

Many languages have inherently complex words that use different morphemes to express the same grammatical functions. For example, Spanish verbs belong to one of three inflectional classes (IC) that determine the form of the infinitive suffix: AR, ER, IR (pg. 3). However, it is unclear what role this added complexity plays in lexical processing. Using a visual lexical decision task (LDT), we test how statistical generalizations over phonological (Exp. 1) and semantic (Exp. 2) properties of stems, grouped by their inflectional class, are used during processing. We contrast two possible hypotheses: lexical facilitation and competition. If these generalizations reflect lexical facilitation, then the more “typical” an item is for its class, the more support the system has that the phonological/semantic representation exists in the mental lexicon. Alternatively, if these generalizations reflect lexical competition, then a “typical” item for its class incurs a higher cost in differentiating between similar alternative phonological/semantic representations [4 - 6].

Exp. 1: We model phonological generalizations by training the UCLA learner [7], an iterative learning algorithm that generates gradient phonological generalizations, on stems grouped by their IC. Each word is assigned an IC phonological violation score based on the weighted sum of violations from the algorithm. We test whether these violation scores affect processing using a visual LDT megastudy [8]. Real and nonce word data is analyzed separately. Logistic regressions were fit for accuracy and linear regressions for response time with main effects for: avg. bi-letter freq., length, lemma log freq., verbal violation score, # of phon. neighbors, avg. freq. of neighbors, and IC (ref: AR). Due to high collinearity, all variables but the IC:IC-violation interaction term were first run through a PCA.

Results: For the AR/IR classes, participants were more accurate/faster at rejecting ill-formed nonce words and less accurate/slower at accepting ill-formed real words. These results are consistent with lexical facilitation—it is easy to reject a phonologically atypical nonce word, but it is hard to accept an atypical real word. The ER class, with the exception of nonce word accuracy, showed effects consistent with competition.

Exp. 2: We use contextual word embeddings [12] as proxies for each verb’s semantic representation. Each verb is assigned an IC semantic violation score based on the cosine distance between that verb and the average semantic vector of all verbs in that class (fig. 1). Semantic coherence of each class was calculated by a 1000 iteration permutation test. To assess whether semantic generalizations of ICs affect processing, we tested the IC:IC-semantic violation interaction term on the residuals of the models from Exp. 1 (with an additional verbal semantic violation score as a control variable).

Results: The ER/IR classes were more semantically coherent than expected by chance (fig. 2). As the AR class represents 85% of all stems, lack of significance is expected. For all ICs, participants were less accurate at accepting ill-formed real words. For the IR class, participants were likewise slower at accepting atypical real words. These results are consistent with a lexical facilitation—it is hard to accept a semantically atypical real word.

Conclusion: The results are consistent with the lexical facilitation interpretation of IC-level statistical generalizations—the more typical an item is of its class, the more support the system has for its phonological/semantic representation. In contrast to past work on form-meaning typicality that finds typicality effects independent of an item’s actual value [13, 14], the results presented here show typicality tethered to class membership: the impact of typicality depends entirely on the specific IC a stem belongs to.

[1] Kelly 1992; [2] Farmer, Christiansen, Monaghan 2006; [3] Sharpe & Marantz 2017; [4] Luce & Pisoni 1998; [5] Vitevitch & Luce 2016; [6] Grainger & Jacobs 1996; [7] Hayes & Wilson 2008; [8] SPALEX: Aguasvivas et al. 2018; [9] Bergé 2018; [10] Montgomery 1978; [11] Montgomery 1979; [12] Grave et al. 2018; [13] De Zubicaray et al. 2024; [14] de Zubicaray 2025;

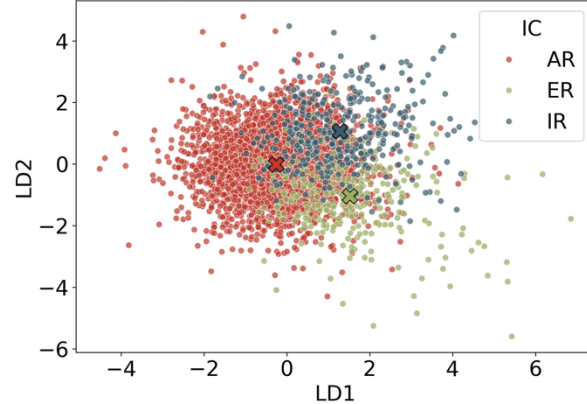
Table 1: Exp. 1 Phonological Violation Interactions

