Modeling Implicit Measures of Receptive Vocabulary Knowledge in Normal Adults

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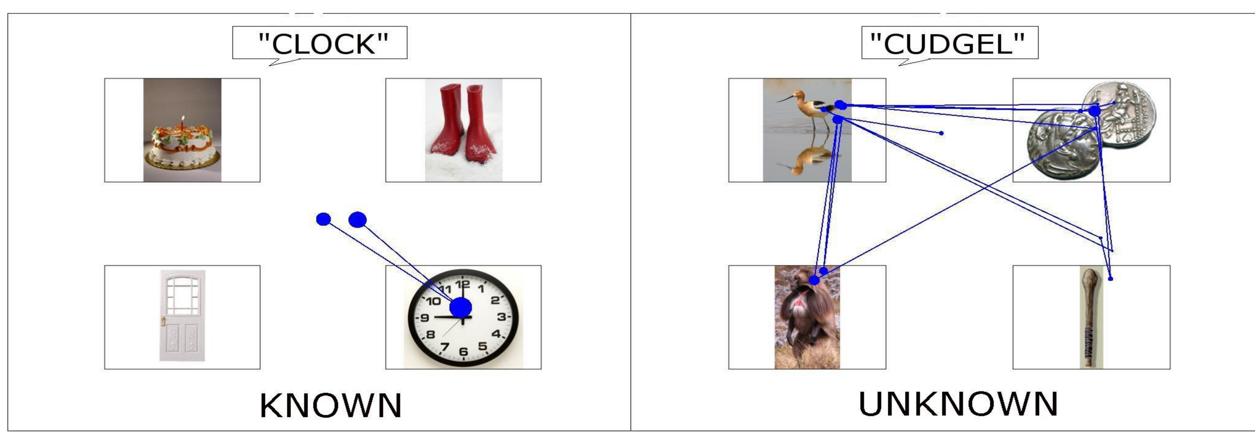
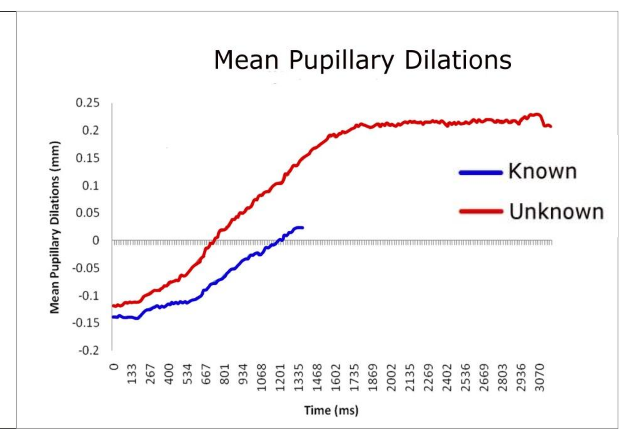
Introduction

Implicit measures of language processing hold huge potential for assessing vocabulary knowledge in populations unable to give overt behavioral responses, such as low-functioning individuals with autism. We have previously used three types of implicit measures as indexes of receptive vocabulary knowledge in normal adults (Ledoux et al., in preparation).

