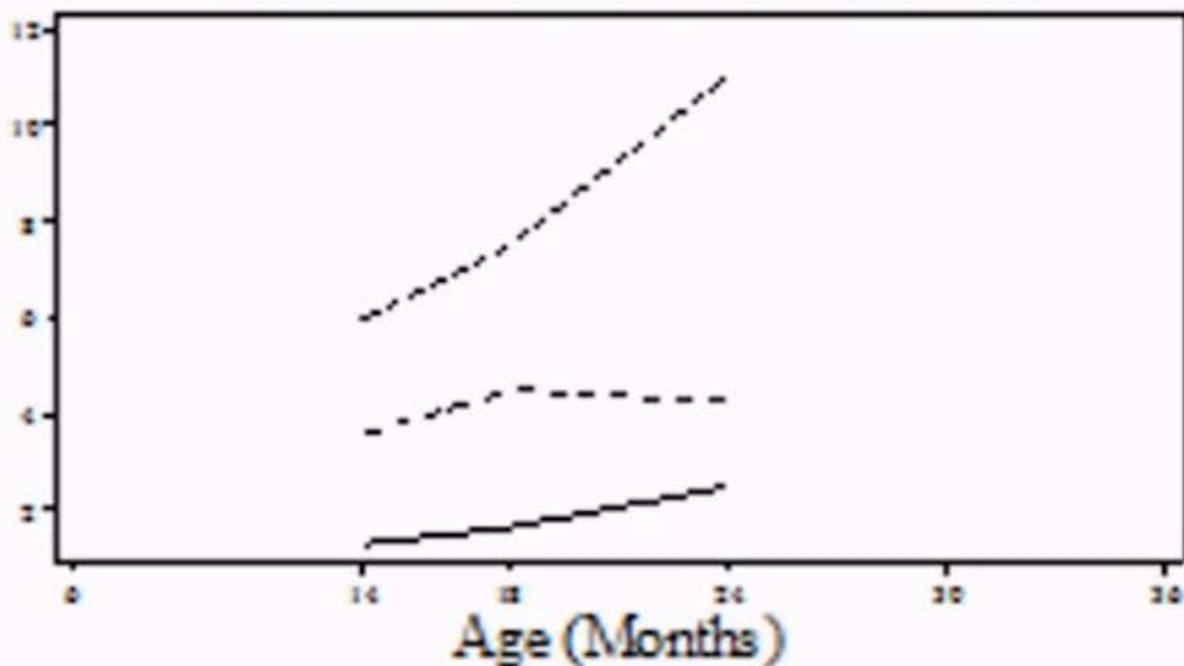


Computers will become “Socially Intelligent”, when they can recognize these human social behaviours.

# Joint Attention

Child initiates somebody to look at something interesting for the purpose of social sharing

CSBS Initiation of Joint Attention



--- Non-ASD group  
- - - Later Dx ASD group  
— Early Dx ASD group



Landa, Gross, Stuart, Faherty. 2013. Child Development



# ASD Atypical Behaviours

Bringing the Early Signs of Autism Spectrum Disorders Into Focus

<http://www.youtube.com/watch?v=YtvP5A5OHpU> (00:00 – 00:45, 04:24 – 07:56)

# Research focus

Developing computational models for machine understanding of human behaviours using non-verbal multimodal cues



Technology that assists clinicians in diagnosing Autism Spectrum Disorders (ASD)