

Why Develop Language Resources for Autism?



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Resources and Clinical Research*

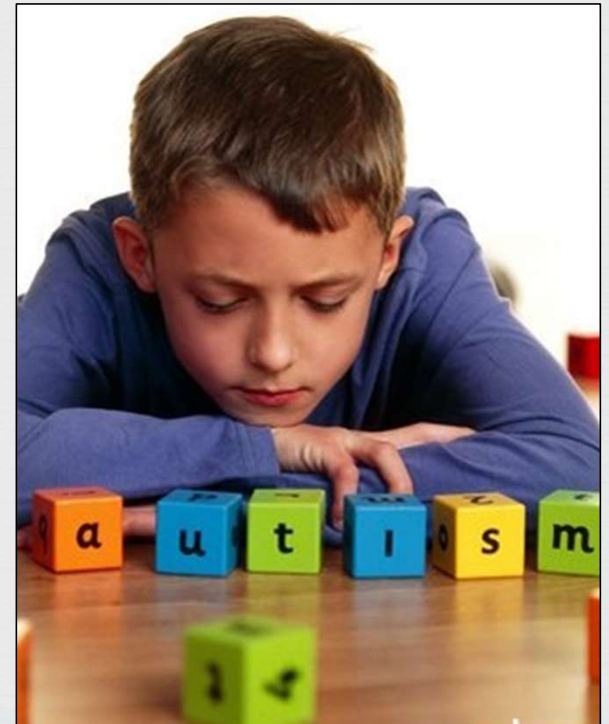
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Today's talk



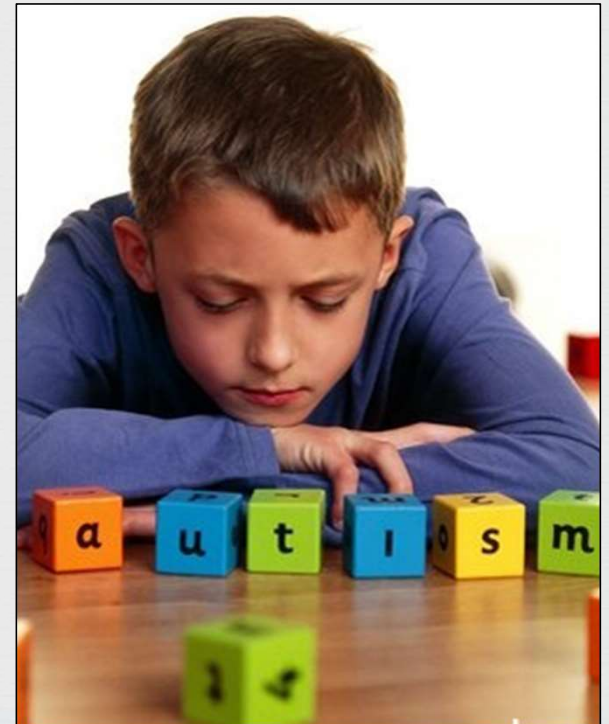
- ∞ Autism Spectrum Disorder (ASD)
 - Overview
 - Why we need large shared resources
- ∞ A new kind of measurement
- ∞ Example results



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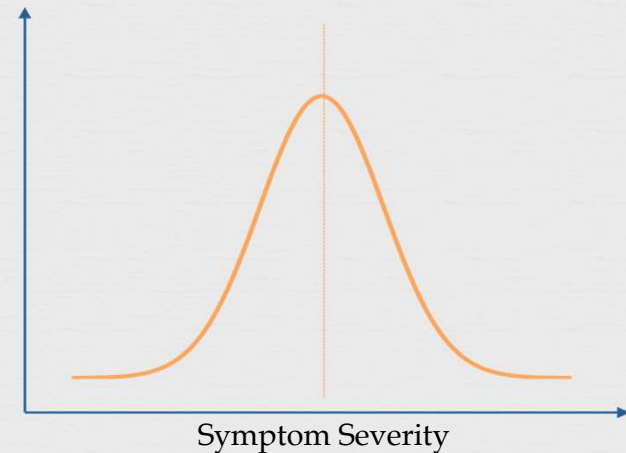
What is autism?