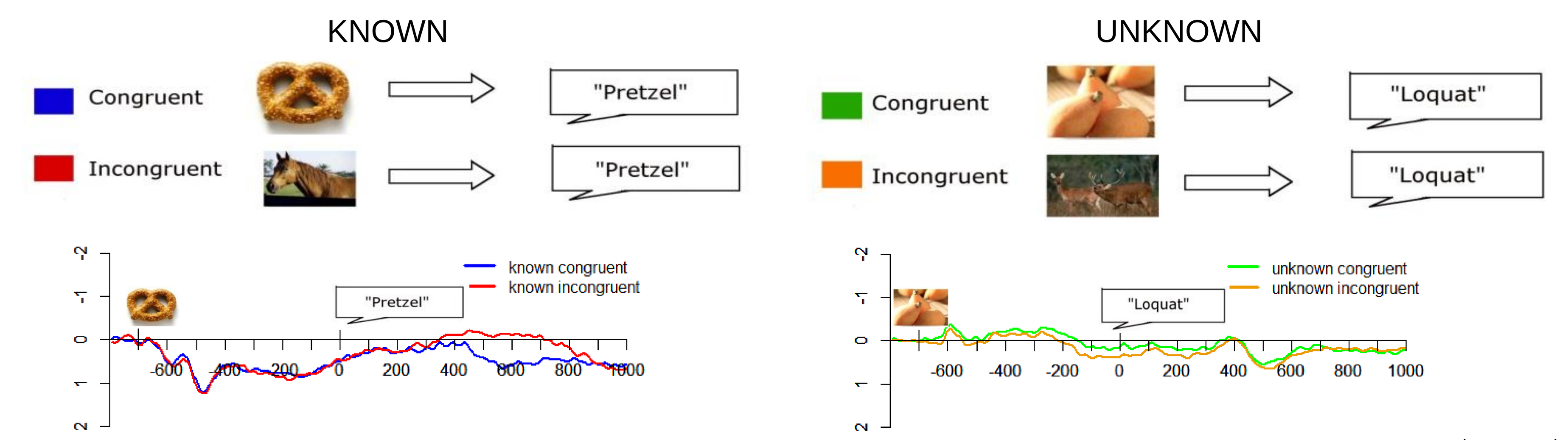
Eye movement monitoring (EM): Eye movements typically reflect current cognitive operations: participants look at objects in a display as they hear those objects named. Such EMs become faster and more precise as normally-developing children learn the meanings of spoken words (Swingley & Fernald, 2002). EMs to pictures of known words are faster and end-of-trial fixations are more accurate compared to unknown words (Ledoux et al., in preparation).



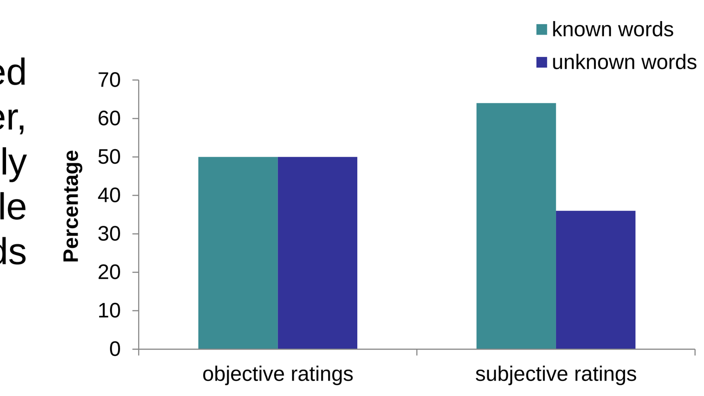


Pupillary dilation monitoring (PD): Time-locked changes in pupil diameter are associated with attentional engagement and information processing. Pupillary dilation increases with task difficulty and has thus been taken as a measure of resource recruitment (Beatty & Lucero-Wagoner, 2000). Pupillary dilation (taken from eye-tracking data) is greater for unknown than known words (Ledoux et al., in preparation)

Event-related potentials (ERPs): The N400 ERP component is associated with semantic processing: words or pictures that are semantically congruent with their proceeding context elicit a smaller N400 amplitude than incongruent words/pictures. This 'N400 congruency effect' (Connolly & D'Arcy, 1999) is elicited for known, but not unknown, words (Ledoux et al., in preparation).



Ledoux et al. demonstrated that these implicit measures distinguished between known and unknown words in normal adults. However, previous classification of known/unknown status was objectively determined by word frequency. Subjective knowledge ratings (on a scale from 0 (unknown) to 9 (known)) indicated that some 'unknown' words were actually known by participants.



Objectives

Aim 1: Model the relationship between subjective knowledge ratings and implicit knowledge measures
Aim 2: Use the model's predicted knowledge ratings to more accurately code data as 'known' or 'unknown'
Aim 3: Predict knowledge ratings in populations that do not give over subjective rating scores.

Methods

Participants
- 23 normal adults, right-handed native English speakers, 18-60 years of age

Equipment
- EM/PD: Applied Scientific Laboratories 504 Eye-Tracking System
- ERP: Electrical Geodesics Inc. GES 300 EEG System with 256-channel Hydrocel Geodesic Sensor Nets

Stimuli:
- 80 "known" high-frequency words (ex. *airplane, camera*)
- 80 "unknown" low-frequency words (ex. *agouti, cainito*)

Tasks:
- ERP paradigm: indicate whether the spoken word matched the picture
- ET session: select the picture matching the spoken word from 4 choices

Model Training (n=20)

Variable selection:
- Mixed logistic regression models were run for all possible combinations of variables and the model with the lowest AIC (774) was chosen.

