Brain & Language 220 (2021) 104977

Contents lists available at ScienceDirect

Brain and Language

journal homepage: www.elsevier.com/locate/b&l

Multilayer networks: An untapped tool for understanding bilingual neurocognition

Holly A. Zaharchuk, Elisabeth A. Karuza *

Department of Psychology and The Center for Language Science, The Pennsylvania State University, University Park, PA 16802, USA

ARTICLE INFO

Keywords:
Bilingualism
Language acquisition
Cross-linguistic similarity
Network science

ABSTRACT

Cross-linguistic similarity is a term so broad and multi-faceted that it is not easily defined. The degree of overlap between languages is known to affect lexical competition during online processing and production, and its relevance for second language acquisition has also been established. Nevertheless, determining what makes two languages similar (or not) increases in complexity when multiple levels of the language hierarchy (e.g., phonology, syntax) are considered. How can we feasibly account for the patterns of convergence and divergence at each level of representation, as well as the interactions between them? The growing field of network science brings new methodologies to bear on this longstanding question. Below, we summarize current network science approaches to modeling language structure and discuss implications for understanding various linguistic processes. Critically, we stress the particular value of multilayer techniques, unique and powerful in their ability to simultaneously accommodate an array of node-to-node (or word-to-word) relationships.

1. Introduction

Cross-linguistic similarity has long been acknowledged as an important factor when learning and communicating in multiple languages. Accordingly, methods of quantifying the degree of cross-linguistic similarity abound. But what, precisely, are the crucial markers for determining the correspondence between languages? Behavioral and neurocognitive studies have largely focused on the overlap in particular (morpho)syntactic and phonological structures, or the proportion of cognates relative to non-cognates. Typological classifications (e.g., synthetic vs. analytic morphology) or language families (e.g., Romance) are another popular method of indexing similarity. Intriguingly, an emerging body of complex systems research has also begun to quantify cross-linguistic similarity through network science measures. Under this approach, shared structural signatures of complexity can be observed in grammatical, sound-based, and meaning-based connections between words or other linguistic units. This framework for measuring language similarity opens up exciting possibilities for neurocognitive bilingualism research. However, like more traditional methods of evaluating similarity, single-layer networks struggle to capture the multitude of ways in which words can be interconnected. Thus, our present aim is to stress the value of a *multilayer* framework[1]—capable of simultaneously capturing connections across multiple levels of the language hierarchy—when examining the effects of cross-linguistic similarity.

Consider the following language pairs, which illustrate both the challenges of operationalizing cross-linguistic similarity and the potential benefits of a multilayer approach. On some level, English and Mandarin Chinese could be considered highly dissimilar languages. A key topic of interest in both the second language acquisition (SLA; e.g., Slabakova, 2015) and neurocognitive (e.g., Li, Jin, & Tan, 2004) literature is the verbal system. To express tense and aspect, English primarily uses suffixation (e.g., *-ed*), while Mandarin relies on aspect markers or context cues, with consequences for the distinction between nouns and verbs (for a review, see Kemmerer, 2014). Moreover, Mandarin, unlike English, is a tonal language, meaning that pitch contours serve a lexically contrastive function. Neuroimaging studies comparing the processing of English and Chinese have also tended to focus on their distinct

* Corresponding author at: Department of Psychology and The Center for Language Science, The Pennsylvania State University, 117 Moore Building, University Park, PA 16802, USA.

E-mail addresses: hzaharchuk@psu.edu (H.A. Zaharchuk), ekaruza@psu.edu (E.A. Karuza).

[1] Note that use of the term multilayer in this context (i.e., as a method of representing multiple forms of association within a language system) is distinct from its use when describing artificial *neural* networks, though multilayer perceptrons certainly have a longstanding history in psycholinguistics (e.g., Plunkett & Marchman, 1991).

https://doi.org/10.1016/j.bandl.2021.104977
Received 5 February 2021; Received in revised form 21 May 2021; Accepted 26 May 2021
0093-934X/

writing systems (e.g., Kim, Liu, & Cao, 2017; Kim et al., 2016). However, these key differences are often highlighted at the expense of a number of features that are, in fact, shared between the languages. Overlap in commonly studied syntactic features such as basic word order and adjective placement may be overlooked, in addition to similarities in orthographic opacity and relatively limited use of inflectional morphology. In contrast, English and Spanish are typically considered more similar in light of their shared writing systems, overlapping consonant inventories, and lexicons, which contain a high proportion of cognates (see Schepens, Dijkstra, & Grootjen, 2012). However, Spanish has significantly higher orthographic transparency than English, relatively high flexibility in word order and morphological complexity, and differences in adjective placement and use of grammatical gender. Taken together, these language pairs demonstrate the need for a method of simultaneously accounting for (dis)similarity both within and across orthography, phonology, semantics, and (morpho)syntax.

Multilayer networks meet this need, as they are a workable, flexible, and data-driven tool, capable of capturing multiple levels of linguistic analysis. Before expanding on this point, we begin by reviewing existing applications of single-layer language networks in the cognitive sciences. We then discuss the particular strengths of multilayer networks relative to their single-layer counterparts. Subsequent sections stress the importance of cross-linguistic similarity for understanding issues of language use and representation in the bilingual lexicon and the promise of network science in expanding the toolbox available for bilingualism research.

