Grammatical cues are largely, but not completely, redundant with word meanings in natural language

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Abstract

The combinatorial power of language has historically been argued to be enabled by syntax: rules that allow words to combine hierarchically to convey complex meanings. But how important are these rules in practice? We performed a broad-coverage cross-linguistic investigation of the importance of grammatical cues for interpretation. First, English and Russian speakers (n=484) were presented with subjects, verbs, and objects (in random order and with morphological markings removed) extracted from naturally occurring sentences, and were asked to identify which noun is the agent of the action. Accuracy was high in both languages (~89% in English, ~87% in Russian), suggesting that word meanings strongly constrain who is doing what to whom. Next, we trained a neural network machine classifier on a similar task: predicting which nominal in a subject-verb-object triad is the subject. Across 30 languages from eight language families, performance was consistently high: a median accuracy of 87%, comparable to the accuracy observed in the human experiments. These results have ramifications for any theory of why languages look the way that they do, and seemingly pose a challenge for efficiency-based theories: why have grammatical cues for argument role if they only have utility in 10-15% of sentences? We suggest that although grammatical cues are not usually necessary, they are useful in the rare cases when the intended meaning cannot be inferred from the words alone, including descriptions of human interactions, where roles are often reversible (e.g., Ray helped Lu/Lu helped Ray), and expressing non-canonical meanings (e.g., the man bit the dog). Importantly, for such cues to be useful, they have to be reliable, which means being ubiquitously used, including when they are not needed.

1. Introduction

A signature of human languages is their ability to express a multitude of complex, propositional meanings. Traditionally, this ability has been ascribed to syntax—a set of constraints on how words can combine to create phrase- and clause-level meanings. For example, most languages differentiate grammatical roles such as subjects and objects, either through word order or through case marking and/or agreement. These rules allow different meanings to be conveyed and represented using the same set of lexical items. In English, one can use word order to differentiate “The dog bit the cat” from “The cat bit the dog.” And in Russian, one can use case marking to differentiate “Dog-Nominative bit cat-Accusative” from “Dog-Accusative bit cat-Nominative”.

Researchers have long speculated about the importance of cues like word order and morphological markings for conveying linguistic information (Dryer, 2002, 2002; Fenk-Oczlon & Fenk, 2008; Greenberg, 1963; Kiparsky, 1997; Koplenig et al., 2017; Levshina, 2020, 2021; Sinnemäki, 2008). But critical to theories of language are actual patterns of language use. How important are grammatical, or morpho-syntactic, cues to inferring complex meanings in practice? At least in some cases, formal grammatical cues are not necessary because lexical semantics (word meanings)
strongly constrain interpretation. For example, in a sentence like “The dog chewed the bone”, it is readily inferable that “dog” is the agent and “bone” is the patient from the meanings of the words. In a hypothetical language in which word meanings always provide strong cues to interpretation, one could imagine having no constraints on word order and no case marking: “dog chew bone,” “dog bone chew,” “bone dog chew,” “bone chew dog,” “chew dog bone,” and “chew bone dog” would all refer to an event of a dog chewing a bone, because alternative meanings are implausible. It is an empirical question how much human languages resemble this hypothetical language where word meanings always provide cues to interpretation, and thus where formal cues are redundant for unambiguously expressing complex meanings. To address this question, we here perform a cross-linguistic assessment of the importance of grammatical cues for inferring complex meanings, with a focus on transitive clauses.

Simple transitive clauses, consisting of a subject (S), a verb (V), and an object (O), have been extensively studied across different sub-fields of language research, from linguistic theory (e.g., Comrie, 1989; Dryer, 1991; Du Bois, 1987; Du Bois et al., 2003) to psycholinguistics (Bates & MacWhinney, 1989; Gibson, Piantadosi, et al., 2013; Goldin-Meadow et al., 2008; Hall et al., 2014; Kim & Osterhout, 2005; Kuperberg et al., 2007; Schouwstra & de Swart, 2014; Sinclair & Bronckart, 1972), to neurolinguistics (e.g., Bates et al., 1987; Berndt et al., 1996; Bornkessel et al., 2002; Caramazza & Zurif, 1976; Keller et al., 2001; Schwartz et al., 1980; Stromswold et al., 1996), to computational linguistics (e.g., Palmer et al., 2013; Papadimitriou et al., 2021), and are commonly brought up in discussions of the importance of formal grammatical marking (e.g., how else would you differentiate between “The dog bit the cat” and “The cat bit the dog”?).

We draw on human data and data from a computational language model to evaluate how often the correct meaning of naturalistic sentences can be inferred from just the sentence’s key words in the absence of other information, thus estimating the redundancy of formal grammatical cues in a constrained domain. Despite the centrality of redundancy as a concept in any information-theoretic account of human language, redundancy has been studied previously mostly only at the level of orthographic characters (Cover & King, 1978; Shannon, 1951), sounds (Marslen-Wilson & Tyler, 1980), and words (Bentz et al., 2017). There has been less work on the kind of “grammatical redundancy” (Wit & Gillette, 1999) that we study here (but see Levshina, 2021), by estimating the redundancy of formal marking.

What is at stake, theoretically? If natural languages are indeed like the hypothetical language introduced above—where word meanings always strongly constrain interpretation—then the existence of formal cues like word order and case marking/agreement conventions in most languages (cf. Ergin et al., 2018; Gil, 2013; Jackendoff & Wittenberg, 2017) would present a puzzle: there would be no obvious justification for the effort required to learn and deploy word order and case marking/agreement rules.
To foreshadow our results, we found that for a large majority of sentences across typologically diverse languages, humans and a computational language model can correctly infer the propositional meaning of a sentence without word order information. However, doing so is not possible for ~10-15% of sentences. We speculate that these relatively rare, but potentially important, instances may motivate formal grammatical systems across languages. In order to serve as reliable cues in the rare instances where they are critically needed, formal grammatical markings have to be used consistently, including in cases when they are redundant. Nevertheless, the fact that most of the time, word meanings constrain interpretation likely explains why some languages appear to lack formal grammatical markings (e.g., Ergin et al., 2018; Gil, 2013; Jackendoff & Wittenberg, 2017).