∞ Neurodevelopmental condition

∞ Behaviorally defined

- Diagnosed using *behavior only*
- No genetic test
- No brain scan



∞ Symptom severity lies on a continuum - Autism Spectrum Disorder

Core features



∞ Impaired social communication

∞ Repetitive behaviors and restricted interests

- Present since early childhood
- Interferes with everyday functioning



Who has autism?



Estimated prevalence approximately 1-1.5%

- 1 in 54 U.S. school children (CDC, 2020)

~4:1 boy:girl ratio

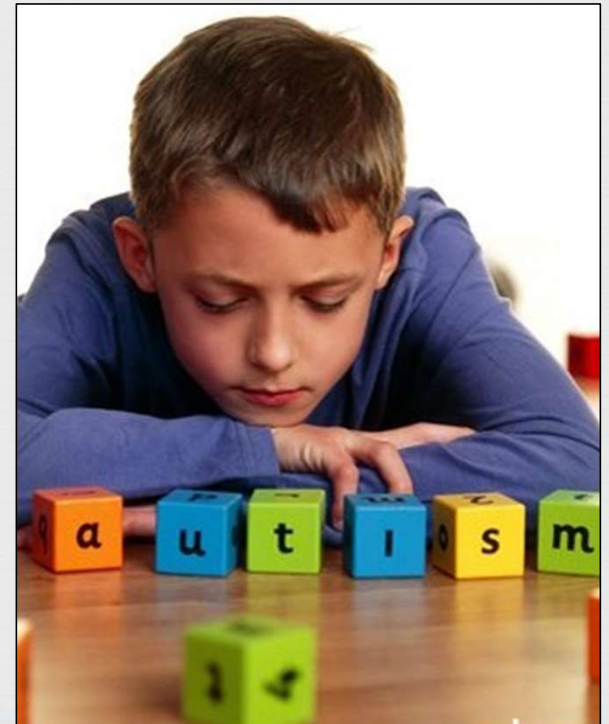
- Traditionally thought to vary with IQ



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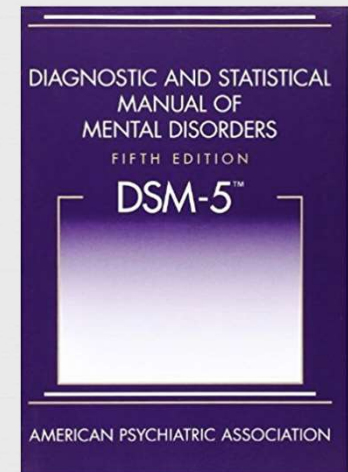


Why do we need large shared resources?

1. Diagnosis is expensive and difficult



- ☞ “Gold Standard” in the U.S. – expert clinician consensus
 - Autism Diagnostic Observation Schedule (ADOS)
- ☞ Based on observable behavior using human judgment
- ☞ Problem: imperfect agreement ($\kappa = .69$)



Why do we need large shared resources?

2. Extreme phenotypic heterogeneity



∞ Heterogeneity

- Symptoms vary *between* individuals
- Symptoms vary *within an individual* over the course of a lifetime
- ...and sometimes over the course of a day, or an hour!

∞ Common co-occurring conditions - ASD rarely occurs alone

- Seizures, anxiety, ADHD, OCD, Tourette syndrome, language disorders, learning disorders, intellectual disability



Why do we need large shared resources?

3. Insufficiently granular measurement



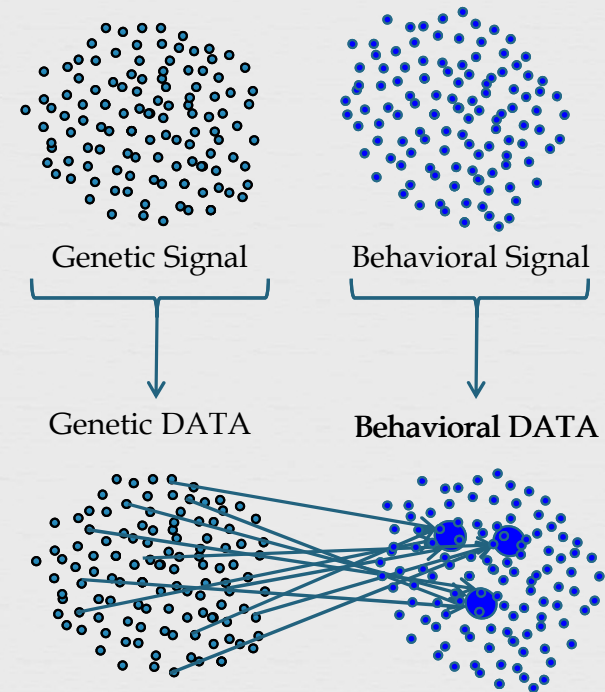
Current diagnosis and characterization methods are:

- Expensive – small samples
- Complicated, time-consuming
- Rely on human judgment of behavior

Mismatch

- Rich genetic or imaging data maps to restricted yes/no dx category

Need: highly **quantifiable, fine-grained signal** that is robust to practice effects



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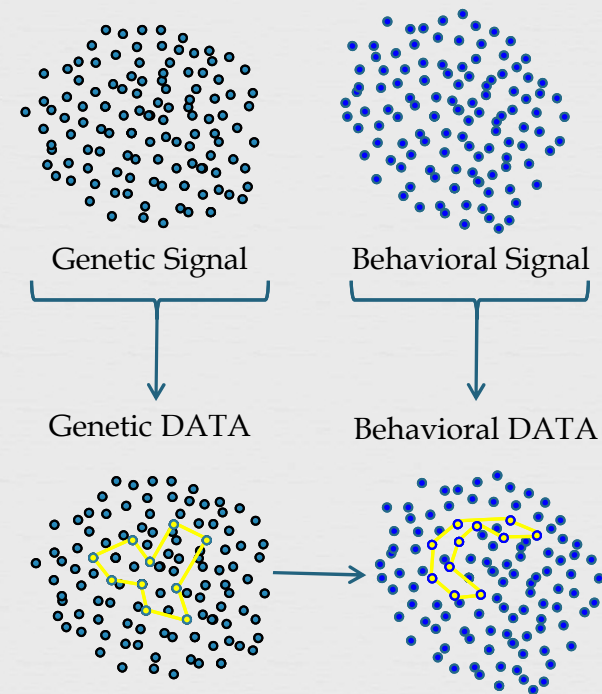
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Behavioral heterogeneity + small samples + poor measurement =

less-reproducible scientific results
suboptimal evidence base for interventions
worse outcomes

How to quantify autism?



- ∞ Autism manifests in the context of live social interaction (2 people)
- ∞ **Need:** High-dimensional, scalable method to capture time-synced human signals from interacting partners
- *Result: Precise behavioral characterization of two interacting systems*

Quantifying social interaction



☞ Turn social interaction into *numbers*

☞ What you **do** (motor) and what you **say** (language)

- Motor: computer vision
- Language: computational linguistics



Analyzing the vocal signal: Challenges

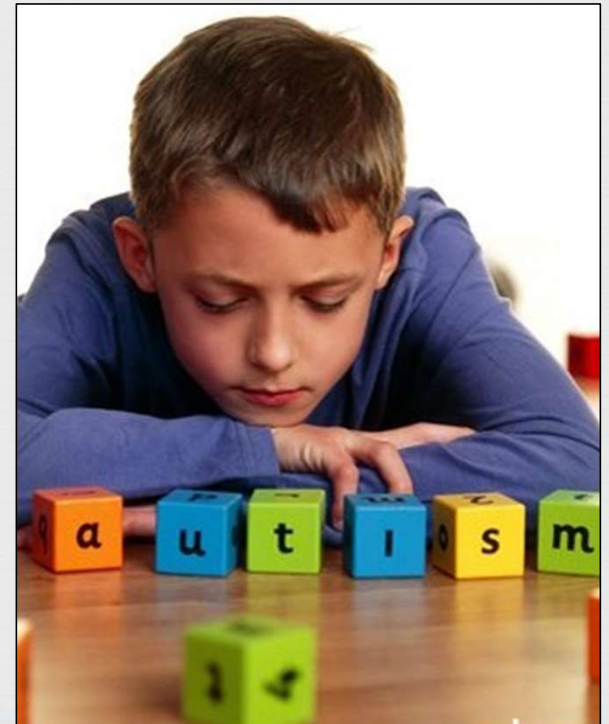


- ∞ Language is highly multivariate (acoustics, words, grammar, conversational dynamics)
- ∞ “Normal” changes across development and sometimes across cultures
- ∞ Neurodevelopmental/psychiatric conditions have different profiles
 - *Opportunity* to create personalized profiles with different treatment indications