	Nonce				Real			
	Accuracy		Response Time		Accuracy		Response Time	
	Estimate	P-val	Estimate	P-val	Estimate	P-val	Estimate	P-val
AR	0.0112	<0.001	-0.0008	<0.001	-0.245	<0.001	0.0039	<0.05
ER	0.0029	<0.001	0.0003	<0.05	0.189	<0.001	-0.0259	<0.001
IR	0.0069	<0.001	-0.0001	0.20	-0.355	<0.001	0.0144	<0.001

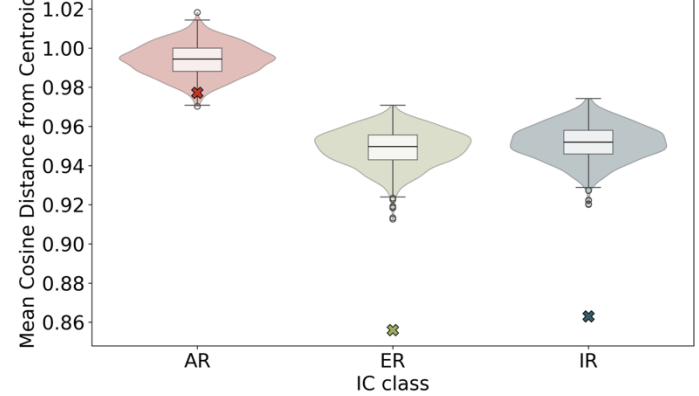
Nonce word responses reflect rejection of stimulus as a non-word of Spanish. Positive Accuracy estimate reflects higher accuracy at rejecting ill-formed nonce word. Positive RT reflects slower rejection of ill-formed nonce word.

Real word responses reflect acceptance of stimulus as a word of Spanish. Positive Accuracy estimate reflects higher accuracy at accepting ill-formed real word. Positive RT reflects slower acceptance of ill-formed real word.

As PCA components are not interpretable, only interaction terms are reported.

Figure 1: LDA of IC Semantics

Linear Discrimination Analysis (LDA) used to represent 300-dimensional semantics in 2D space. Each dot represents semantics of a verb, colored by the verb's inflectional class. As expected, class centroids are not identical while class cluster has overlap.

Figure 2: Semantic Coherence Permutations

Data represents distribution of mean cosine distances for each class composed of randomly selected verbs. "X" represents the observed average cosine distance for the class. An observed average that is lower than simulated distribution indicates that the class has significantly more semantic coherence than expected by chance. All cosine distances were computed over the 300-dimensional vector space [12].

Table 2: Exp. 2 Semantic Violation Interactions

	Real			
	Acc.		RT	
	Estimate	P-val	Estimate	P-val
AR	-0.0653	<0.0001	-0.0003	0.90
ER	-0.0814	<0.0001	0.0027	0.39
IR	-0.0853	<0.0001	0.0081	<0.01

Spanish

Spanish verbs never appear as bare stems and obligatorily take suffixes which represent the tense, mood, subject/number agreement of the verb. Verbal stems belong to one of three inflectional classes which determine the form of the suffix for any given conjugation. An example is given in the table below. As some forms are syncretic across classes (e.g. Imperfect tense for ER/IR classes), the infinitive is used as a proxy in this study for the 3-way underlying distinction that must minimally exist for these classes.

Tense/Aspect/Subject Agreement	AR Class	ER Class	IR Class
Example Stem	<i>bail</i> 'to dance'	<i>com</i> 'to eat'	<i>viv</i> 'to live'
Infinitive	bail-ar	com-er	viv-ir
Future — 2 nd person singular	bail-arás	com-erás	viv-irás
Imperfect — 2 nd person singular	bail-abas	com-ías	viv-ías
...			

Class belonging is not categorically predictable from a stem's phonological, syntactic, or semantic properties. For example, the following near minimal pairs exist:

sed-ar	ced-ar	ped-ir
[seð-ar]	[seð-er]	[peð-ir]
'to sedate'	'to cede'	'to ask'