2. General approach

Our goal is to quantitatively estimate the redundancy of formal cues in transitive clauses, focusing on clauses with two nominals. We presented human participants and a computational language model with triads consisting of a verb, a subject, and an object extracted from naturalistic sentences, and asked them to guess which of the two nouns is the agent. For the human experiments, we tested native speakers of a language that relies primarily on word order cues (English) and a language that relies primarily on case marking and agreement cues (Russian). The two nominals were presented in their base, lemma forms stripped of case information. For the experiments on the computational language model, we tested a diverse sample of 30 languages spanning eight language families. Because of limitations of our corpus, we used wordforms as they appeared in the corpus, not lemmas. As a result, the experiments on the language model focused on evaluating the redundancy of word order information.

If formal marking is not at all redundant with information carried by the word meanings (as in the made-up example of “dog cat bite” above), then we would predict performance on this task to be around 50% (chance level). That is, word order and case marking would always be necessary to extract the correct propositional meaning (i.e., to determine who is doing what to whom). If, on the other hand, formal marking is redundant (as in the made-up example of “dog bone chew” above), then we would expect performance to be near 100%. In this latter case, the existence of word order constraints and case marking would be a mystery from an efficiency-based perspective and a language design perspective. A third possibility is that performance would vary dramatically across languages, suggesting that some languages rely heavily on formal cues for encoding propositional meaning while other languages do not.

It is worth noting that our performance estimates are conservative in the sense that participants (humans or a computational model) have access to less information than is generally available during language comprehension. Participants only see the triad of subject, verb, and object, and not any other arguments of the verb, modifiers of the nominals, or any other parts of the sentence, or the preceding context. Moreover, across many languages (including English and Russian), we
would expect transitive sentences with a pronoun subject or object (which we exclude from our study, but which make up the vast majority of transitive sentences cross-linguistically; Ariel, 1991; Du Bois, 1987; Du Bois et al., 2003) to be nearly perfectly classifiable on this task. Because these other sources of information can disambiguate the argument structure, the accuracies that we report are best interpreted as approximate lower bounds on accuracy, given only the information directly present in the lexical semantics of the verb, its subject, and its object.

3. Human experiments

We conducted five experiments (Experiments 1a-d in English, and Experiment 2 in Russian) where naturalistic examples of transitive verbs with subjects and objects were presented in a scrambled order and with morphological markers removed. If human participants can guess which noun is the agent, that would indicate that the subject-object distinction can be recovered based on the meanings of the nouns and the verb alone, leaving formal marking redundant.

We extracted clauses containing transitive verbs from parsed corpora and reduced each such clause to a subject-verb-object (SVO) triad: the head noun of the subject noun phrase, the head noun of the object noun phrase, and the head lexical verb, each converted to a suitable form to remove morphological marking such as case and agreement which could be used to recover which noun is the agent. Therefore, when an SVO triad was presented in a shuffled order, it contained neither word order nor morphological cues to propositional meaning.

Experiments 1a-d: English

Methods

Participants

Across four experiments, we recruited 395 participants on Amazon Mechanical Turk: 100 in Experiment 1a with 21 excluded for not being native speakers or performing below chance (in Experiments 1b-d, we used catch trials to detect guessing, as detailed below, and excluded participants who answered fewer than 75% of catch trials correctly); 100 in Experiment 1b with 19 excluded; 100 in Experiment 1c with 16 excluded; and 95 in Experiment 1d with 10 excluded. The exclusions left 329 participants for analysis (79 in Experiment 1a, 81 in Experiment 1b, 84 in Experiment 1c, and 85 in Experiment 1d), comprising 309 unique participants (some appeared in multiple experiments; their inclusion does not qualitatively affect the results). The experiment took approximately 20 minutes to complete, and participants were compensated $3.00 for their time.

Experimental materials
A similar set of materials was used across the four experiments; Experiments 1b-d were performed to ensure the robustness and replicability of the results obtained in Experiment 1a, in line with increasing emphasis on replicability in cognitive science and psychology (e.g., Button et al., 2013; Gelman & Carlin, 2014; Gelman & Loken, 2013; Ioannidis et al., 2014; Simmons et al., 2011). 4,286 SVO triads were extracted from the English Web treebank from Universal Dependencies 2.5 (Nivre et al., 2016), a structured linguistic data set that provides syntactic dependency information for sentences across a range of languages. The treebank makes it possible to extract verbs, with their subjects and objects. A triad was identified as any verb (with universal part-of-speech tag VERB) with exactly one dependent of type ‘subject’ (nsubj) and exactly one dependent of type ‘object’ (obj). Triads where the subject, the object, or both were pronouns (n=3,655) were excluded because pronouns contain case marking information. Of the triads with either OSV or SOV word order, 7 were mis-parsed (e.g., contained a verb in the object position), and were consequently flipped (e.g., “remedies the trustee is seeking” → “the trustee is seeking remedies”) to constitute an SVO triad using information from the rest of the sentence.

This initial filtering left 631 triads (14.7% of the original set; transitive sentences with two full nominal arguments are generally rare cross-linguistically; Ariel, 1991; Du Bois, 1987; Du Bois et al., 2003). Further, 42 triads were excluded for various reasons (e.g., offensive content or repeats), leaving 589 triads, and 278 of these were slightly edited (e.g., changed verb tense to past simple to get rid of the agreement cues). For Experiment 1a, the 589 triads were distributed across 5 experimental lists (118 triads in Lists 1-4 and 117 triads in List 5) for presentation. (For this and all other experiments, the materials, including the original, excluded, and edited triads, are available at OSF: https://osf.io/kbtga/.) For Experiment 1b, we additionally excluded 20 and edited 330 triads, and distributed the remaining 569 triads across 5 experimental lists (114 triads in Lists 1-4 and 113 triads in List 5). For Experiment 1c, we additionally excluded 50 triads, and distributed the remaining 519 triads across 5 experimental lists (104 triads for Lists 1-4, and 103 triads for List 5). Finally, for Experiment 1d, we randomly sampled 500 triads from the set of 519, and distributed them across 5 experimental lists (100 each).