Model diagnostics:
- A Hosmer-Lemeshow test was run on the model's observed and fitted values. The test indicated a significant lack of fit to the data (p = 0.02), so five high-influence data points (residuals +/-2) were removed from the original data and the model was re-fitted. The resulting Hosmer-Lemeshow test showed a non-significant lack of fit (p =0.07).

Variable	Included in model
N400effect	X
PDperchange	X
perFDTstim	X
AVGFixDurStimulus	X
FirstpassFixDur	
LatencytofirstFix	
LatencytofirstRefix	X
FirstDwell	X
percDwellStimulus	X

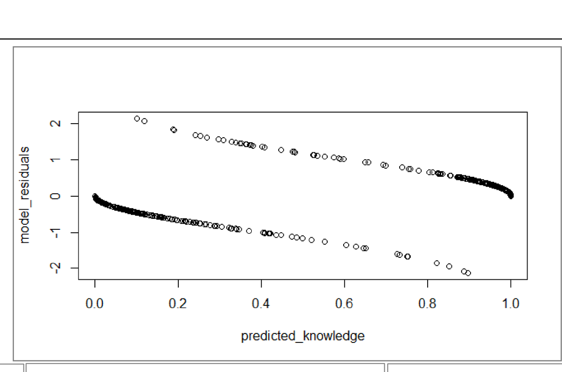
Fit of final model:
- To calculate the error rate, predicted values were re-classified as known or unknown (predicted probability < 0.5 = unknown; predicted probability > 0.5 = known).

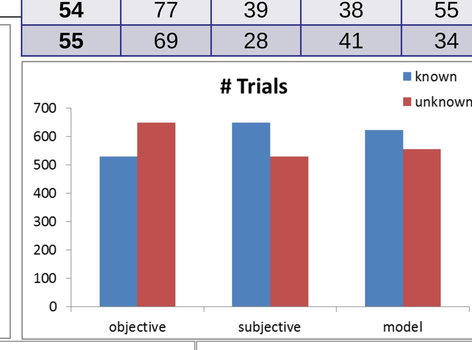
$$\text{model error rate} = \frac{\text{\# times predicted rating} \neq \text{observed rating}}{\text{total number of predictions}} * 100$$

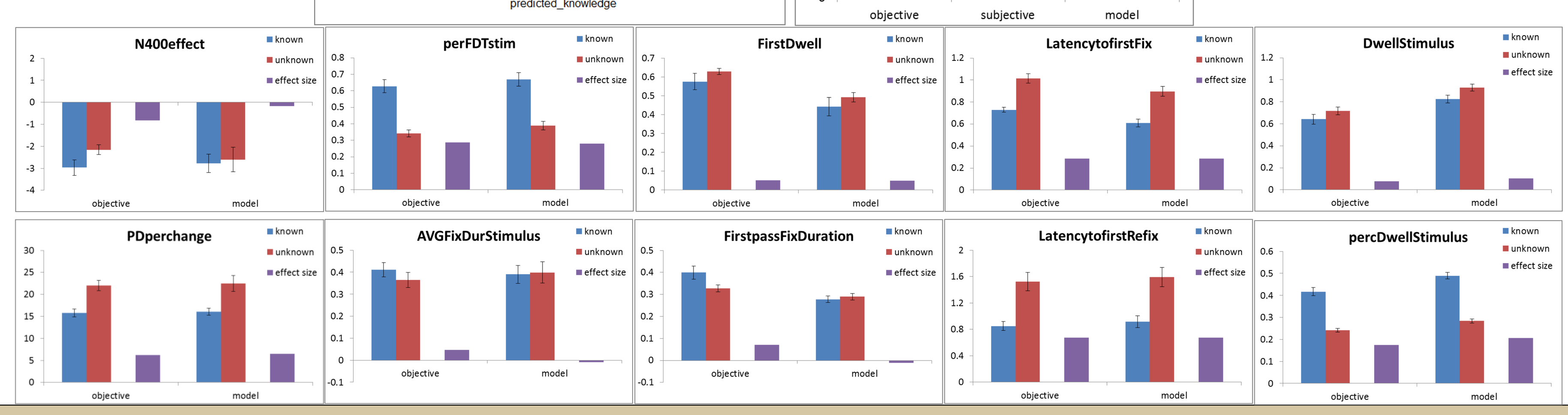
- The final model had an AIC of 738 and an error rate of 5%.

```
mixlog.2
Generalized linear mixed model fit by maximum likelihood ['glmerMod']
Family: binomial (logit)
Formula: factor(knowledge_dichot) ~ perFDTstim + PDperchange + N400effect + AVGFixDurStimulus + LatencytofirstRefix +
FirstDwell + percDwellStimulus + (1 | Subject) + (1 | word)

      AIC       BIC    logLik  deviance
 737.7373  788.4530 -358.8686  717.7373

Random effects:
 Groups  Name        Variance Std.Dev.
 word    (Intercept) 19.547   4.421
 Subject (Intercept)  2.524   1.589
Number of obs: 1178, groups: word, 159; Subject, 20

Fixed effects:
                    Estimate  Std.Error z value  Pr(>|z|)
(Intercept)          2.42234   0.85496   2.833  0.004607 **
perFDTstim           2.77773   1.34948   2.058  0.039555 *
PDperchange         -0.07089   0.02019  -3.511  0.000446 ***
N400effect          -0.01601   0.02402  -0.667  0.505008
AVGFixDurStimulus   -2.48005   1.03936  -2.386  0.017026 *
LatencytofirstRefix -0.76702   0.23339  -3.286  0.001015 **
FirstDwell          -0.86608   0.53296  -1.625  0.104153
percDwellStimulus    4.93136   1.98819   2.480  0.013126 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05
```