2. Starting at the single layer: the powerful convergence of network and language science

Network science offers a data-driven, quantitative approach to representing and investigating complex information systems (Barabási & Albert, 1999). Of greatest relevance to the psycholinguist, these systems can be external linguistic inputs (i.e., the language environment, in the case of the naïve learner) or internal mental lexicons (i.e., the knowledge listeners and speakers draw on to comprehend and produce language). Thus, tools from network science enable researchers to examine emergent, relational patterns in language.

The process of transforming a system into a network (or graph) first depends on the definition of pairwise connections (links or edges) between individual components (nodes or vertices). Orthographic (e.g., Kello & Beltz, 2009) and phonological (e.g., Vitevitch, 2008) networks typically have links between words that can be transformed into one another through the addition, deletion, or substitution of one letter, character, or substring (*bear* – *beer*) or phoneme (/bɛɹ/ – /bɪɹ/), respectively. Approaches to building semantic networks can include edges determined by features (e.g., Hills, Maouene, Maouene, Sheya, & Smith, 2009a)—normed perceptual and conceptual attributes ("is an animal" as a feature for *bear*)—or meaning-based associations (e.g., Steyvers & Tenenbaum, 2005)—either related word pairs derived from psycholinguistic production experiments (*bear* – *claw*) or thesauri of semantic categories. Dependency networks (e.g., Ferrer i Cancho, Solé, & Köhler, 2004), built from syntactic associations, rely on grammatical formalisms to map the binary relations between individual words (in "the bears like honey," *bears* connects to *the* and *like*). Thought to capture a blend of semantic and syntactic relations (Beckage, Smith, & Hills, 2011; Borge-Holthoefer & Arenas, 2010), co-occurrence networks (e.g., Ferrer i Cancho & Solé, 2001) are constructed by analyzing the proximity between words in a corpus, such that adjacent or nearly-adjacent words share an edge. All of these network types provide quantitative measures that enable the precise description of lexicons and corpora, offering insight beyond more traditional descriptive measures (Siew, Wulff, Beckage, & Kenett, 2019; Vitevitch & Luce, 2016).

2.1. *Relevance for understanding linguistic processes*

The value of representing language structure via graph theory is highlighted when considering the influence of various network properties on human behavior (Karuza et al., 2016). These properties can range from the microscale, corresponding to local measures of individual nodes, to the macroscale, corresponding to global measures of entire graphs. Between these levels, mesoscale measures capture the interrelations between groups of nodes (or communities; Siew, 2013). Through this range of measures, word-, lexicon-, and syntax-level features can be studied and compared within the same analytical framework, while bearing in mind their implications for language learning and access.

At the microscale level, the number of edges incident to a target node (degree), corresponding to the established psycholinguistic concept of neighborhood density, has been shown to significantly impact production and comprehension. For example, high-degree words in networks built from semantic association norms are acquired earlier in development than low-degree words (Hills, Maouene, Maouene, Sheya, & Smith, 2009b). Similar results have been observed in phonological networks examining the link between vocabulary learning in children and node degree (Fourtassi, Bian, & Frank, 2020). High semantic neighborhood density also generally facilitates word recognition across a variety of psycholinguistic tasks and network types (Buchanan, Westbury, & Burgess, 2001; De Deyne, Navarro, & Storms, 2013; Mirman & Magnuson, 2008; Yates, Locker, & Simpson, 2003). In phonological networks, words in dense neighborhoods are generally more easily produced (Peramunage, Blumstein, Myers, Goldrick, & Baese-Berk, 2011; Vitevitch, 2002; Vitevitch & Sommers, 2003), recalled (Roodenrys, Hulme, Lethbridge, Hinton, & Nimmo, 2002), and learned by adults (Storkel, Armbrüster, & Hogan, 2006). However, they can be more slowly or less accurately recognized (Dufour & Frauenfelder, 2010; Vitevitch & Luce, 1999; Yao & Sharma, 2017; Ziegler & Muneaux, 2007; Ziegler, Muneaux, & Grainger, 2003) relative to those with fewer connections. They are also more easily misperceived as other high-degree phonological neighbors (Vitevitch, Chan, & Goldstein, 2014) and tend to form large communities, or modular groups of nodes, with other short, high-degree, frequent words (Siew, 2013). When examining bilingual speakers, increasing between- and within-language neighborhood density has been shown to impact both (1) production and recognition; and (2) L1 and L2 use (Marian, Blumenfeld, & Boukrina, 2008). The inhibitory effect of phonological, as well as orthographic and homophone, neighborhood density on recognition is also reflected in the event-related potential (ERP) responses of English (Holcomb, Grainger, & O'Rourke, 2002; Hunter, 2013; Laszlo & Federmeier, 2011; Taler & Phillips, 2007; Vergara-Martínez & Swaab, 2012), French (Dufour, Brunellière, & Frauenfelder, 2013), Spanish (Müller, Duñabeitia, & Carreiras, 2010), and Mandarin (Wang, Li, Ning, & Zhang, 2012) speakers.