In Experiments 1b-d, 20 triads with clear thematic roles (animate agents, inanimate patients, and a prototypical agent-patient relationship with respect to the verb: e.g., pharmacist prescribed medicine) were included in each list as ‘catch trials’ to ensure that participants engage with the task. Catch trials were randomly interspersed with the critical triads and were excluded from the critical analyses. Participants who did not identify the agent correctly in 15 or more of the catch trials were excluded.

Procedure

On each trial, participants saw a verb that was followed by two nouns (whether the subject or the object appeared first on each trial was random) and were asked to choose one noun, which they
think is the agent, or do-er, of the action described by the verb. At the beginning of the task, participants were provided with an example trial that was not a part of the experimental stimulus set (*chewed bone dog*) and told that the correct answer is *dog* because dogs chew bones. All trials were presented on one web page (the order was randomized for each participant) with the brief instructions (i.e., *Click on the do-er of the action*) appearing above each triad as a reminder. Prior to the critical task, participants were asked to indicate their native language and told that the payment is not contingent on their answer.

In Experiments 1b–d, the instructions were edited to include a description of what nouns and verbs are (i.e., nouns - words that denote people, things, phenomena, and verbs - words that denote actions), and participants were asked to guess who is doing the action described by the verb (because based on informal feedback and the presence of some participants with below-chance performance in Experiment 1a, the term “agent/do-er” appeared to be confusing for some participants).

**Results**

**Overall performance**

The results were similar across the four human experiments (Figure 1, top panel). In *Experiment 1a*, the mean percent correct, across participants, was 88.9 [95% CI on participant means 87.8%, 89.9%]. The item with the maximum accuracy had correct answers 100% of the time, the item with the lowest accuracy was correct 0% of the time, and the median item accuracy was 100%. 80.5% of items had over 80% accuracy, and 71.1% had over 90% accuracy.

The results were similar in Experiments 1b, 1c, and 1d. In *Experiment 1b*, one item was excluded from the analysis because the participants reported a display error. The mean percent correct, across participants, was 88% [95% CI on participant means 86.8%, 89.2%]. The item with the maximum accuracy had correct answers 100% of the time, the item with the lowest accuracy was correct 0% of the time, and the median item accuracy was 100%. 79.1% of items had over 80% accuracy, and 71.2% had over 90% accuracy. In *Experiment 1c*, the mean percent correct, across participants, was 89.7 [95% CI on participant means 88.8%, 90.6%]. The item with the maximum accuracy had correct answers 100% of the time, the item with the lowest accuracy was correct 5.9% of the time, and the median item accuracy was 100%. 82.5% of items had over 80% accuracy, and 71% had over 90% accuracy. Finally, in *Experiment 1d*, the mean percent correct, across participants, was 89.6% [95% CI on participant means 87.7%, 91.6%]. The item with the maximum accuracy had correct answers 100% of the time, the item with the lowest accuracy was correct 5.6% of the time, and the median item accuracy was 94.7%. 84.6% of items had over 80% accuracy, and 68% had over 90% accuracy. Across experiments, only for 5% of the items was
accuracy lower than 50%, suggesting that most items in the sample could be guessed at a level better than chance.

These results suggest that lexical-semantic information (word meanings) alone is sufficient to identify the agent of a transitive verb in approximately 89% of the cases. Most items show high accuracy, while a minority of items show consistently worse accuracy.

**Animacy analysis**

To better understand this trend and given that animacy is a strong cue to agency in language (Ariel, 1991; Comrie, 1989; Dahl, 2008; Dixon, 1979; Dixon & Dixon, 1994; Everett, 2009; Osgood, 2013), we categorized each subject and object across the entire set of materials used in Experiments 1a-d as animate or inanimate, and ran a post-hoc analysis exploring the accuracy across the 4 ‘conditions’: animate subjects + animate objects (n=88 triads; e.g., *Petrarch meets Laura, Johnson deployed troops*), animate subjects + inanimate objects (n=436; e.g., *guys cooked food*), inanimate subjects + animate objects (n=48; e.g., *shops have owners*), and inanimate subjects + inanimate objects (n=518; e.g., *alternatives do not have requirements*).

Triads with animate subjects and inanimate objects were the overall easiest to classify, as can be seen in Figure 2. The inverse triads (with inanimate subjects with animate objects) were the most difficult to classify and generated a high rate of incorrect guesses. The two symmetric conditions, where both the subject and object are animate or both are inanimate, fell in-between, but the both-animate triads were harder. This is likely because these sentences tend to be semantically “reversible” (Caramazza & Zurif, 1976): “Petrarch meets Laura” is just as plausible as “Laura meets Petrarch” (but not always: e.g., “Johnson deployed troops”). The both-inanimate triads tend to be less reversible and thus might offer clearer cues (e.g., *camera requires reboot*, compared to the less plausible *reboot requires camera*).