		Objective ratings		Subjective ratings		Model predictions		
subject	Total # trials	known # trials	unknown # trials	known # trials	unknown # trials	known # trials	unknown # trials	**Model Error Rate (%)**
5	62	34	28	36	26	35	27	5
6	86	29	57	41	45	36	50	6
7	99	46	53	47	52	48	51	1
8	61	25	36	33	28	32	29	2
9	122	61	61	79	43	79	43	11
13	37	19	18	22	15	21	16	3
16	62	26	36	32	30	30	32	10
18	31	5	26	12	19	8	23	19
19	44	24	20	25	19	25	19	0
21	103	59	44	69	34	64	39	9
22	18	8	10	8	10	8	10	0
28	33	9	24	19	14	16	17	9
39	28	7	21	16	12	16	12	7
40	49	24	25	31	18	31	18	4
43	40	20	20	22	18	22	18	5
44	45	28	17	28	17	29	16	2
45	53	13	40	17	36	16	37	6
50	64	25	39	26	38	25	39	2
54	77	39	38	55	22	50	27	14
55	69	28	41	34	35	33	36	4







Modeling Procedure

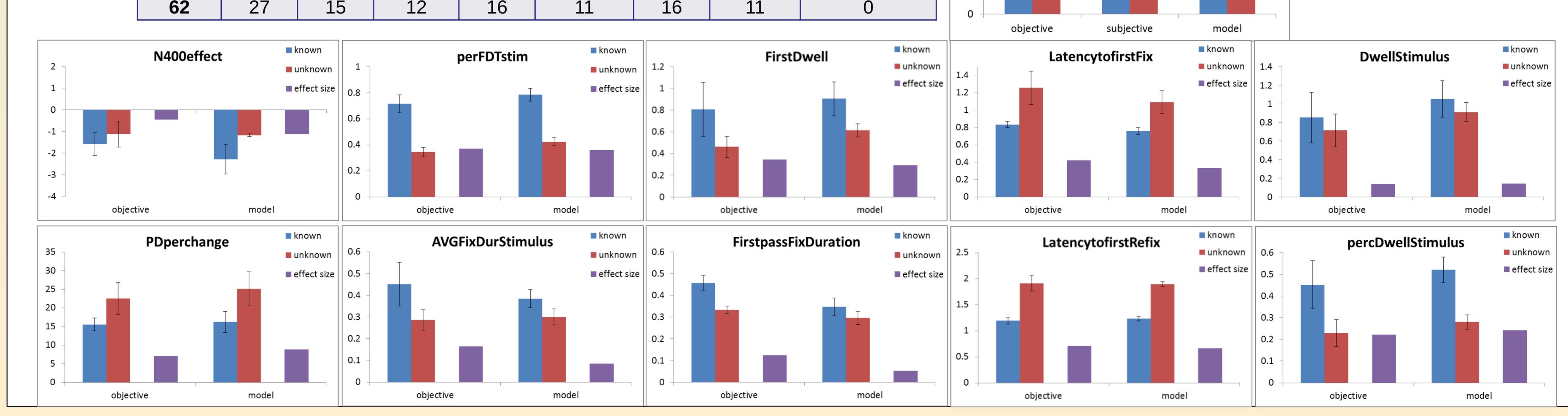
Modeling:
- Mixed logistic regression model fit in R using the lme4 package (Bates et al., 2013)
- ***Random effects:*** Subject, word
- ***Dependent variable***:
  - Subjective knowledge ratings: 0 = unknown, 1 = known
- ***Independent variables/fixed effects***:
  - *ERP measures*
    - N400effect: magnitude of the N400 effect (amplitude difference between incongruent and congruent conditions)
  - *PD measures*
    - PDperchange: Maximum percent change from baseline over the entire trial
  - *EM measures*
    - perFDTstim: percent fixation duration on the correct stimulus
    - AVGFixDurStimulus: average fixation duration on the correct stimulus
    - FirstpassFixDur: first pass fixation duration on the correct stimulus
    - Latencytofirstfix: latency to first fixation on the correct stimulus
    - LatencytofirstRefix: latency to first re-fixate on the correct stimulus
    - FirstDwell: cumulative time (all fixations and saccades) of first entry to correct area
    - percDwellStimulus: percentage of total time spent dwelling on the correct stimulus

Intercorrelation Matrix	PDperchange	N400effect	perFDTstim	AVGFixDurStim	FirstpassFixDur	LatencytofirstFix	LatencytofirstRefix	FirstDwell	DwellStim	percDwellStim
PDperchange	1									
N400effect	0.02	1								
perFDTstim	-0.13	-0.03	1							
AVGFixDurStimulus	-0.01	0.04	0.43	1						