Several other local measures influence linguistic behavior. For instance, the extent to which neighbors of a given node are interconnected (clustering coefficient) affects language processing differently than node degree. High phonological clustering increases the difficulty of word recognition (Chan & Vitevitch, 2009; Vitevitch, Chan, & Roodenrys, 2012; Yates, 2013) and production (Chan & Vitevitch, 2010), but decreases the difficulty of learning (Goldstein & Vitevitch, 2014) and immediate recall (Vitevitch et al., 2012). The distance separating a target node from another (shortest path or edge length) or between a target node and all others in a network (closeness centrality), are also important local indices. Distantly related words (Engelthaler & Hills, 2017) and centrally located words (De Deyne & Storms, 2008) tend to be acquired earlier in life than closely related or peripheral words in semantic networks. In adult language processing, path length interacts with degree during lexical retrieval, with high-degree words cueing closer phonological associates than low-degree words (Vitevitch, Goldstein, & Johnson, 2016). Closeness centrality also influences lexical retrieval from phonological networks by facilitating word recognition overall, while increasing difficulty for low frequency words (Goldstein & Vitevitch, 2017). Finally, building on dependency-based theories of syntactic complexity (e.g., Gibson, 2000), network-oriented approaches have indirectly linked dependency distance to demands on verbal working memory (Jiang & Liu, 2015; Liu, 2008a; Liu, Xu, & Liang, 2017; Wang & Liu, 2017).

In terms of macroscale properties, language networks share certain structural signatures with non-linguistic complex systems (Newman, 2003). Firstly, they exhibit small-world properties (Watts & Strogatz, 1998), with relatively short characteristic path length—when averaging across all pairs of nodes—and highly clustered neighborhoods. Secondly, they exhibit scale-free (size-invariant) properties (Strogatz, 2001). In scale-free networks, a subset of high-degree hub nodes are orbited by low-degree nodes, yielding a degree distribution that adheres to a power law. Pioneering research by Ferrer i Cancho and Solé (2001), Steyvers and Tenenbaum (2005) demonstrated that language networks exhibit the global topological properties that define complex networks, as opposed to random or regular networks. When applied to understanding linguistic processes, the complex network features of language have been said to reflect both how a speaker or listener accesses the mental lexicon and how the network grows or changes over time (De Deyne, Kenett, Anaki, Faust, & Navarro, 2017). Thus, this seminal work not only brought language *structure* under the conceptual and methodological purview of network science (Baronchelli, Ferrer i Cancho, Pastor-Satorras, Chater, & Christiansen, 2013), but also made testable predictions about language *cognition* that built on existing spreading-activation theories of language processing (e.g., Collins & Loftus, 1975).

2.2. From topology to typology

Undoubtedly, a significant proportion of complex network approaches in psycholinguistics has focused on English. However, computational linguists have also explored in-depth the network topology of Chinese (e.g., Li & Zhou, 2007; Li, Wei, Li, Niu, & Luo, 2005; Liu, 2008b, 2009; Liu, Zhao, & Li, 2009; Zhou, Hu, Zhang, & Guan, 2008). In addition, syntactic dependency networks have been constructed for Czech (Čech & Mačutek, 2009; Čech, Mačutek, & Žabokrtskỳ, 2011; Ferrer i Cancho et al., 2004), and Dutch (Čech et al., 2011; Ferrer i Cancho, Mehler, Pustylnikov, & Diaz-Guilera, 2007), among other Indo-European and Uralic languages. Generally, all of these networks exhibited small-world and scale-free properties at the global level, despite differences in the specifics of network construction. However, certain network metrics have been shown to vary with different typological characteristics.

Several cross-linguistic studies using network science methods have replicated typological classifications from linguistics. For example, in a series of dependency networks, Liu and Li (2010), Liu and Xu (2011), and Liu and Xu (2012) used average degree, path length, and clustering coefficient, as well as network centralization and diameter, to categorize a set of 15 languages, such that groupings reflected the extent and complexity of verb inflection. Average degree, path length, and clustering coefficient in particular also reproduced typologically similar subfamilies of genealogically diverse languages in several co-occurrence network studies (Al Rozz, Hamoodat, & Menezes, 2017; Liu & Cong, 2013; Škrlj & Pollak, 2019; Wachs-Lopes & Rodrigues, 2016). Further research with dependency networks has shown that the proportion of head-final versus head-initial dependency relations, in addition to particular subject-verb-object and noun-adjective order configurations, maps onto categorical syntactic typologies (Liu, 2010). Across construction methods, syntactic networks reflect the foundational characteristics of, and differences between, the world's languages. The success of these studies illustrates the potential for network science to deepen our understanding of cross-linguistic similarity by providing data-driven metrics at scale. However, this particular line of work, while clearly compelling, has generally focused on replicating established typological relations.

What is more, these advances in network-based typological classification have yet to cross over fully into the realm of psycholinguistics. Many of the global topological measures that have successfully distinguished language typologies—such as average degree, clustering coefficient, and path length—have only been *indirectly* linked to comprehension and production processes (though directly linked to first language acquisition; see Beckage et al., 2011). At the same time, many of the *direct* connections between language topology and behavior (e.g., those outlined in Section 2.1) tend to focus on node-level measures such as degree, clustering coefficient, and closeness centrality (for exceptions, see Lange, Miller, Weiss, & Karuza, 2019; Siew & Vitevitch, 2016). Investigations into how individual words are situated within a broader network should be considered alongside the potential effects of aggregate network-level properties (e.g., small-worldness) in language processing and production. Combining the full range of network properties with psycholinguistic measures—not only at the single-layer level but also across networks with multiple layers—would further illuminate how language structure influences language use and representation.