To assess the statistical significance of these animacy-related differences, we ran a mixed effect model predicting whether the answer was correct based on the animacy configuration of the triad (animate-subject/inanimate-object, inanimate-subject/animate-object, both animate, or both inanimate). We included random intercepts for participants and items (but excluded slopes to aid convergence). Including the animacy configuration significantly improved fit by a likelihood ratio test comparing the full model to a simpler model without the animacy predictor ($\chi^2(3) = 155.0, p < 0.00001$). To further test whether the animacy of the subject or object has a larger effect, we fit a second logistic regression predicting whether the answer was correct based on the animacy of the subject, the animacy of the object, and their interaction (with random intercepts for participants and items). As expected, animate subjects were more likely to be identified correctly ($\beta = 0.83, p < 0.00001$), and animate objects were less likely to be identified correctly ($\beta = -1.46, p < 0.00001$). Although the interaction term was not significant ($\beta = -0.46, p = 0.13$), the effect of object animacy
Figure 1. The x-axis shows the mean accuracy for each experiment. The top panel shows human experiments (for English and Russian); performance is shown with 95% confidence intervals. The two bottom panels show computational experiments on the Universal Dependency corpora across languages, split into languages that use case (middle panel) and languages that do not (bottom panel). Performance is consistently high and comparable between human participants and the language model.
Figure 2. Accuracy as a function of animacy, for English and Russian human participants. The individual data points represent means for individual sentences. Error bars represent 95% confidence intervals over sentences. Because there were fewer sentences overall in Russian, the conditions with fewer naturally occurring examples (animate subject + animate object, inanimate subject + animate object) are particularly noisy, as is reflected by the large error bars. In both English and Russian, sentences with animate subjects and inanimate objects exhibited the highest accuracies, and sentences with inanimate subjects and animate objects exhibited the lowest accuracies.

is almost twice larger than the effect of subject animacy. This asymmetry is consistent with the observation that, across languages, differential object marking—the use of optional morphological marking on objects, often on animate objects rather than inanimate objects—is more common than differential subject marking (Aissen, 2003; Haspelmath, 2019; see Section 5.2 for more discussion of connections to differential object marking).

Further analysis of sentences with pronouns

In Experiment 1, 85.3% of transitive sentences in our initial sample were excluded because they contained pronouns (an estimate broadly consistent with cross-linguistic findings as to the rarity of transitive sentences with multiple full nominal arguments; Du Bois et al., 2003). These omitted materials often contained grammatical information, because many English pronouns are marked for case. Because of these exclusion, our estimate of human performance on the task (~88%) reflects the redundancy of word order in the absence of case marking since there is no case marking on English nouns.

We can get an estimate of how redundant English transitive argument word order is overall – not just in sequences with full NPs – by putting together our 88% estimate in full NP sequences (15%
of sequences) together with an estimate of how often case-marking disambiguates the other 85% of triads. To do this, we analyzed 200 randomly sampled sentences that were excluded from our initial study because they contained pronouns as arguments. We then excluded 31 of these sentences where the pronoun was a relative clause marker, leaving 169 sentences for analysis. Of these, 111 (66%) had disambiguating case information on the pronoun (e.g., I, me, we, us, they, them). The remaining 34% were similar to the sentences that we used in Experiment 1 in that they were not disambiguated by case. Assuming that this 34% can be guessed at a similar rate as in our sample of full NPs (88%), then we arrive at an overall estimate for how often word order is redundant in these triads: Full NPs, estimated experimentally: (.88 * .15) + Pronouns, case-marking disambiguated: (1 * .66 * .85) + Pronouns, case-ambiguous: (.88 * .34 * .85) = 94.7%. Thus, when sentences with pronouns are considered, word order is even more redundant, because pronouns often provide unambiguous case information.

**Experiment 2: Russian**

The goal of Experiment 2 was to investigate the same question as in Experiments 1a-1b in a typologically distinct language. We chose Russian because unlike English, Russian word order is highly flexible whereas most words are morphologically marked with case and/or agreement.

**Methods**

**Participants**

We recruited 89 participants (a mix of Russian native speakers residing in the US and those residing in Russia) through word of mouth. 10 were excluded for answering fewer than 75% of catch trials correctly, leaving 79 participants for analysis.

**Experimental materials**

1,047 SVO triads were extracted from the SynTagRus corpus from Universal Dependencies. A similar procedure was used to the one used for English to identify transitive clauses and to extract the triads. Triads where the subject, the object, or both were pronouns (n=218) were excluded because pronouns contain case marking information. Further, 226 triads were excluded for various reasons (e.g., mis-parsing, or containing fixed expressions, which would facilitate the identification of the subject), leaving 603 triads (57.5% of the original set), and 601 of these (99.7%) were slightly edited (in order to remove agreement cues and/or to clarify the meaning). (The original, excluded, and edited triads are available at OSF: [https://osf.io/kbtga/](https://osf.io/kbtga/))

We randomly sampled 500 triads from the set of 603, and distributed them across the 5 experimental lists (100 each). Additionally, as in Experiments 1b-d, 20 triads with clear thematic
roles (animate agents, inanimate patients, and a prototypical agent-patient relationship with respect to the verb; e.g., родители купить подарки – parents buy gifts) were included in each list as ‘catch trials’ to ensure that participants engage with the task. Catch trials were randomly interspersed with the critical triads and were excluded from the critical analyses.

Procedure

The procedure was identical to that used in Experiment 1a-d, except that participants were not recruited through Amazon Mechanical Turk, but were provided with a link for the task.

Results

The mean percent correct, across participants, was 86.7 [95% CI on participant means 85.3%, 88.1%]. The item with the maximum accuracy had correct answers 100% of the time, the item with the lowest accuracy was correct 0% of the time, and the median item accuracy was 94.4%. 79% of items had over 80% accuracy, and 65.6% had over 90% accuracy.

To explore the effects of animacy, similar to what we did for English, we categorized each subject and object as animate or inanimate, and explored the accuracy across the 4 ‘conditions’: animate subjects + animate objects (n=29 triads), animate subjects + inanimate objects (n=257), inanimate subjects + animate objects (n=197), and inanimate subjects + inanimate objects (n=27). Similar to what we found for English, triads with animate subjects and inanimate objects were the overall easiest to classify, as can be seen in Figure 2. The inverse triads (with inanimate subjects with animate objects) were the most difficult to classify, although note that this set consisted of only 6 sentences, so the sample is very small.

The mixed effect models (same as those described for the English data) revealed that including the animacy configuration significantly improved fit by a likelihood ratio test comparing the full model to a simpler model without the animacy predictor ($\chi^2(3) = 133, p < 0.00001$). Further, as with English, animate subjects were more likely to be identified correctly ($\beta = 1.86, p < 0.0001$), and animate objects were less likely to be identified correctly ($\beta = 2.61, p < 0.001$). As with English, the interaction term was not significant ($\beta = -.49, p = .41$).

