Screening for Alzheimer's with psycholinguistics

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Introduction

Accurate and non-invasive screening for Alzheimer's disease (AD) is critical to allow patients time to plan for the future and access early treatment. The present work studies the effectiveness of well-known psycholinguistic measures at detecting likely cases of AD from narrative speech.

Data

Publicly available DementiaBank corpus [1]

Narrative speech elicited through Cookie Theft descriptions

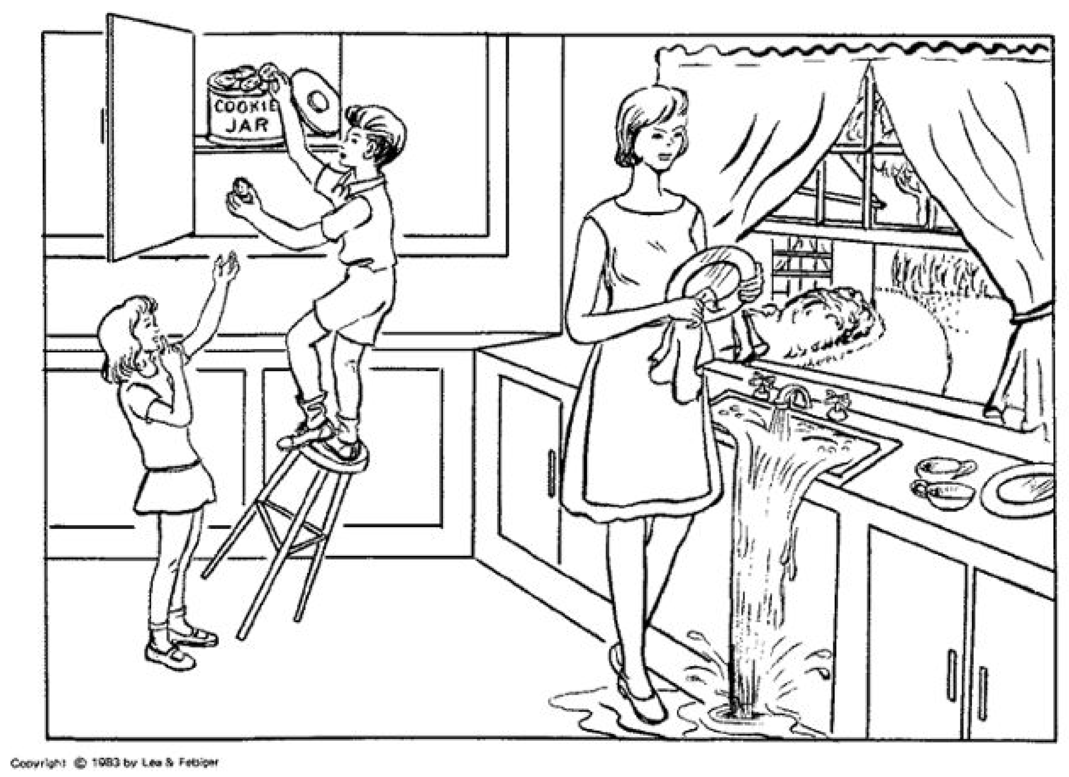

Figure 1 : 'Cookie Theft' elicitation picture [3]

	AD	Controls
n	167	98
MMSE	19.3	29.1
Age	71.8	63.8
Education	12.0	13.9
Sex (M/F)	55/112	40/58

Table 1 : Subject demographics

Baseline Model

Fixed Effects:
Main effects and two-way interactions for sentence position, word length and log unigram frequency

Random Effects:
A random intercept and maximal random slopes for word types (including test predictors)

Unigram frequencies were drawn from the SUBTL spoken word frequency corpus [2].

Embedding Depth

load = 1

(1) Somehow both $\boxed{\text{the filter is dirty}}$ and the flow decreases …

(2) Either $\boxed{\text{both } \boxed{\text{the filter is dirty}} \text{ and the flow decreases}}$ or …

load = 2

load = 1

During sentence processing, words generate expectations which must be maintained in order to correctly comprehend the sentence. For example, 'either' generates an expectation of 'or', which helps a reader correctly bind the conjunct at the appropriate level in the sentence. When these expectations are nested, greater memory load is required to maintain multiple simultaneous expectations.

The embedding depth measure was computed by a left-corner parser [4], which reports the weighted average embedding depth for each observation according to the probability of each incremental parse hypothesis.

Embedding Difference

Either	both	the	filter	is	dirty	and	the	flow	decreases	or	…
0	1	1	0	0	0	-1	0	0	0	-1	…

As embedding depth changes, working memory must be updated to reflect the current required memory load. The effect can be estimated by observing how weighted embedding depth changes after each new observation. The resultant measure (*embedding difference*) fits reading times well [5].

Experiment

Logistic mixed regression was used to predict: AD (1) or non-AD (0) diagnosis for each word given preceding context.
Half of each subject group was used for data exploration and the rest were used for significance testing.

Exploration Results

	Coef	p-value
Baseline	–	–
5-grams	-0.128	<0.0001
Surprisal	0.150	0.0003
Embedding difference	-0.026	0.2333
Embedding depth	0.109	0.0003

Table 2 : Results on exploratory data
$n = 22537$

Test Results

	Coef	p-value
Baseline	–	–
5-grams	-0.163	<0.0001
Surprisal	0.068	0.1186
Embedding difference	-0.030	0.2371
Embedding depth	0.279	<0.0001

Table 3 : Results on confirmatory data
$n = 21843$

Significance is shown for each model compared to a model containing all preceding factors.
Weakness of embedding difference suggests memory difficulties in AD may stem from maintenance rather than from updating working memory.

Conclusion

- Psycholinguistic measures of frequency and memory load are robust predictors of AD.
- They can be easily applied to language produced during traditional diagnostic tests for AD.

Coefficient Details

Factor	Coef	p-value
word length	-0.025	0.561
surprisal	0.093	0.035
position:word length	0.015	0.612
position:1-gram	0.017	0.575
position	-0.283	<0.001
1-gram	0.174	<0.001
5-gram	-0.081	0.013
embedding depth	0.109	<0.001
word length:1-gram	0.094	<0.001

Table 4 : Coefficients on exploratory data

References

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