Predicting Autism from Head Movement Patterns during Naturalistic Social Interactions

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Autism Spectrum Disorder (ASD)

- Neurodevelopmental condition defined by difficulties in three social areas:
  - (i) social–emotional interaction
  - (ii) nonverbal communication
  - (iii) forming and maintaining relationship

- Differences in nonverbal communication, a core trait of children with autism
  - eye gaze, facial expression, body actions, and head movements

Head Movements for Behavioral Analysis

- Head Movements in everyday social communication
  - Convey meaning, engagement and turn taking, provide structure
  - Variations meaningful for mental and emotional states of interaction partners
- Sparse research on head movement for social communication
  - One difficulty: precisely measuring characteristics of head movement, especially during natural social interactions
  - Manual annotations can be time-consuming or lack scalability, reliability and granularity

Head Movements in ASD

- Differences in head movements between autistic and neurotypical children
  - During infancy: such as head lag
  - During toddlerhood: rate, acceleration and complexity of head movements while watching movies
  - Later in childhood: greater and more stereotypical head movements during dyadic social interactions

Contributions

- Computationally modeling patterns of head movements during conversation
- Monadic and dyadic analysis to better capture broader social context of head movement
- Distinguishing between autistic and neurotypical individuals with 80% using head movement data

Methods: Experimental Procedure

- Battery of tasks: a modified version of the Contextual Assessment of Social Skills (CASS)
  - Semi–structured assessment of conversational ability designed to mimic real–life first–time encounters.
  - 3-minute face-to-face conversation between participant and confederate
  - Confederates were trained to speak for no more than 50% of the time and to wait 10s to initiate the conversation.

Methods: Participants

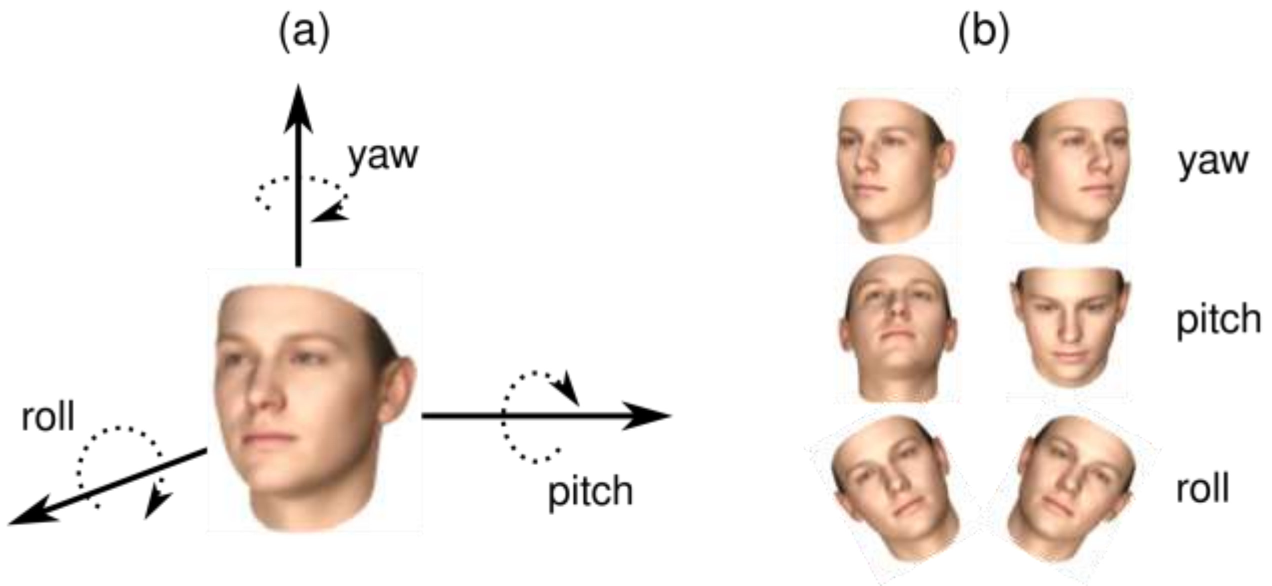
- 15 autistic and 27 neurotypical individuals
- Age range: 19.7 – 49.5
- Mean age 28.2
- 36 males, 6 femals