Redundancy of word order in Russian when case information is available

Because pronouns were excluded and case information was stripped from nouns before running the experiment on Russian triads, our results reflect the redundancy of word order and case information combined. We could also ask about the redundancy of word order information alone, by studying sentences where case marking is present and pronouns are not excluded. To explore that, we analyzed triads from 200 transitive sentences from our initial corpus sample, without
removing case marking and including sentences with pronouns. After excluding 6 misparsed sentences, we were left with 194 triads for analysis. Of these, 168 (86.6%) triads were unambiguous based on morphological marking. The remaining 13.4% were similar to the sentences that we used in Experiment 1 in that they were not disambiguated by case. Assuming that this 13.4% can be guessed at a similar rate as in our sample of full NPs (86.7%), then we arrive at overall estimate for sentences that include pronouns and case information on nouns: \( (1 \times .866) + (.867 \times .134) = -98\%. \) Compared to our estimate of information in word meanings alone (86.7%), this estimate confirms the observation that word order cues are often redundant in Russian (~98% of the time).

**Comparison of Russian data to English data**

To formally assess whether the Russian data pattern differed significantly from the English data pattern, we fit a mixed effect model predicting whether the answer was correct, based on language (English or Russian), with random intercepts for subjects and items (slopes prevented convergence). The accuracies in the Russian experiment were slightly lower but not significantly so \( (\beta = -0.02, p = 0.8) \).

**4. Computational experiments**

Our results from human participants reveal two striking patterns, to our knowledge previously unreported. First, in the majority of instances in usage, formal marking of the subject-object distinction is redundant: the subject of a transitive clause can be identified from the lexical semantics of the nouns and the verb alone, without any need for marking via word order, case, or agreement. And second, the accuracy with which people can identify the subject of a transitive clause is the same (~85-90%) in two distinct languages, English and Russian. The similarity of these accuracy scores is all the more surprising considering the differences between these languages (English predominantly relying on word order cues, and Russian – on case marking and agreement), between the participant pools, and between the materials—the English triads and Russian triads were not translation-equivalent; they were drawn from independent corpora.

To evaluate the broader cross-linguistic generality of these patterns, we carried out a number of computational experiments using 42 Universal Dependencies 2.5 treebanks of 30 languages across eight language families, in which we study the extent to which the subject of a triad can be identified based on word embeddings—representations of the meaning of a word in terms of high-dimensional vectors, which have rapidly become the state-of-the-art method for representing word meanings in the field of natural language processing (Devlin et al., 2019; Mikolov et al., 2013; Pennington et al., 2014) and which capture human semantic judgments on diverse tasks (e.g., Pereira et al., 2016).
In particular, we report a series of computational experiments that examine the extent to which word order is redundant as a cue to the subject-object distinction. Due to corpus limitations, we are not able to examine the effects of morphological marking. As a result, for languages that use case marking, model accuracies reflect contributions from both lexical semantics and case marking; for languages that do not use case marking, model accuracies more veridically reflect contributions from lexical semantics alone.

**Methods**

*Corpus extraction.*

Similar to what we did for the human experiments, SVO triads were extracted from the Universal Dependencies 2.5 corpora by searching for all verbs with exactly one dependent of type ‘subject’ (*nsubj*) and exactly one dependent of type ‘object’ (*obj*). We included only languages for which we could extract at least 1,600 triads by these criteria.

*Word embeddings.*

Our goal was to determine the extent to which the subject of an SVO triad could be identified solely based on the word meanings. To do so, we represented each distinct word as an embedding: here, a point in a 300-dimensional space. Specifically, we used fastText, a set of word vectors constructed by training on the Wikipedias of a large number of languages (Bojanowski et al., 2017). Because fastText does not provide vectors for lemmas, only for wordforms, it was not possible to eliminate morphological information as we did in the human experiments. To get a vector representation of a triad as a whole, we concatenated these vectors (first the verb, then the subject, and the object, the latter two in a random order) to form a 900-dimensional vector.

*Classifiers.*

Once we represented these triads as vectors, we fit classifiers to predict subjecthood (whether the first noun in the shuffled SVO triad is the subject or the object). Following standard practice in natural language processing, we used feedforward neural networks as classifiers. The neural network takes the 900-dimensional triad vector as input, then runs it through two layers of hidden units with ReLU activation (Nair & Hinton, 2010), with softmax activation for the final output. The number of hidden units is determined on a per-language basis by hyperparameter search, as described below.
Training and validation.

We trained neural network subjecthood classifiers by backpropagation using the Adam optimizer (Kingma & Ba, 2014). For each corpus, we fit several neural network classifiers, with learning rate drawn from \{.001, 0001\}, and with the number of hidden units in the first layer drawn from \{32, 64, 128\}, and the number of hidden units in the second layer drawn from \{32, 64, 128\}, a total of 18 classifiers per corpus. Each Universal Dependencies corpus has separate training, development, and test sets defined by the Universal Dependencies project. Individual classifiers were trained on the UD training set. For each corpus, we selected the best-performing classifier by taking the classifier with the highest accuracy on the UD development set.\(^1\) We analyzed the final results based on accuracy on the UD test set. This procedure of holding out data guards against overfitting: final accuracy is always evaluated based on data that was not used during the process of fitting or optimizing the classifier.

Results

Test-set classifier accuracies are shown in the middle panel (for languages with case marking) and the bottom panel (for languages without case marking) of Figure 1. All classifiers performed better than chance on the test set. The median accuracy of the classifiers across corpora was 87% [mean of 85% with a 95% CI 83%, 88%], with a minimum of 65% for the simplified Chinese GSD corpus and 68% for the standard Chinese GSD corpus and a maximum of 99% for the Hungarian-Szeged corpus. Half of the corpora fell between 81% and 91% in accuracy. The three English corpora in the sample fell between 82% and 91% accuracy, and the Russian corpus had 92% accuracy.

