Introduction

- Alzheimer’s disease (AD) affects 6 million Americans and has no known cure [1].
- Existing neuropsychological assessment tools can be insensitive to subtle cognitive changes, making early diagnosis difficult.
- They also require expertise, extensive time, travel, invasive tests, and expense.
- Thus: people are often assessed only after they are noticeably impaired, and it is impractical to perform regular assessments to track progression.
- Speech production can show effects of cognitive decline, possibly before other behavioral symptoms [2, 3, 4, 5].
- Speech avoids many of the logistical challenges of traditional clinical instruments.

Research Questions

- Do linguistic features exist which are reliable indicators of a person’s cognitive status?
- Can these features be calculated automatically (rather than the time- and labor-intensive process of manual annotation)?

Methods

- **Participants:** Offspring Study of Racial and Ethnic Disparities in Alzheimer’s Disease, a community-based study of middle-aged adults in upper Manhattan.
  - N = 112
  - Age: 32 – 89 years (mean 56)
  - Sex: Female: 62 / Male: 50
  - Race: Black: 17 / non-Hispanic white: 50 / Hispanic: 44 / more than one race: 1
  - Education: more than high school: 90 / high school or less: 22
  - First language: English: 78 / Spanish: 31 / other: 3
  - Participants chose which language (English or Spanish) to perform the tasks.
  - All participants’ data analyzed here were tested in English.

- **Neuropsychological battery:**
  - Selective Reminding Test (SRT) delayed recall score
  - SRT total recall score
  - Semantic fluency (animal naming)

- **Spontaneous speech production tasks:**
  - Series of questions about participants’ life (who influenced you, accomplishments, etc.)

- **Linguistic features:** lexical-semantic properties calculated automatically using python
  - Average lexical frequency, lexical diversity, empty vs. content words, total word count, filler word count, definite vs. indefinite articles, part-of-speech counts [6].
- **Demographic variables:** age, sex, race, ethnicity, college education, first language

Analysis

- **Multiple linear regressions:**
  - Predictors (entered jointly): Linguistic features (14) and demographic variables (6)
  - Outcome variables (separate): SRT delayed recall; SRT total recall; Semantic fluency
  - Model comparison was used to investigate whether adding linguistic features provided explanatory power over and above that of demographics alone.

Results

- **SRT Delayed Recall:**
  - Linguistic features significantly predicted delayed recall over demographics alone (Fig. A) (Adjusted R² = 0.499, R² = 2.825, p < .0002)
- **SRT Total Recall:**
  - Linguistic features did not predict total recall (Fig. B) (Adjusted R² = 0.344, R² = 1.145, p n.s.)
- **Semantic Fluency:**
  - Linguistic features added an enormous amount of predictive power for semantic fluency over demographics alone (Fig. C) (Adjusted R² = 0.621, R² = 3.764, p < .0001)
  - Linguistic features alone (without moderating demographic variables) significantly predicted semantic fluency (Fig. D) (Adjusted R² = 0.468, R² = 3.226, p < .0003)

Conclusions

- Lexical-semantic features of spontaneous speech are predictive of performance on neuropsychological tests which capture episodic memory and semantic fluency in middle-aged adults.
- Spontaneous speech can be collected easily and thus frequently.
- Meaningful linguistic features can be computed and analyzed automatically.
- This reduces the barrier of time-intensive manual annotation, making it possible to test at-risk individuals earlier, or administer assessments regularly.
- The speech-based prediction could be shared with a doctor or family member, allowing for further clinical screening.
- This could lead to earlier detection and better monitoring.

Future Directions

- Increase sample size
- Add Spanish-speaking participants
- Investigate relationship between speech and imaging and genetic markers
- Roll spontaneous speech collection out in the wild

References