Methods: Data Collection

- Continuous audio and video of the 3–minute CASS recorded using a specialized "BioSensor"
- Two HD cameras pointing in opposite directions and two microphones
- Simultaneous recording
- Minimal device footprint and intrusiveness

Methods: Data Pre-Processing

- First and last 3 seconds trimmed
- Rate of 30 fps
- 3D face modeling
  - 3 time-dependent signals extracted: *yaw*, *pitch*, and *roll* head angles



Methods: Movement Patterns

- *K-Means* clustering to group head movement snapshots by similarity
  - Set *K = 12*
- Split signal into overlapping windows
  - 4 seconds per window (120 instances), 8 instance overlap
  - Each windows standardized (0 mean, 1 standard deviation)
- Two K-Means models containing all angles: *roll*, *pitch*, and *yaw*
  - *One with the original time signals, the other with differences between time steps*

Methods: Feature Construction

- Essence: for each participant count the number of times they exhibit certain head movement patterns based on trained K-Means clusters
  - *Monadic* case: only participant data used
  - *Dyadic* case: participant and confederate data used to provide context
- For each case concatenate the head angle and velocity signals

Methods: Predicting ASD Diagnosis

- Classification
  - SVM classifier with linear kernel: ASD diagnosis vs neurotypical
  - 100 times 10-fold cross-validation
- Features that contributed most strongly to classification accuracy

Results: Classification

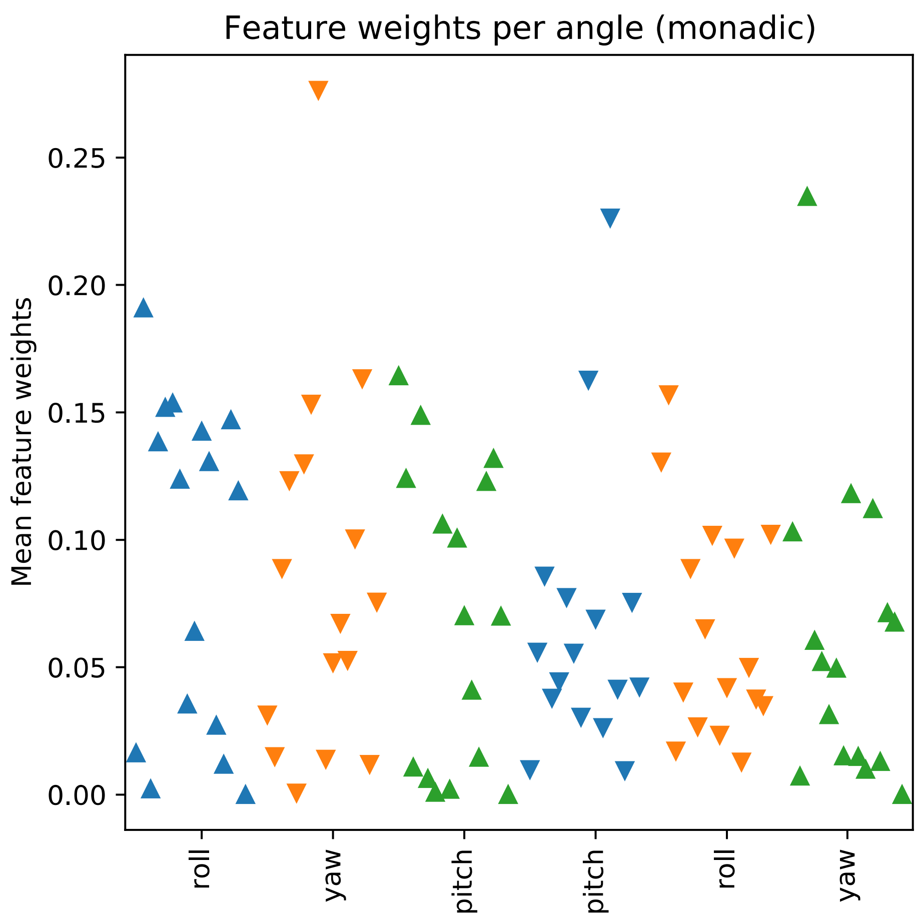
Table 1. Classification results for both *monadic* and *dyadic* features and their combination. The reported scores are means of the 100 experimental runs. For each case, the 10–fold cross validation scores and leave-one-out cross validation (LOO) are reported.