These results were similar in magnitude to those from the human experiments. There was some variation across languages, but there was also variation between different corpora from the same language (e.g., accuracy was 90% for English EWT, a corpus of web text, but only 85% for English GUM, a corpus of mixed genres). Some of the anomalously low accuracies may be due to issues with the word embeddings—for example, the Chinese corpora have low accuracies, possibly because the fastText vectors use embeddings of character sequences, and this scheme may be less well suited to Chinese characters than to Latin characters. More generally, these computational estimates can be thought of as lower bounds on the potential accuracy of this task since better architectures and larger data sets could well lead to improved performance.

Because, as described in Methods, the study used wordforms and not lemmas, languages with case marking have more information available to the model than languages without case marking and than our human experiments in English and Russian (where we excluded case information). Languages without formal case marking have, in principle, the same information available as our

\(^1\) The Universal Dependencies datasets come with predefined train-dev-test splits consisting of 80%-10%-10% of the data; which were used here.
human experiments. As expected, case-marked languages exhibited better performance (89% on average) than languages without case marking (82% on average). To assess the statistical significance of this difference, we ran a mixed effect model predicting the mean accuracy for a particular corpus based on a binary coded variable for whether the language has case marking, with a random intercept for language. Including the case-marking variable significantly improved fit by a likelihood ratio test comparing the full model to a simpler model without the case-marking predictor ($\beta=.07, \chi^2(1) = 7.52, p<.01$). Crucially though, even for languages with no case marking, performance was well above chance suggesting that word meanings alone are enough for the model to differentiate the subject and object.

5. General Discussion

In this study, we used a combination of human experiments and experiments with a computational language model to evaluate how often the correct propositional meaning of naturalistic transitive clauses can be inferred from just the meanings of the key words in the absence of formal grammatical cues, like word order and case and agreement markers. Across typologically diverse languages, we found that for the majority of sentences, formal marking was redundant, although case markers did show a small contribution in the experiments with the computational language model such that the model was better able to identify the agent in case-marked languages than in languages without case-marking. For human participants, animacy was an important cue to agency (see also Ariel, 1991; Comrie, 1989; Dahl, 2008; Dixon, 1979; Dixon & Dixon, 1994; Everett, 2009; Osgood, 2013).

We believe that our human experiments in English and Russian, in which we stripped wordforms of morphology and did not include sentences with pronoun arguments, represent a lower bound on the redundancy of grammatical cues. As can be seen by considering English sentences with pronouns (which, by our estimate, clearly mark the subject or object 66% of the time), the redundancy of word order for transitive sentences in general is likely even higher. Our estimates are also conservative in that they do not give participants access to the rich contextual information that characterizes most language use. Below we discuss these results and their implications in more detail.

5.1 Challenges for efficiency-based accounts of language

It is commonly argued that different formal grammatical cues trade off in conveying meaning efficiently. For example, word order might trade off with the use of morphology (e.g., Fenk-Oczlon & Fenk, 2008; Koplenig et al., 2017; Levshina, 2020, 2021; McFadden, 2003). In the case of transitive clauses, if the subject of a verb is distinguished by morphology, then there should be no need to mark it by word order, and vice versa. But this reasoning presupposes the general utility of formal cues for conveying complex meanings.
Contra this presupposition, we showed that i) in English and Russian, both word order and morphology are largely redundant with the information conveyed by word meanings; and ii) across a variety of languages in our computational sample, word order is largely redundant. This redundancy is present even for languages that lack case-marking systems. And although the language model performs better on case-marked than non-case-marked languages, this difference is relatively small (a 7% difference in accuracy, on average) and we observe that some models trained on non-case-marked languages actually outperformed models trained on case-marked languages (e.g., English-EWT vs. Slovak-SNK), despite lacking access to overt morphological information. If case and word order traded off perfectly efficiently and case supplied all the relevant information, then we would have expected the case-marked models to perform near perfectly and the non-case-marked models to perform at chance.

These data therefore challenge the simple view that word order and morphology trade off since the benefits of the added grammatical complexity associated with any formal marking (word order / case marking / agreement rules) appear to be limited.

5.2 Formal grammatical systems are critical for conveying meanings of semantically reversible and implausible events

Given that word meanings constrain interpretation in the large majority of sentences, why do (most) languages have formal cues (cf. Ergin et al., 2018; Gil, 2013; Jackendoff & Wittenberg)? One possibility is that being right most of the time is not good enough, and the small number of sentences where, absent formal cues, the meaning is ambiguous are sufficient to give rise to regularized grammatical rules. Such cases include i) semantically reversible events where the two nominals both denote plausible agents, typically clauses with two animate entities (e.g., Ray helped Lu / Lu helped Ray), and ii) events that are unusual, i.e., violate the statistics of the world (e.g., the man bit the dog; cf. the more common event of the dog biting the man). Both instances occur often enough (sentences with animate subjects and animate objects occur ~10% of the time in our English sample; sentences with inanimate subjects and animate objects ~5% of the time) that there seems to be a functional benefit to being able to handle them in the grammar of a language. Moreover, the ability to grammatically identify the agent in sentences with animate subjects and objects may be a particularly important capacity since “humans like to talk about humans” (MacWhinney, 1977; Everett, 2009), and the ability to draw fine-grained distinction about who did what to whom may have been important in the evolution of human society (see, e.g., work on the role of gossip in human language evolution (Dunbar, 1998; Nowak & Sigmund, 2005; Sommerfeld et al., 2007)). And being able to say implausible things like “man bit dog” is a hallmark of language that allows for several of its most celebrated design features (Hockett, 1960), such as prevarication (lying) and displacement (talking about things that are not present or that do not even exist).
Although these cases are relatively rare, word order cues would only work if they are used consistently, even if they are usually redundant with word meanings. Otherwise, word order would not be reliable and thus not useful. For example, imagine a linguistic system in which the word order is SVO 70% of the time and OVS 30% of the time. An agent wishing to convey an implausible sentence like “man bit dog” would be able to say either “man bit dog” or “dog bit man.” A rational language producer, knowing that SVO is more common, might use the word order SVO in hopes that the comprehender would infer that man was the subject (since subjects usually precede objects in this hypothetical language). However, given that the prior probability of the utterance would be highly biased towards “dog bit man,” the comprehender would still be likely to infer that the intended meaning was “man bit dog”. On the other hand, if the language categorically used SVO order and categorically excluded OVS order, then “man bit dog” would be interpreted with ‘man’ as the subject and ‘dog’ the object, despite the implausibility of the resulting meaning.