2.3. From single-layer to multilayer networks

Whether focused on the relationship between topology and behavior or topology and typological classification, current network science approaches to language have typically investigated phonology, semantics, or (morpho)syntax separately, at the single-layer level. While this body of work has yielded significant new insights, there is also value in considering methods more suited to grappling with the complex interplay between different levels of linguistic analysis (see, e.g., Araújo & Banisch, 2016). Consider the following: psycholinguistic research, mainly focusing on English, has shown that word recognition is facilitated by high semantic degree, but inhibited by high phonological degree, and vice-versa. Production data has shown the reverse pattern, with high phonological degree having a facilitatory effect. However, in Spanish (Sadat, Martin, Costa, & Alario, 2014; Vitevitch & Rodríguez, 2005; Vitevitch & Stamer, 2006), Russian (Arutiunian & Lopukhina, 2020), and Mandarin (Neergaard, Britton, & Huang, 2019; but see Yao & Sharma, 2017), increasing phonological neighborhood density can actually facilitate recognition and inhibit production. While Arbesman, Strogatz, and Vitevitch (2010) attributed this pattern in Spanish to a relatively rich morphological system that increases the semantic relatedness of phonologically similar forms, other studies with Spanish speakers have found effects in line with English (Baus, Costa, & Carreiras, 2008; Cervera-Crespo & González-Álvarez, 2019; Müller et al., 2010; Pérez, 2007). Moreover, morphological complexity does not explain the contradictory effects observed in Mandarin word recognition. Even studies with classic effects for phonological neighborhood density have found the opposite pattern for orthographic neighborhood density (Ziegler & Muneaux, 2007; Ziegler et al., 2003). As evidenced below, multilayer networks are not a panacea, but they do offer a potential means of simultaneously accounting for patterns that arise at levels ranging from phonological to the semantic (Fig. 1). Because of this feature, they allow for cross-linguistic comparisons that take into account holistic patterns across levels, as well as the inter-relatedness between levels.

3. Developments at the frontier: multilayer networks

Construed in a broad sense, multilayer networks allow for the separation of a complex system into inter-connected "slices" determine by node- or edge-level attributes (for reviews, see Aleta & Moreno, 2019; Hammoud & Kramer, 2020; Kivelä et al., 2014). Multiplex networks, a popular subset of the multilayer class, are defined by layers of at least partially overlapping nodes that are internally connected via unique intra-layer edge types. Multiplex networks are often represented as a series of monoplex graphs in which inter-layer edges connect nodes to

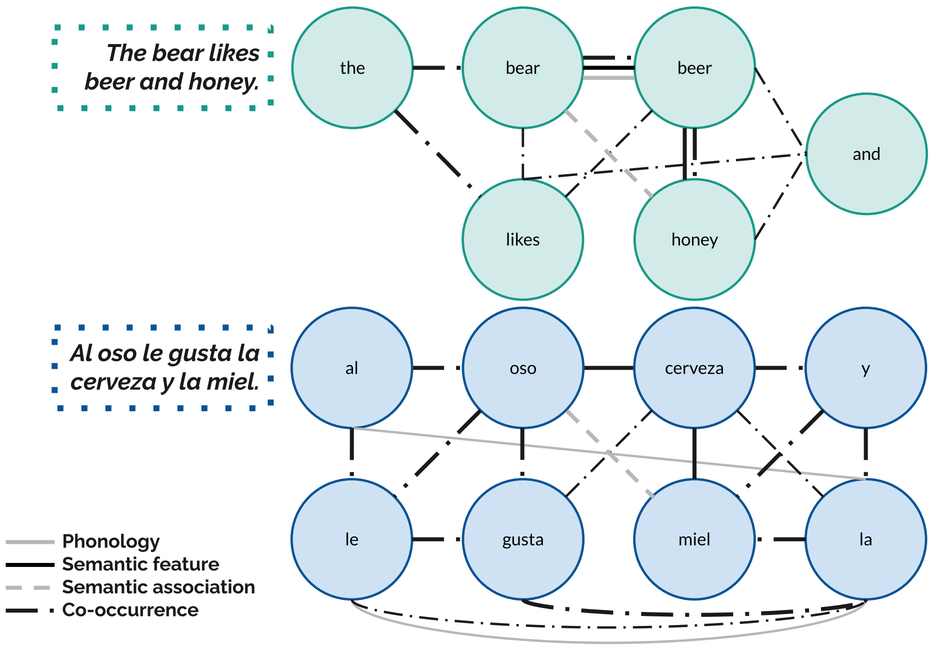

Fig. 1. A multilayer approach to cross-linguistic similarity. The two graphs above simultaneously reflect the phonological, semantic, and co-occurrence connections (edges) between words (nodes) in two parallel sentences: in English, *The bear likes beer and honey*, and in Spanish, *Al oso le gusta la cerveza y la miel* (beer [*la cerveza*] and [*y*] honey [*la miel*] are pleasing [*le gusta*] to the bear [*al oso*]; singular *gusta* used for liking something in general, even with multiple subjects, as here). The importance of considering the variety of ways in which words are related is highlighted by the *honey* node. If we relied exclusively on semantic features to construct the English graph, *honey* would only be sparsely connected; however, when other forms of word-to-word relationships are considered, it is clearly richly connected. Moreover, we can compare the *honey* node in the English graph to the *miel* node in the Spanish graph, where the co-occurrence structure is quite different. These examples correspond to single sentences, but this same approach can be applied to vast corpora. Once fully-fledged, language-specific graphs are constructed, their topologies can be characterized and compared.