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Dyadic biosensor

U.S. patent pending, J. Parish-Morris (Co-Inventor)



Keith Bartley



Bob Schultz

- Multi-channel directional microphones for automated analyses
- Video, audio, heart rate, skin conductance, accelerometers
- “Shovel ready” for machine learning

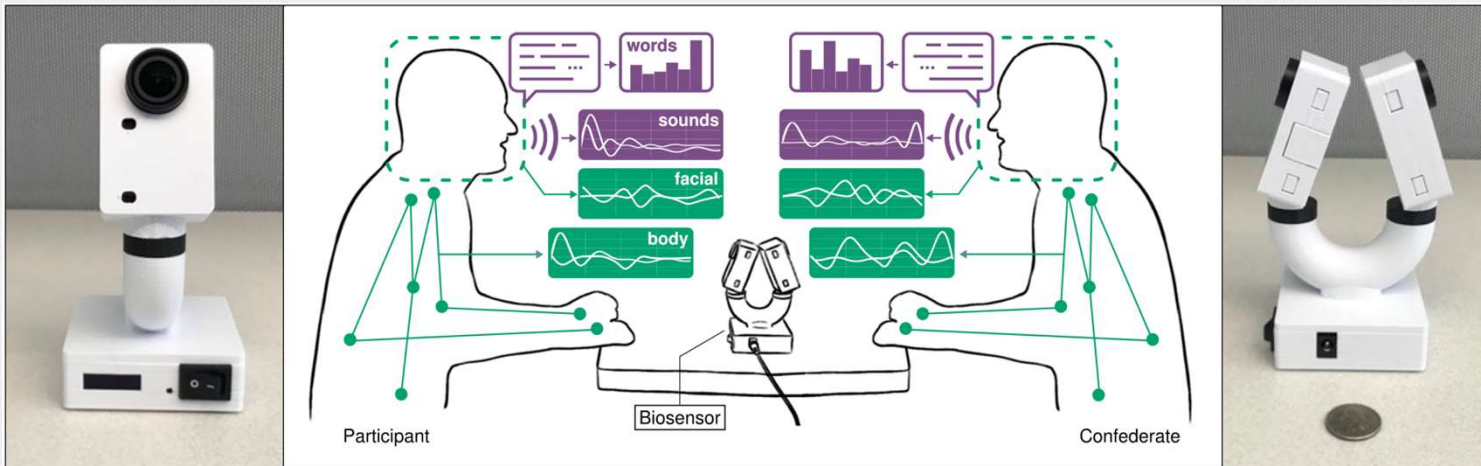


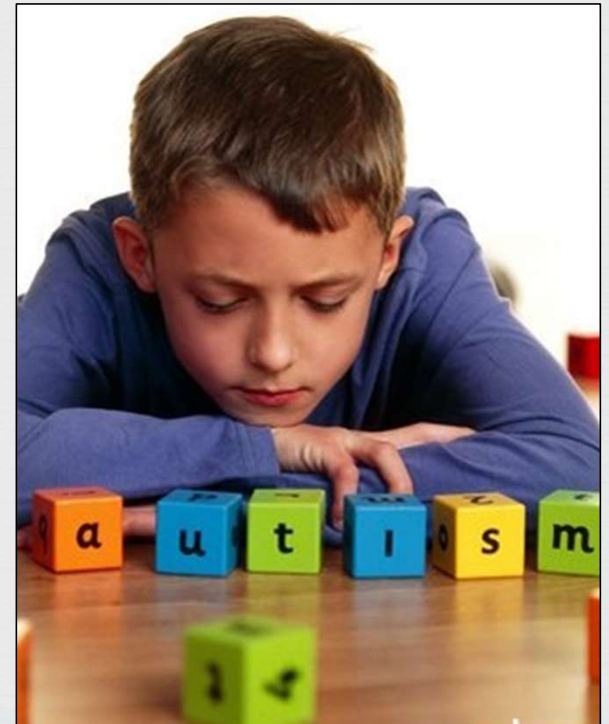
Fig.1 The Biosensor captures everything participants say and do with perfect synchronization.