The same logic does not apply to case or agreement marking because these cues, unlike word order, can be optional. For instance, one could imagine an efficient linguistic system in which case marking was not required to convey the plausible meaning “dog bit man”, but was required if one wanted to convey the implausible meaning “man bit dog”. In fact, differentially marking non-prototypical objects (e.g., human or animate objects) is a relatively common phenomenon across languages (e.g., in Spanish, specific human objects are marked by a preceding a, whereas most other objects are not), called differential object marking (Aissen, 2003). Therefore, for case or agreement marking to be a reliable cue, it does not need to always be present, unlike word order.

This account offers a possible explanation for why languages like English have relatively strict word orders even though, as our experiments show, most meanings can be inferred from word meanings alone. Were the word order not strict even in redundant instances, it would not be a sufficiently strong cue for overriding the plausibility of the meaning conveyed when needed. That is, without strict word order, it would be impossible to say things like “the bone chewed the dog.”

From the perspective of computational linguistics, this account also may explain why successful artificial neural network language models (e.g., BERT; Devlin et al., 2019) are effective for a variety of natural language processing tasks even when they are trained on word-order-scrambled input or without access to word order information (Anonymous, 2022; Clouatre et al., 2021; Hessel & Schofield, 2021; Ravishankar et al., 2021; Sinha et al., 2021). Given that in most cases word order information is redundant with word meanings, it is plausible for the overall performance of

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2 In fact, even with strict word order as in modern English, there is evidence from the literature on noisy-channel sentence processing (Gibson, Bergen, et al., 2013; Gibson et al., 2016, 2017; Ryskin et al., 2020) that meaning-based priors (e.g., that dogs chew bones and not vice versa) can sometimes cause human comprehenders to assume that an error had occurred somewhere in production or comprehension and to override grammatical cues in favor of the more plausible utterance (e.g., assuming that, even though they heard “the bone chewed the dog,” the intended meaning was “the dog chewed the bone”).
a model trained on scrambled input to be high. Our account predicts, however, that such models would suffer in cases where word order information is crucial. Relatedly, in human language processing also, scrambling word order does not reduce neural responses in the language-selective network unless local semantic composition is blocked (Mollica, Siegelman et al., 2020), suggesting that word order information is not critical for the mental operations carried out by the language system.

5.3 Additional reasons for the emergence of formal grammatical systems

Two other reasons for the existence of syntactic marking are worth mentioning. First, the simplest justification for redundancy in any communication code is the presence of noise in the transmission and receipt of signals (Shannon, 1948). Redundancy allows information to be recovered even in the presence of signal loss. Given that transmission in linguistic exchanges is often lossy, redundancy plausibly makes linguistic communication more robust to noise in terms of conveying its intended message (e.g., Aylett & Turk, 2004; Fenk-Oczlon & Fenk, 2008; Gibson, Bergen, et al., 2013; Jaeger, 2010; Levy, 2008; Wit & Gillette, 1999).

Another possible justification for the existence of word order constraints has to do with increasing efficiency on the side of the language producer (e.g., see MacDonald, 2013). Language production is a complex cognitive feat, where a producer must select some words from among tens of thousands of words in their active vocabulary and combine them appropriately to convey some intended meaning. Producers are faster when they are faced with fewer choices: objects for which multiple labels are possible (e.g., couch, futon, sofa) are slower to name than objects for which only one possible name exists (Lachman, 1973; Torrance et al., 2018). This phenomenon is an instance of a more general pattern where human choice behavior is slower when there are more options (Hick, 1952; Hyman, 1953). Rigid word order rules imply that the order of words in a sentence is fully determined by their grammatical roles, thus reducing the number of choices a speaker must make. Such rules may also make information more ‘accessible’ to a comprehender—including during language learning—by ensuring a relatively low entropy over utterances, i.e. making utterances more predictable, on average (Levy, 2008).

5.4 Investigations of semantically reversible sentences

Hundreds of behavioral and brain imaging investigations with diverse populations have examined the processing of semantically reversible sentences (e.g., Berndt et al., 1996; Caramazza & Zurif, 1976; Gibson et al., 2013; Luzzatti et al., 2001; Grodner & Gibson, 2005; Martin et al., 2013; Noble et al., 2011; Richardson et al., 2010; Thothathiri et al., 2012). Such sentences continue to be in common use in language research. The rationale for their use is that such materials allow researchers to isolate morpho-syntactic demands from those associated with the processing of word meanings and plausibility information. However, we would encourage the language research community to not simply ignore the fact that comprehenders can usually infer propositional
meanings based on word meanings alone. Although focusing on unusual sentences may be informative for some research questions, it may also lead to misguided theorizing and overestimating the importance of morpho-syntactic processes in natural language comprehension, including postulating syntax-specific machinery (e.g., Friederici, 2011, 2012; Grodzinsky & Santi, 2008; Pylkkänen, 2019; Tyler et al., 2011; Ullman, 2016; cf. Fedorenko et al., 2020). Furthermore, paradigms that use semantically reversible materials often include task demands beyond language comprehension (to ensure participants deeply engage with the materials), which may lead to the engagement of domain-general executive mechanisms that are not engaged during naturalistic comprehension (e.g., Diachek, Blank, Siegelman et al., 2020; see Fedorenko & Shain, 2021, for a review).