themselves; however, they can also be represented as an aggregate multigraph containing edges that are color-coded according to the relationships they represent (Kivelä et al., 2014). Modern multilayer frameworks for representing complex systems are over a decade old (see De Domenico et al., 2013), and they are now a rather widespread technique for examining key questions in the social, behavioral, and neurosciences. One of the most well-known applications of the multilayer framework is functional connectivity analyses in the human brain (e.g., Bassett et al., 2011; Muldoon & Bassett, 2016). Under classic approaches to connectivity, nodes represent brain regions and edges represent synchronized neural activation between pairs of brain regions over time. Neural data is parsed into short temporal windows, each of which represents a unique network layer of functionally connected nodes. These layers are then joined via inter-layer edges connecting nodes to themselves in adjacent time windows. Therefore, while network nodes are maintained across layers, intra-layer edges correspond to functional relationships within specific intervals; inter-layer edges represent shared node identity. This example demonstrates but one application of the multilayer framework, in this case to the temporal domain. In fact, various flavors of this network type exist, including those in which layers are composed of different node sets or those in which inter-layer edges do not connect nodes to themselves. It is the immense flexibility of multilayer networks that makes them such a powerful tool (Fig. 2).

Of particular relevance to the present review, multiplex networks have just begun to emerge as a method of examining linguistic processes. Given the hierarchical nature of human language, wherein units (e.g., phonemes, morphemes) are combined to form increasingly complex

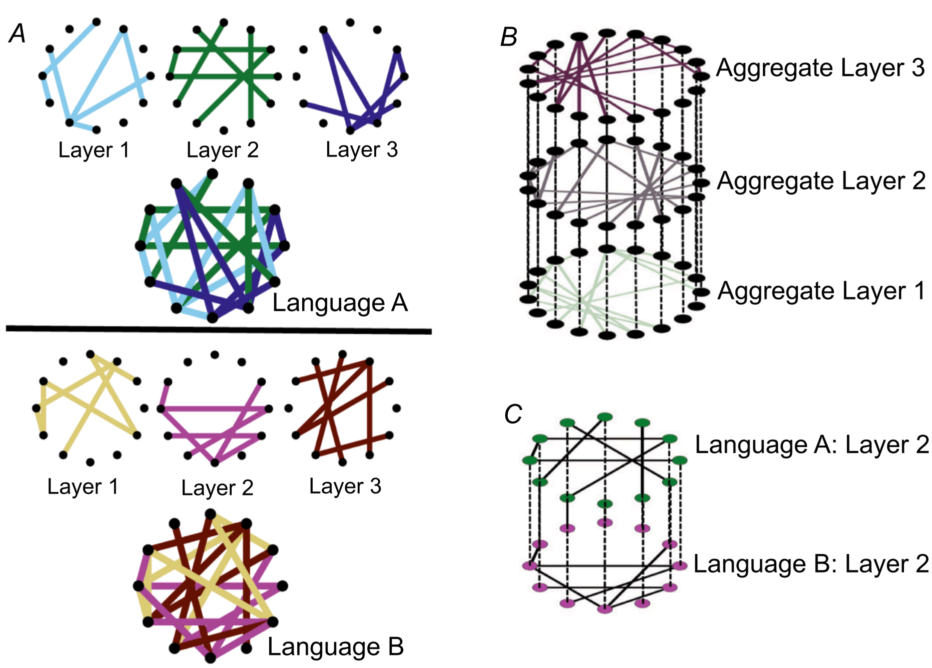

Fig. 2. The flexibility of the multilayer framework. *Panel A* represents one method of evaluating the similarity between two languages (A and B) by computing network diagnostics on their respective edge-colored graphs, a technique comparable to that found in Stella and colleagues (2017). In this example, words are repeated across layers in each language, while color-coded edges could represent a host of unique linguistic relationships (e.g., phonological similarity, shared neural context, semantic associations). *Panel B* displays an aggregate multiplex network in which words from both languages are combined and connected to themselves (via dashed edges) across layers. Intra-layer edges in this case represent possible linguistic relationships shared between words from both languages considered together. Note that this particular network could equivalently be displayed as a single edge-colored graph. *Panel C:* A node-colored multilayered network in which words from the two languages are separated into distinct layers, though the method of determining intra-layer edges is identical. In this toy example, intra-layer edges might represent phonological overlap, while dashed inter-layers could correspond to roughly synonymous relationships between words in both languages, as in Bujok, Fronczak, and Fronczak (2014).

structures, the multiplex approach offers a means of simultaneously modelling a vast array of possible interdependencies. Multiplex analyses have perhaps been most effectively applied to the study of language acquisition by Stella, Beckage, and Brede (2017), who sought to predict the time course of word learning through a multiplex model of the mental lexicon. To accomplish this task, they first selected a set of words from a database capturing the productive vocabulary of young toddlers. Next, they organized these words into four layers, connecting nodes within each layer based on free association norms, semantic features, phonological overlap, and word co-occurrence. When predicting order of acquisition, the resulting multiplex model significantly outperformed single-layer networks focused exclusively on one of the four edge types. Since that influential study, multiplex networks have been used to examine such topics as picture naming in individuals with aphasia (Castro & Stella, 2019), creativity (Stella & Kenett, 2019), concept degradation in ageing (Stella, 2020), and even priming effects (Stella, 2018). They have also been effectively applied to bridge phonological and orthographic systems; Siew and Vitevitch (2019) developed a multiplex "phonographic" network, observing a facilitative relationship between visual word recognition and degree and, likewise, between spoken word recognition and clustering coefficient. Castro and Siew (2020) have even proposed an innovative method of integrating multilayer approaches to studying linguistic phenomena with neuroimaging data, suggesting that shared neural context (e.g., similar activation patterns) might be taken into account when constructing network layers and edges. Despite these steps forward, multiplex models have been relatively untapped when it comes to the study of cross-linguistic similarity and its influence on bilingual cognition. The handful of studies that have successfully adopted a multilevel framework to characterize hierarchical language structure (e.g., Liu & Cong, 2014; Martinčić-Ipšić, Margan, & Meštrović, 2016) have not explicitly tied observed patterns to behavioral phenomena. We submit that the time is ripe for applying multilayer techniques to the study of bilingual language learning, comprehension, and production. In particular, we encourage the use of multilayer language networks to quantify the distance between languages across orthographic, phonological, semantic, and (morpho)syntactic domains. As we detail in the following section, developing holistic measures of cross-linguistic (dis)similarity is critical for understanding the neurocognitive correlates of language processing.