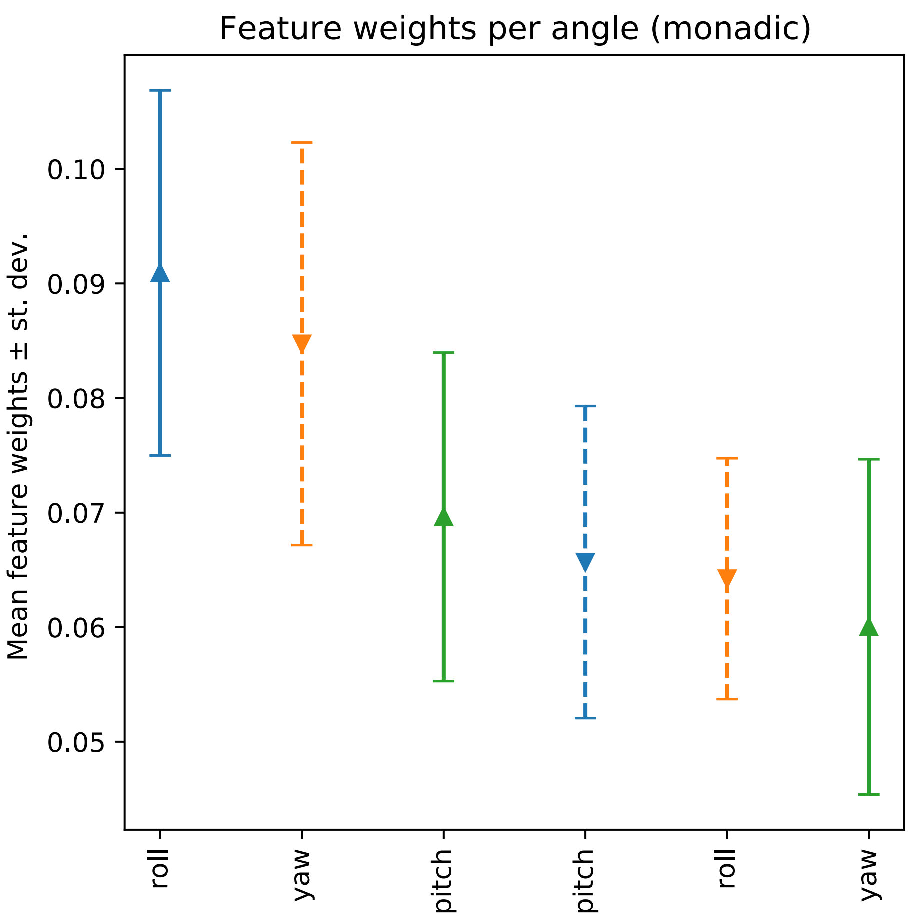
	Accuracy	Sensitivity	Specificity	PPV	NPV
Monadic 10–fold	69.2%	54.5%	77.4%	57.5%	75.5%
Monadic LOO	66.7%	53.3%	74.1%	53.5%	74.1%
Dyadic 10–fold	80.0%	55.9%	93.3%	82.4%	79.2%
Dyadic LOO	78.6%	53.3%	92.6%	80.0%	78.1%
Monadic & Dyadic 10–fold	79.7%	56.0%	92.6%	80.0%	78.1%
Monadic & Dyadic LOO	78.6%	53.3%	92.6%	80.0%	78.1%