FirstpassFixDur	-0.01	0.03	0.28	0.75	1					
Latencytofirstfix	0.13	0.05	-0.38	0.00	0.05	1				
LatencytofirstRefix	0.25	0.05	-0.40	0.32	0.27	0.43	1			
FirstDwell	-0.08	0.01	0.57	0.49	0.48	-0.07	-0.21	1		
DwellStimulus	-0.01	0.01	0.51	0.50	0.26	-0.23	0.03	0.69	1	
percDwellStimulus	-0.17	-0.03	0.81	0.46	0.29	-0.49	-0.44	0.72	0.70	1

Model Testing (n=3)

- To simulate Aim 3, the final model was used to predict knowledge ratings on 3 normal adults who were the last to be tested. These subjects were not included in the training phase, so their subjective ratings did not contribute to the model's predictions.

		Objective ratings		Subjective ratings		Model predictions		
subject	Total # trials	known # trials	unknown # trials	known # trials	unknown # trials	known # trials	unknown # trials	**Model Error Rate (%)**
57	31	13	18	15	16	17	14	13
58	101	54	47	75	26	70	31	13
62	27	15	12	16	11	16	11	0



Discussion

The model was able to successfully predict known and unknown word status using a combination of ERP, PD, and EM implicit variables.

The model produced more accurate knowledge predictions for known than for unknown words.

	Error rate	
	Known	Unknown
Train	4%	9%
Test	7%	18%

The modeling raised three important issues:
- Only trials which did not have any missing variables could be modeled, meaning that for some subjects with particularly messy data, there was a high amount of data lost.
- Subjective knowledge ratings were dichotomized from the original 10-point scale, so ratings of 'unfamiliarity' were not captured. The model's predicted probabilities can be broken into multiple categories to capture these intermediate ratings.
- The degree of generalizability to different groups, especially clinical populations, is unclear.

Our results suggest that these implicit techniques may be valid methods for assessing single-word comprehension, particularly in populations that are minimally verbal or nonverbal. We are currently working on testing this model in typically-developing children and both high- and low-functioning adults with autism.

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