4. Effects of cross-linguistic similarity on language processing

A major goal of models of bilingual comprehension (e.g., Dijkstra & Van Heuven, 2002) and production (e.g., Green & Abutalebi, 2013) is to account for competition among neighboring words in two languages, whether through parallel activation of lexical candidates or language non-selective access to them. Language similarity, and competition effects that can arise as a result of cross-linguistic relations, also have important implications for understanding how multiple languages are acquired (MacWhinney, 2005). A well-documented outcome of the simultaneous activation of two languages is cross-language transfer. *Positive transfer* between similarly instantiated linguistic features facilitates processing, while different instantiations of similar features lead to *negative transfer* that interferes with processing. Neural signatures of first and second language processing reflect this tension between facilitation and interference. More specifically, *assimilation*, in which brain regions involved in L1 processing readily support L2 processing, contrasts with *accommodation*, in which L2 processing recruits additional neural resources compared to L1 processing (Perfetti & Liu, 2005). The patterns of linguistic transfer and neural adaptation reviewed below highlight the potential for interaction between levels of the language hierarchy during processing, which serves to support the advantages of multilayer networks for investigating questions of language use and representation.

4.1. Event-related potential (ERP) correlates of cross-linguistic similarity

ERP studies have investigated similar, dissimilar, and unique (morpho)syntactic constructions in bilingual sentence processing, with mixed results (for reviews, see Caffarra, Molinaro, Davidson, & Carreiras, 2015; Kotz, 2009; Tolentino & Tokowicz, 2011). Behaviorally, accuracy on grammaticality judgment tasks tends to be higher for similar and unique (morpho)syntactic features relative to analogous, but dissimilar, features (Dowens, Vergara, Barber, & Carreiras, 2010; Zawiszewski, Gutiérrez, Fernández, & Laka, 2011; see also Tolentino & Tokowicz, 2014). However, some studies find equivalent levels of performance across similar, dissimilar, and unique features in the L2 (Alemán Bañón, Fiorentino, & Gabriele, 2014; Díaz et al., 2016; Mickan & Lemhöfer, 2020), reflecting inter-language and -speaker variability in judgment accuracy across studies. Neurally, violations in similar constructions elicit similar ERP components, typically indexing syntactic reanalysis (P600), in highly proficient L2 speakers compared to monolinguals (Alemán Bañón et al., 2014; Díaz et al., 2016; Dowens et al., 2010; Foucart & Frenck-Mestre, 2011; Kotz, Holcomb, & Osterhout, 2008; Mickan & Lemhöfer, 2020; Zawiszewski et al., 2011). In this set of studies, violations in dissimilar structures either fail to elicit ERP effects (Foucart & Frenck-Mestre, 2011) or elicit distinct patterns (Mickan & Lemhöfer, 2020; Zawiszewski et al., 2011) in L2 speakers relative to native speakers. Findings for structures unique to the L2 are again mixed, with some studies finding similar ERP patterns (Alemán Bañón et al., 2014; Kotz et al., 2008) and others finding dissimilar effects (Díaz et al., 2016; Dowens et al., 2010; Zawiszewski et al., 2011) when comparing bilingual and monolingual groups.

Bearing in mind these partially-conflicting reports, we now dive into a key example that captures the range of outcomes reported above. In recent work from Mickan and Lemhöfer (2020), German-speaking learners of Dutch at beginner, intermediate, and advanced levels of proficiency read Dutch sentences that varied orthogonally in terms of (in)correct word order in Dutch and (dis)similarity to word order in German. The control group of native speakers, regardless of similarity, showed P600 effects for verb position violations compared to grammatical verb placement. Intermediate and advanced learners showed the same effects for sentences with identical word order in German, while beginners showed N400 effects instead, reflecting reliance on the L1 lexico-semantic system for L2 processing. When Dutch verb placement was in conflict with that of German, P600 effects were reduced and delayed in intermediate and advanced learners compared to native speakers, despite high behavioral performance, while ERP effects were absent in beginners. These results illustrate the interaction between (morpho)syntactic (dis)similarity and proficiency during language processing.