Discussion

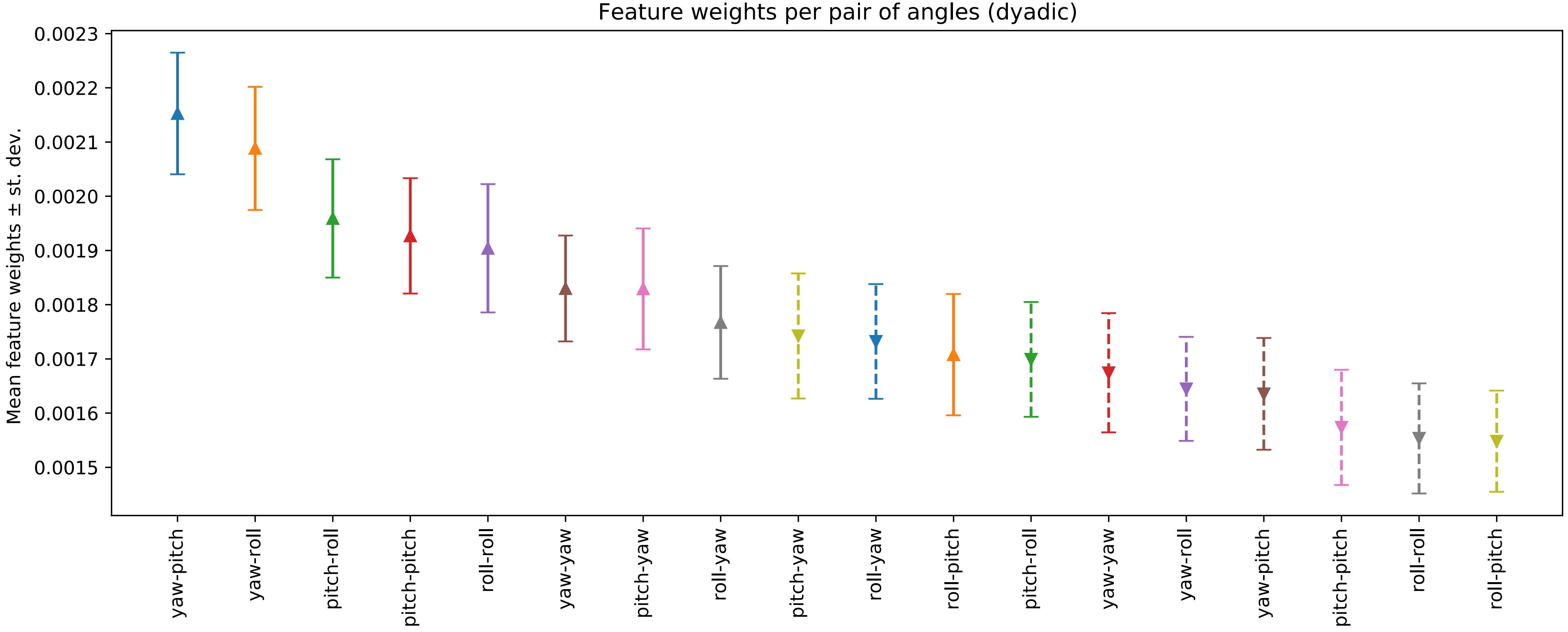
- All performance metrics: significantly better than chance
  - Suggests the existence of informative signals in head movement patterns
- Dyadic signals: 80% accuracy, however not intended for diagnostic purposes
  - Low sensitivity: 55.9%
- Monadic case: lower accuracy (69.2%)
  - ASD emerging within social situations
- In all cases, specificity better than sensitivity
  - More accurately identifying neurotypicals
  - Expected due to small, imbalanced sample size

