# UNIVERSITY

# Introduction

Semantics: relationships between words and the signified knowledge.

Semantic representation in healthy adults:

- left-lateralized in frontal, temporal parietal, and prefrontal regions<sup>1</sup>
- Controlled semantic cognition (CSC)<sup>2</sup>: ATL, PFC, pMTG, IPS, pre-SMA, ACC/mPFC.
- Multiple-demand network<sup>3</sup>.

Semantic representation in individuals with aphasia (PWA): distributed network involved in access to or executive control of langu Category-specific representation: anatomically distinct account<sup>5</sup>; distributed account<sup>6</sup>; continuous account<sup>7</sup>.

Feature-specific representation: semantic typicality

- Faster and more accurate access to *typical* than *atypical* exemplars in healthy adults<sup>8</sup>; Inconsistent behavioral performance in PW
- Hierarchical theory of object processing: early visual regions and higher temporal regions in healthy adults<sup>10</sup>.
- Prediction in PWA: different neural representation of typicality than healthy adults.

Multi-voxel pattern analysis<sup>18</sup> (MVPA): machine learning algorithms (e.g., LSVM) extract information from brain activity patterns, a corresponding condition of interest in fMRI task.

- Searchlight-based MVPA<sup>11</sup>: reduce overfitting; no *a priori* region specification is needed
- Linear classifier:  $f(\mathbf{x}) = g(\mathbf{w}_1\mathbf{x}_1 + \mathbf{w}_2\mathbf{x}_2 \dots \mathbf{w}_v\mathbf{x}_v)$

# Objectives

1. Which brain regions show neural encoding of semantic typicality associated with behavioral performance in healthy adults?

- Hypothesis: faster and more accurate responses in typical than in atypical exemplars; above-the-chance (%50) classification accurac visual and temporal regions.
- 2. Which brain regions show neural encoding of semantic typicality associated with behavioral performance in PWA?
- Hypothesis: behavioral typicality effect would vary from healthy adults; different brain regions differentiating between typical and a exemplars. Above-the-chance (%50) classification accuracy in these brain regions.

# Methods

### **Subjects**

- 35 PWA due to left MCA infarct<sub>1</sub>, 14 excluded (N = 21, 7F, mean age =  $60.76 \pm 10.64$  y, mean months post onset =  $65.71 \pm 102.13$ ) lesion volume (SD) =  $104,647 \pm 69,682.17 \text{ mm}^3$
- 21 neurologically healthy adults, 3 excluded (N = 18, 8F, mean age =  $59.86 \pm 10.50$  y)

Standardized Language Assessments



### fMRI Task Stimuli and Procedure

*Picture stimuli:* 36 color photos (half typical and half atypical) of real items from each of five semantic categories: birds, vegetables, furniture, clothing, fruits; 36 scrambled pictures; split across two runs

- Balanced for: familiarity, length, lexical frequency, concreteness<sup>12</sup>
- Each subject viewed fruits + two other categories (counterbalanced across subjects)
- Semantic features: Core, prototypical, and distinctive; controlled for type of information conveyed, and whether defining or characteristic of the category



# Predicting Typicality Effect from Brain Activation Patterns in Healthy Adults and Individuals with Aphasia: a Multi-Voxel Pattern Analysis Ran Li<sup>a</sup>, Tyler Perrachione<sup>a</sup>, Jason Tourville<sup>a</sup>, and Swathi Kiran<sup>a</sup> <sup>a</sup>Sargent College of Health & Rehabilitation Sciences, Boston University