Online measures such as these provide evidence not only of positive and negative transfer effects, but also of assimilation for similar structures and accommodation for dissimilar structures. While these findings are compelling, they are, out of necessity, somewhat restricted in scope. To provide a clean test of neurocognitive response to related or unrelated structures, stimuli are designed with specific grammatical features in mind (e.g., word order, tense-marking). While this approach is clearly informative, it is also important to consider the many levels on which languages can resemble or conflict with one another. Indeed, investigations into cognates and interlingual homographs (i.e., false cognates) reveal that semantic and orthographic/phonological congruence facilitates processing, while conflict generally produces interference (e.g., Dijkstra, Miwa, Brummelhuis, Sappelli, & Baayen, 2010). Thus, the complex inter-relationships between languages, and their influence neurocognitive processes, are not limited to the realm of (morpho)syntax. As seen below, multiple competitive or facilitative forces can come into play during processing.

4.2. Functional magnetic resonance imaging (fMRI) correlates of cross-linguistic similarity

FMRI studies also illustrate the potential for interaction between levels of the language hierarchy. Investigations of bilinguals with different L1s (Mandarin or Korean) and the same L2 (English or Japanese; Jeong, Sugiura, Sassa, Yokoyama, et al., 2007) or trilinguals (Korean L1 with English and Japanese L2s; Jeong, Sugiura, Sassa, Haji, et al., 2007) have found evidence for negative transfer based on (morpho)syntactic dissimilarity. This negative transfer was reflected in increased activation during L2 processing depending on the L1-L2 pair (see also Kim et al., 2017, 2016; Yokoyama et al., 2013). At the same time, comparisons of L1 and L2 processing revealed significant overlap in the patterns of activation between (morpho)syntactically similar language pairs, suggesting both positive transfer and assimilation (see also Kim et al., 2017, 2016). Crucially, however, these results belie the potential roles of writing system and orthographic differences across these (morpho)syntactically (dis)similar language pairs. In particular, Korean and English are both alphabetic systems that differ in their orthographies, while Chinese is a logographic system (for both Mandarin and Cantonese), and Japanese combines logographic and syllabic systems (Perfetti & Liu, 2005). The (morpho)syntactic features examined by Jeong, Sugiura, Sassa, Yokoyama, et al. (2007) and Jeong, Sugiura, Sassa, Haji, et al. (2007) via auditory sentences covary with each of these languages' graphical representations. Specific investigations of orthography have demonstrated that similarity is associated with assimilation, while dissimilarity is associated with accommodation (Cao et al., 2017, 2019; Kim et al., 2017, 2016; Yokoyama et al., 2013; but see Ma et al., 2020). Overall, these results suggest that while (morpho) syntactic similarity leads to positive transfer and assimilation, orthography may also play a role in determining the patterns of neural activity associated with processing in an L2.

Relatedly, relative orthographic transparency, or the consistency of grapheme-to-morpheme mappings, between L1 and L2 also influences the neural signatures of bilingualism (Nelson, Liu, Fiez, & Perfetti, 2009). Comparisons of L2s with more opaque orthography to those with more transparent orthography, relative to an L1, have revealed increased left-lateralized activation in frontal areas, primarily during visual word processing (Cao et al., 2017, 2019; Liu & Cao, 2016). It has been suggested that this pattern of neural recruitment reflects the need to resolve the arbitrary relation between orthography and phonology through lexico-semantic mediation (see Liu & Cao, 2016). The processing of more transparent compared to more opaque L2s recruits additional areas involved in phonological processing in response to increased form-sound regularity (Cao et al., 2017; 2019;; Liu & Cao, 2016). Looking across these fMRI studies of (dis)similarity, we can see that defining language distance involves not only multiple linguistic levels—here, orthography and (morpho)syntax—but also multiple facets of each level (e.g., for orthography, writing system, and transparency).

4.3. Levels of structure: A complicating factor

From the fMRI and ERP findings discussed in this section, three points are clear: (1) cross-linguistic similarity influences the neural and cognitive resources involved in learning and processing a second language; (2) understandably, neurocognitive investigations of cross-linguistic similarity tend to focus on (dis)similarities between specific linguistic features; and (3) when expanding beyond specific features, cross-linguistic similarity is challenging to quantify, particularly when considering the hierarchical structure of language. We now return to the benefits of multilayer networks in addressing the obstacle presented in point (3). Importantly, enhancing measures of cross-similarity will make predictions about L2 learnability more precise, refine comparisons across different language pairs, and ultimately enable investigators to home in on mechanisms of transfer and adaptation in bilinguals. We expect that these methods will enable integrative investigations of the bilingual lexicon.

5. A multilayer approach to bilingual neurocognition

The power of multilayer networks lies in their ability to capture the relations within and between elements of a complex system. As described above, prevailing approaches to studying the influence of topology on linguistic processes tend to scrutinize patterns within single layers, typically phonological, semantic, or syntactic, but do not directly address connections throughout the language hierarchy. Perhaps because of this isolated approach, patterns of facilitation and interference seem to provide conflicting results. This trend holds, not only between different languages, but also within a single language, as we observed above with English and Spanish phonological networks (see discussion in Sadat et al., 2014). The ability to define, via multilayer techniques, specific metrics that characterize the complex interrelations between levels of the language hierarchy—simultaneously allowing for edges defined by orthography, phonology, semantics, (morpho)syntax, or even similar neural activation patterns—opens countless opportunities to clarify the impact of network structure on language cognition (Castro & Siew, 2020). Indeed, Vitevitch (2019) outlines the promise of uniting mind, brain, and behavior (including language processing) under the "lingua franca" of network science. While this work has, to date, largely focused on monolingual speakers, multiplex measures of cross-linguistic similarity would readily expand the current scope of research to bilinguals.