Results: Relevant Features Monadic

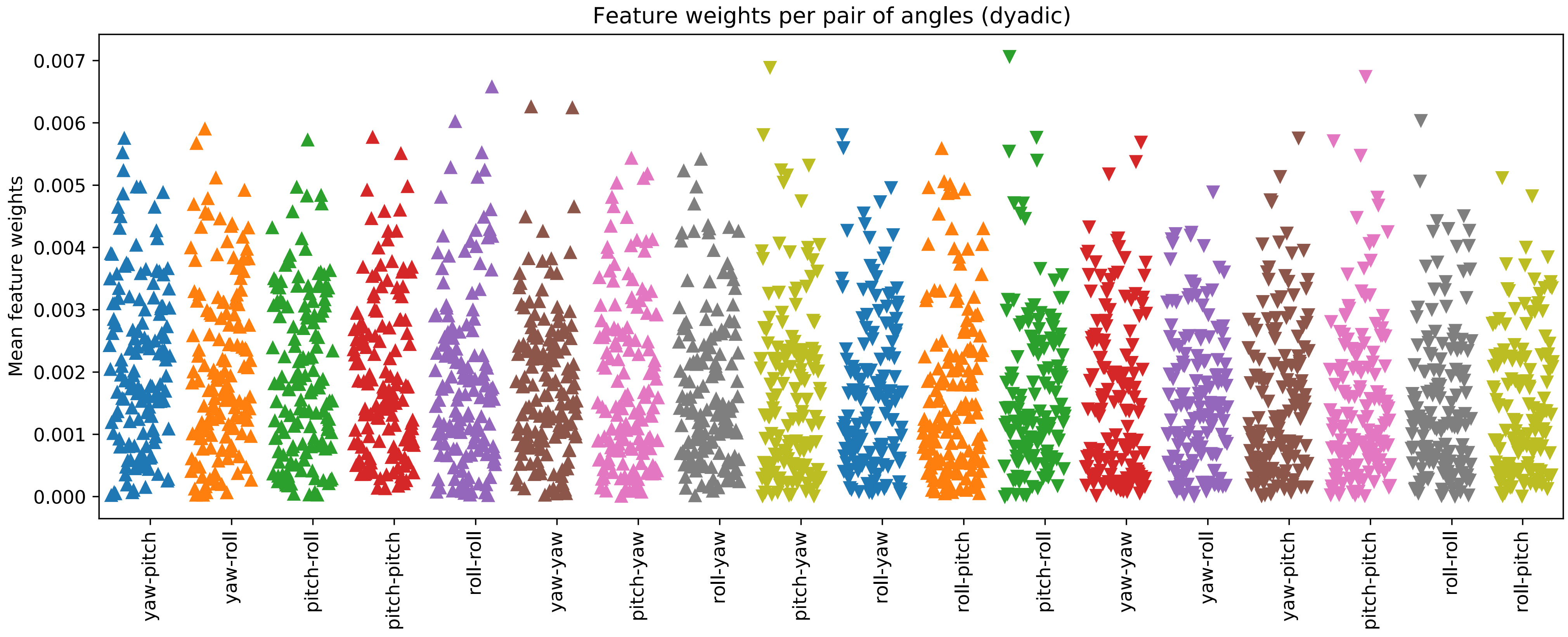




Results: Relevant Features Dyadic



Results: Relevant Features Dyadic



Discussion

- Primarily relying on dyadic features, due to higher accuracy
- Movement angles more influential than changes in them
- Pitch and yaw angles have the highest impact on the classification accuracy
  - Pitch movements (nodding) used to show agreement, attentiveness, etc.
  - Yaw movements (shaking, rotating head) may show disagreement, orientation etc
- We should investigate how these features unfold over time in more detail
- Investigate the combination of movements along all three directions for real, semantically meaningful head motion events

Summary

Predicting Autism from Head Movement Patterns during Naturalistic Social Interactions

- Computational models using computer vision and machine learning: 80% accuracy

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