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Example Study



Goal: Quantify restricted/repetitive behavior during naturalistic conversation using *computational linguistics* and *computer vision*

Compare behavioral diversity/entropy in adults with and without ASD in the domains of:

1. Language
2. Oral-motor movement

Participants



- ∞ Forty-four consenting adults, all native English speakers
 - Autism Spectrum Disorder (ASD): N=17
 - Typically developing (TD): N=27
- ∞ Diagnosed using according to DSM-5 criteria, informed by the Autism Diagnostic Observation Schedule – 2nd Edition¹

Variable	ASD Mean (SD)	TD Mean (SD)	Statistics	<i>p</i> -value
Age (years)	26.9 (7.3)	28.1 (8.4)	W = 234	0.923
Sex (Male, Female)	15, 2	23, 4	χ^2 : 0.08	0.774
Full-Scale IQ	102.1 (19.8)	111.7 (9.5)	W = 157	0.080
Verbal IQ	112.6 (22.1)	112.4 (11.2)	W = 215	0.736
ADOS Total	13.1 (3.0)	1.1 (0.9)	W = 442	< 2e-8*
ADOS Social Affect	9.8 (2.3)	1.0 (0.9)	W = 442	< 1e-8*
ADOS RRB	3.3 (1.5)	0.1 (0.3)	W = 441	< 1e-9*

1. Lord, C., Rutter, M., DiLavore, P. C., Risi, S., Gotham, K., & Bishop, S. (2012). Autism diagnostic observation schedule–Second edition (ADOS-2). Los Angeles: Western Psychological Services.

Paradigm



- ∞ Contextual Assessment of Social Skills (CASS)¹
- ∞ 3-minute semi-structured assessment of conversational ability designed to mimic real-life first-time encounters
 - Framed as “getting to know each other”; no specific prompts provided
- ∞ CASS confederates:
 - 10 undergraduate students or BA-level research assistants
 - Trained to speak for no more than 50% of the time
 - Wait 10s to initiate the conversation; wait 5s before re-initiating conversation after pauses



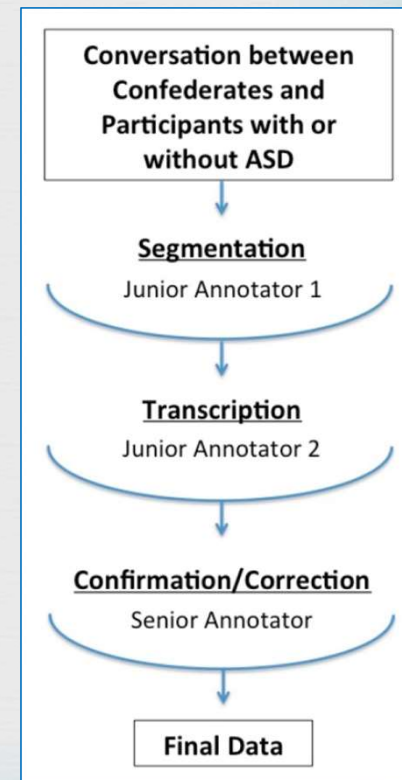
1. Ratto, A. B., Turner-Brown, L., Rupp, B. M., Mesibov, G. B., & Penn, D. L. (2011). Development of the contextual assessment of social skills (CASS): A role play measure of social skill for individuals with high-functioning autism. *Journal of autism and developmental disorders, 41*(9), 1277-1286.