Existing models of bilingual language comprehension, production, and learning describe interactions between linguistic levels, but can fall short in formalizing these relations. The updated Bilingual Interactive Activation (BIA+) model, for instance, posits that input strings activate corresponding orthographic, phonological, and semantic representations during visual word recognition (Dijkstra & Van Heuven, 2002). Activation initially cascades through these codes sequentially, but "resonates" over time, such that both feedforward and feedback activation flows between levels (p. 183). This model clearly envisions a highly interconnected lexicon, both across multiple levels of representation and between languages themselves. In fact, cross-linguistic neighborhood density effects provided an empirical foundation for this model's development (e.g., Van Heuven, Dijkstra, & Grainger, 1998). However, the bi-directional relations between linguistic codes remain abstract; as a result, it is unclear exactly which aspects of one representation are expected to interact with which aspects of another. This is further complicated by cross-linguistic considerations: for example, the extent to which orthography-phonology relations differ for languages with alphabetic or logographic writing systems. Taking a multilayer approach would define these relations between levels of the language hierarchy. Lexical items in the phonological network layer could be connected directly to their representations in the orthographic layer, and so on, quantifying both single- and cross-layer effects. In addition, this approach could accommodate cross-language connections in the bilingual lexicon by linking relevant competitors at different levels of representation (Fig. 2).

More broadly, multilayer language networks can provide valuable quantitative measures of cross-linguistic similarity. Direct, holistic comparisons between languages will not only improve psycholinguistic investigations into the relation between network properties and behavior, as noted earlier in this section, but also increase the information available to SLA research. Such approaches could plausibly account for the effects of, say, the phonological and semantic properties of competing L1 and L2 lexical items during acquisition of inflectional morphology. This degree of control over related elements across linguistic space can inform predictions of word learning trajectories, as exemplified by Stella et al. (2017), as well as pedagogical practices in the classroom. Research on morphology acquisition in the field of applied SLA has previously demonstrated that the effectiveness of explicit instruction interacts with language similarity (Tolentino & Tokowicz, 2014). Moreover, it has been demonstrated that emphasizing the commonalities between L1 structures and L2 targets, particularly when they share meaning but differ in form, improves learning (McManus & Marsden, 2017). Similarly, patterns of neural assimilation and accommodation in L2 learning have been shown to vary with the mode of instruction (Cao et al., 2017; 2019). Recent network science approaches have also begun to model the effects of different vocabulary learning strategies (Jia et al., 2018; Li, Jiang, Shang, & Chen, 2019), as well as the properties of different stages of second language acquisition (Jiang, Yu, & Liu, 2019). Finally, brain-based network analyses of functional connectivity during L1 and L2 processing have been shown to capture individual differences in SLA success (Li & Grant, 2016). Multilayer methods could integrate and expand these lines of inquiry by identifying especially effective points of positive transfer, as well as particularly challenging points of negative transfer from L1 to L2. In turn, this knowledge could lead to the development of strategies for promoting or mitigating these transfer effects to enhance long-term learning outcomes.

5.1. Conclusions and additional considerations

While multilayer networks expand the scope of potential research in psycholinguistics, they are not without limitations. For one, sufficient data is needed to construct each layer of the network, including thorough documentation of a language's phonological structure, free association norms, and syntactic treebanks or other tagged databases. Unfortunately, languages for which these data are currently unavailable (a significant proportion of the world's languages) are not yet able to benefit fully from network approaches. Even co-occurrence networks, while freer from these specific constraints, often require large and representative texts.[2] This paucity of resources is perhaps the single greatest limitation in applying multilayer analysis techniques, and network science techniques more broadly, to the study of cross-linguistic similarity and its relevance for bilingual cognition. Simply put, it severely restricts the scope of languages that can be investigated, and at what depth.

From an analysis perspective, multilayer networks call for a number of additional considerations, one of which is the potential for differences in the strength of the contribution of each network layer. In other words, some layers, or types of node-to-node relationships, might have greater explanatory power than others. Stella et al. (2017), for example, observed only a negligible contribution of the phonological layer in their multiplex lexical network, a potential pitfall that was handled via a layer optimization procedure. Their weighted-layer approach represents one effective solution; other filtering and weighting procedures, whether at the layer- or edge-level, generally offer a buffer against this challenge. A related issue is the time-course of access to information both within and across layers, particularly when investigating the influence of multilayer topology on real-time processing and production. It is well-established in psycholinguistics that access to linguistic information is not necessarily instantaneously and simultaneously available. For example, during spoken word recognition, though competitors are activated, the unfolding of phonetic information systematically narrows the set of possible word candidates (Allopenna, Magnuson, & Tanenhaus, 1998). In light of this, multilayer networks that take into account this aspect are likely to be particularly useful. Finally, it is important to note that extraction of standard single-layer network metrics (clustering coefficient, path length, etc.) from multilayer networks is a topic of some debate, although several promising solutions have been proposed (Kivelä et al., 2014).

Despite these challenges, we strongly advocate for increased incorporation of cutting-edge network science approaches to bilingual neurocognition. Multilayer networks offer not only quantitative measures of cross-linguistic similarity, but also tools that are well-suited to capturing both the structure and neural underpinnings of the bilingual lexicon. Especially considering the complexity of this topic, its study calls for the blurring of disciplinary boundaries and consideration of powerful methods made possible through developments in network science.

[2] Whether or not use of parallel, or at least closely matched, texts would increase insights gained from this approach remains an open question.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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