Methods						
fN	IBI Doto Acquisi	ition and Pr	processing			
• 3.0 T Siemens Trio Tim using 20-channel head + neck coil						
• $T1 \cdot TR = 2300 \text{ ms}$ TE = 2.91 ms 176 sagittal slice	<ul> <li>J.0 I Stemens 1110 Thirdshig 20-channel flead + fleck con</li> <li>T1: TR = 2300 ms, TE = 2.01 ms, 176 sogittal slices, 1 x 1 x 1 mm yoyals, 256 x 256 matrix, EOV = 256 mm, flip and slices slices is a slice of the slice of</li></ul>					
direction = AP	23, 1 A I A I IIIII V	OACIS, 250 A	200 matrix,	101 2501	inn, mp an	
• <i>T2*-weighted EPI:</i> TR = 2570ms, TE = 30ms, 40 a	axial slices, 3mm	slices interle	aved with 2 x	x 2 x 3 mm v	oxels, 80 x	
220 mm, 40 axial, flip angle = $90^{\circ}$						
	Data	Analysis				
<b>Percentage of spared tissue:</b> volume of the spared tiss	sue ROIs divided	by the total v	volume of the	e region from	AAL Atla	
<b>Behavioral analysis</b> : linear mixed-effects model (acc	irate RTs) and ger	peralized mix	ed_effects m	odel (accurac	$vv \cdot 1 = acc$	
• Fixed factors: typicality group category typicality	<i>i</i> -by-group: <i>randc</i>	m intercent.	subject		y, 1 – acc	
<i>Tixea jaciors</i> : typicanty, group, category, typicanty	oy group, ranao		subject			
	Preprocess	ing (SPM12	<sup>13</sup> )			
1) Slice timing						
<ol> <li>Spatial realignment with 4<sup>th</sup></li> <li>Corregistration</li> </ol>	degree B-spline					
4) Structural segmentation						
5) Spatial and functional norm	alization to the M	/NI space; h	igh-pass filte	er with a cuto	ff of 1/128	
6) *Spatial smoothing with 4n	nm Gaussian kern	el (for univa	riate analysi	S)		
•				•		
fMRI Univariate Analysis (SPM12)				Search	light MV	
1) 1 <sup>st</sup> -level GLM: typical, atypical, scrambled		The	Decoding T	Coolbox (TDT	<sup>14</sup> ); Radiu	
• Typical > Atypical Input: beta values from 1 <sup>st</sup> -level univ					vel univar	
• Atypical > Typical Onsets and durations convolved with the cononical	UDE	(un	smoothed)	M with loove		
and its temporal derivative		Out	<i>put:</i> individu	ual's accuracy	/ map (-5(	
2) $2^{nd}$ -level: one-sample <i>t</i> test ( $p < .001$ ); corrected	l for	Gro	<i>up-level:</i> sm	noothing with	6mm FW	
multiple comparison (FDR at $p < .05$ )		(p <	< .001), corre	ected for mult	tiple comp	
Results						
Behavioral (a) Res	ponse Accuracy					
Behavioral (a) Res	ponse Accuracy					
Behavioral         (a) Res           1.25         1.00	ponse Accuracy				Main e	
$\begin{array}{c} \textbf{Behavioral} \\ 1.25 \\ 1.00 \\ \hline \hline$	ponse Accuracy				Main e .34,	
Behavioral     (a) Res       1.25     1.00       1.00     1.00       Solution     1.00	ponse Accuracy			typ	Main e .34,	
Behavioral       (a) Res         1.25       1.00         1.00       1.00         (§) 0.75-       0.50-	sponse Accuracy	-		typ Atypical Typical	Main e .34,   Main e	
Behavioral       (a) Res         1.25       1.00         1.00       (b) 0.75         (b) 0.75       (c) 0.50	sponse Accuracy			typ Atypical Typical	Main e .34, $ $ Main e  z  = 2	
Behavioral       (a) Res         1.25       1.00         1.00       (b) 0.75         (c) 0.50       (c) 0.50         0.25       (c) 0.25	sponse Accuracy			typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res	sponse Accuracy			typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res	Sponse Accuracy	Patient		typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res	sponse Accuracy	Patient		typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res 1.25 1.00 0.05 0.05 0.05 0.05 0.05 Control (b) F	Sponse Accuracy	Patient		typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res 1.25 1.00 (b) F (b) F	sponse Accuracy Group Reaction Times	Patient		typ Atypical Typical	Main e .34,   Main e  z  = 2	
Behavioral (a) Res 1.25 1.00 (b) F 2000	Sponse Accuracy	Patient		typ Atypical Typical	Main e .34,   Main e  z  = 2	





- 1) Spearman's rank correlation between behavioral language performance (total RTs, accurate RTs, % PAPT, WAB-AQ) and classification accuracies in LMOG and R Calcarine in all PWA (N = 21), Anomic (N = 9), and Broca's (N = 9):
- Significant correlation between accurate RTs and classification accuracy in LMOG ( $\rho = .77, p < .05$ ) in Anomic PWA
- ROI classification in PRoNTo 2.1<sup>15</sup>, binary LSVM with leave-one-run-out cross validation 2) Linear mixed-effects model predicting ROI classification from behavioral measures: main effect of accurate mean RTs ( $\beta = .08$ , |t| = 2.77, SE = .03, p < .05) in the Anomic Group.

## Discussions

- 1. Which brain regions show neural encoding of semantic typicality associated with behavioral performance in healthy adults?
- Neural representation of typicality is built by the visual system at an intermediate processing stage<sup>16</sup>
- Hierarchical organization of category structure, whose influence on the organization of neural patterns becomes apparent as early as visual regions<sup>2</sup>
- LMOG: shape discrimination of objects<sup>17</sup>; R Calcarine: processing certain semantic categories<sup>18</sup>
- 2. Which brain regions show neural encoding of semantic typicality associated with behavioral performance in PWA? • Similar behavioral typicality effect as healthy adults, but different neural typicality.
- Maybe semantic typicality does not directly modulate the neural representation of typical and atypical stimuli in early visual processing due to a damaged semantic network post-stroke, or such effect is not perceived as early as in healthy adults<sup>10</sup>.
- LMOG is still associated with accurate processing of semantic typicality in less severe PWA, but comes at a cost with longer processing time suggesting not as automatic as in healthy adults.

Future studies: functional/structural connectivity between the visual cortex and semantic network in PWA.

# **Selected References**

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effect of typicality ( $\beta = -$ |z| = 2.46, SE = .14, p< .05) effect of group ( $\beta = -.98$ ,

= 9mm

o 50)

e analysis

t cross validation

M; one-sample *t* test

ons (FWE at p < .0

2.45, SE = .40, p < .05)

Main effect of typicality ( $\beta =$ 106.61, |z| = 3.66, SE = 29.11. *p* < .01)