Lexical pipeline



- ∞ Verbatim, orthographic, time-aligned transcription of utterances by participant and confederate
- ∞ Reliable, blinded annotators using Xtrans¹
- ∞ All spoken words included, no stemming, stopwords remain
 - Diversity includes morphological differences like “want” and “wanted”
- ∞ Total word count and entropy calculated per speaker using qdap²

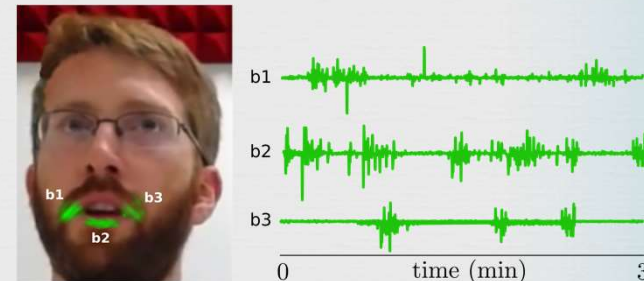
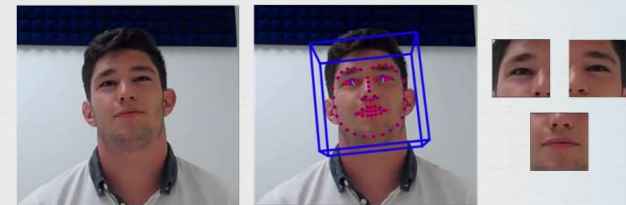
1. Glenn, M. L., Strassel, S. M., & Lee, H. (2009). XTrans: A speech annotation and transcription tool. In *Tenth Annual Conference of the International Speech Communication Association*.
2. Rinker, T. W. (2017). qdap: Quantitative Discourse Analysis Package. 2.3.0. Buffalo, New York. <http://github.com/trinker/qdap>



Oral-motor pipeline



- ∞ 3 steps: Face detection, face registration, and movement quantification
- ∞ Detection and localization of landmarks (eyes, lip corners, nose etc.)
 - Publicly available tool (OpenFace)¹
- ∞ Registration
 - Part-based registration²
 - Video stabilization to eliminate jitter
- ∞ Quantification
 - Facial Bases method³
 - 60 mouth bases
 - Normalized the total activation count of each basis by the maximum count observed for the same basis of confederates



1. Baltrušaitis, T., Zadeh, A., Lim, Y.C. & Morency, L.P.(2018). OpenFace 2.0: Facial Behavior Analysis Toolkit, *IEEE International Conference on Automatic Face and Gesture Recognition*.
2. Sariyanidi, E., Gunes, H., & Cavallaro, A. (2015). Automatic analysis of facial affect: A survey of registration, representation, and recognition. *IEEE transactions on pattern analysis and machine intelligence*, 37(6), 1113-1133.
3. Sariyanidi, E., Gunes, H., & Cavallaro, A. (2017). Learning bases of activity for facial expression recognition. *IEEE Transactions on Image Processing*, 26(4), 1965-1978.

Statistical approach



- ∞ Entropy: the amount of information a data modality carries
- ∞ Shannon entropy¹ where b is the base of the logarithm ($b=2$; our measure of entropy is in bits)

$$H = - \sum_{i=1}^n p(x_i) \log_b p(x_i)$$

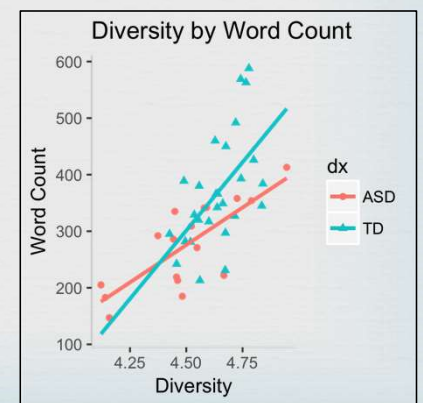
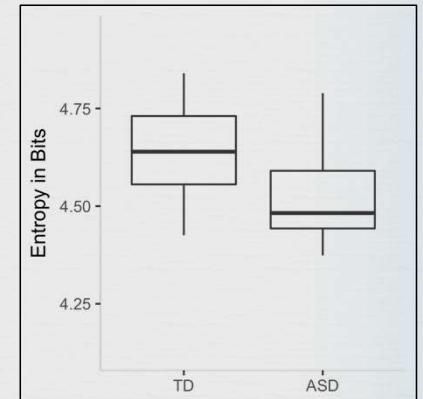
- **High entropy** is expected when participants make a rich set of facial expressions and produce a variety of words while speaking
- **Low entropy** is expected when participants generate a restricted set of mouth movements and produce repetitive speech patterns
- ∞ Tests:
 - Wilcoxon rank sum tests with continuity correction; exploratory correlation analyses
 - Linear mixed models (lme4) or simple linear models in R
 - ✓ Random effects of confederate identity and fixed effects of sex, age, and IQ checked for significance; excluded when non-significant
 - ✓ Facial analyses included speaking length and head motion as covariates

1. Cover, T. M., & Thomas, J. A. (2012). *Elements of information theory*. John Wiley & Sons.

Results: Lexical entropy



- ⌘ Reduced entropy in participants with ASD as compared to TD participants, $t(42)=2.85$, $p=0.007$, Cohen's $d=0.82$
 - The effect of diagnosis on entropy was significant after accounting for age, IQ, and gender, $t(39)=3.25$, $p=0.002$
 - Diversity of confederate language did not differ by participant diagnosis, $t(35.26)=0.17$, $p=0.86$
- ⌘ There was a (neurotypical) association between word count and entropy^{1,2}
 - ⌘ A second model tested the interactive effect of word count and diagnosis on participant lexical diversity
- ⌘ The slope of the relationship between word count and diversity was greater in the TD group than the ASD group, interaction $t=-3.51$, $p=0.001^*$

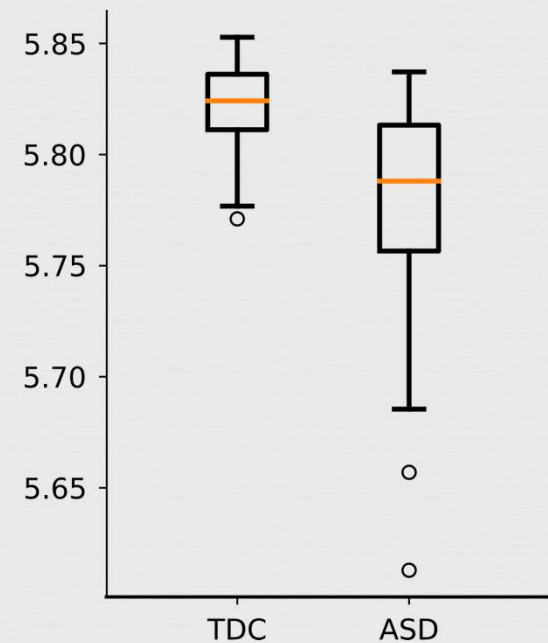


1. Shannon, C. E. (1951). Prediction and entropy of printed English. *Bell Labs Technical Journal*, 30(1), 50-64.
2. Witten, I. H., & Bell, T. C. (1990). Source models for natural language text. *International Journal of Man-Machine Studies*, 32(5), 545-579.

Results: Oral-motor entropy



- ⌘ Reduced mouth movement diversity in the ASD group as compared to the TD group (Cohen's $d=1.0$, $t=-2.73$, $p=0.009$)
 - Model included head movement and speech length as covariates
 - Difference remained significant when age, sex, and IQ were included as covariates (Cohen's $d=1.0$, $t=-2.52$, $p=0.016$)
 - No covariates contributed significantly to the model



Discussion



- ☞ **Take home:** Reduced behavioral diversity, across domains, captures an underlying dimension of restriction and repetition that distinguishes autistic adults from typical controls
- ☞ Restriction in mouth movement (motor) not driven by restriction in words produced (cognitive) – uncorrelated – contributing unique variance

Future Research



- ❧ **Build** a large, shared resource of ASD conversations at LDC to accelerate the pace of discovery
- ❧ **Test** real-world effects of subtle linguistic differences in ASD (e.g., likelihood of referral, peer friendships)
- ❧ **Explore** linguistic markers of complex phenotypes (e.g., depression, ASD + anxiety, ASD + depression or ADHD)
- ❧ **Develop** targeted social communication interventions that are *personalized* for the unique challenges faced by a given individual





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