5.5 Conclusion

We propose that explaining the quantitative level of grammatical redundancy in natural language, which appears to be consistent across languages, should be a central goal in functional linguistics. From an information-theoretic perspective, the redundancy of natural language is one of its most distinctive features. Characterizing and explaining this redundancy has the potential to elucidate the relationship between form and function and to clarify the pressures that shape human language.
References

Aissen, J. (2003). Differential object marking: Iconicity vs. Economy. Natural Language & Linguistic Theory, 21(3), 435–483.

Anonymous. (2022). When classifying grammatical role, BERT doesn’t care about word order. . . Except when it matters. Preprint Submitted to ACL ARR. https://openreview.net/pdf?id=nB4zLycibom

Ariel, M. (1991). The function of accessibility in a theory of grammar. Journal of Pragmatics, 16(5), 443–463.

Aylett, M., & Turk, A. (2004). The smooth signal redundancy hypothesis: A functional explanation for relationships between redundancy, prosodic prominence, and duration in spontaneous speech. Language and Speech, 47(1), 31–56.

Bates, E., Friederici, A., & Wulfeck, B. (1987). Comprehension in aphasia: A cross-linguistic study. Brain and Language, 32(1), 19–67.

Bates, E., & MacWhinney, B. (1989). Functionalism and the Competition Model. In B. MacWhinney & E. Bates (Eds.), The Crosslinguistic Study of Sentence Processing (pp. 3–76). Cambridge University Press.

Bentz, C., Alikaniotis, D., Cysouw, M., & Ferrer-i-Cancho, R. (2017). The Entropy of Words—Learnability and Expressivity across More than 1000 Languages. Entropy, 19, 275–307.

Berndt, R. S., Mitchum, C. C., & Haendiges, A. N. (1996). Comprehension of reversible sentences in “agrammatism”: A meta-analysis. Cognition, 58(3), 289–308.

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching Word Vectors with Subword Information. Transactions of the Association for Computational Linguistics, 5, 135–146. https://doi.org/10.1162/tacl_a_00051

Bornkessel, I., Schlesewsky, M., & Friederici, A. D. (2002). Grammar overrides frequency: Evidence from the online processing of flexible word order. Cognition, 85(2), B21–B30.

Button, K. S., Ioannidis, J. P., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. Nature Reviews Neuroscience, 14(5), 365–376.

Caramazza, A., & Zurif, E. B. (1976). Dissociation of algorithmic and heuristic processes in language comprehension: Evidence from aphasia. Brain and Language, 3(4), 572–582.

Cloutatre, L., Parthasarathi, P., Zouaq, A., & Chandar, S. (2021). Demystifying Neural Language Models’ Insensitivity to Word-Order. ArXiv Preprint ArXiv:2107.13955.

Comrie, B. (1989). Language universals and linguistic typology: Syntax and morphology. University of Chicago press.
Cover, T., & King, R. (1978). A convergent gambling estimate of the entropy of English. *IEEE Transactions on Information Theory, 24*(4), 413–421.

Dahl, Ö. (2008). Animacy and egophoricity: Grammar, ontology and phylogeny. *Lingua, 118*(2), 141–150.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4171–4186. https://doi.org/10.18653/v1/N19-1423

Diachek, E., Blank, I., Siegelman, M., Affourtit, J., & Fedorenko, E. (2020). The domain-general multiple demand (MD) network does not support core aspects of language comprehension: A large-scale fMRI investigation. *Journal of Neuroscience, 40*(23), 4536–4550.

Dixon, R. M. (1979). Ergativity. *Language, 59–138.*

Dixon, R. M., & Dixon, R. M. (1994). *Ergativity.* Cambridge University Press.

Dryer, M. S. (1991). SVO languages and the OV: VO typology. *Journal of Linguistics, 27*(2), 443–482.

Dryer, M. S. (2002). Case distinctions, rich verb agreement, and word order type (Comments on Hawkins’ paper). *Theoretical Linguistics, 28*(2), 151–158.

Du Bois, J. W. (1987). The discourse basis of ergativity. *Language, 805–855.*

Du Bois, J. W., Kumpf, L. E., & Ashby, W. J. (2003). *Preferred argument structure: Grammar as architecture for function.* John Benjamins Publishing.

Dunbar, R. I. M. (1998). *Grooming, gossip, and the evolution of language.* Harvard University Press.

Ergin, R., Meir, I., İlkbahar, D., Padden, C., & Jackendoff, R. (2018). The development of argument structure in Central Taurus Sign Language. *Sign Language Studies, 18*(4), 612-639.

Everett, C. (2009). A reconsideration of the motivations for preferred argument structure. *Studies in Language. International Journal Sponsored by the Foundation “Foundations of Language,” 33*(1), 1–24.

Fedorenko, E., Blank, I. A., Siegelman, M., & Mineroff, Z. (2020). Lack of selectivity for syntax relative to word meanings throughout the language network. *Cognition, 203*, 104348.

Fedorenko, E., & Shain, C. (2021). Similarity of computations across domains does not imply shared implementation: The case of language comprehension. *Current Directions in Psychological Science, 30*(6), 526–534.
Fenk-Oczlon, G., & Fenk, A. (2008). Complexity trade-offs between the subsystems. Language Complexity: Typology, Contact, Change, 94, 43.

Friederici, A. D. (2011). The brain basis of language processing: From structure to function. Physiological Reviews, 91(4), 1357–1392.

Friederici, A. D. (2012). The cortical language circuit: From auditory perception to sentence comprehension. Trends in Cognitive Sciences, 16(5), 262–268.

Gelman, A., & Carlin, J. (2014). Beyond Power Calculations: Assessing Type S (Sign) and Type M (Magnitude) Errors. Perspectives on Psychological Science, 9(6), 641–651. https://doi.org/10.1177/1745691614551642

Gelman, A., & Loken, E. (2013). The garden of forking paths: Why multiple comparisons can be a problem, even when there is no ‘fishing expedition’or ‘p-hacking’and the research hypothesis was posited ahead of time. Downloaded January, 30, 2014.

Gibson, E., Bergen, L., & Piantadosi, S. T. (2013). Rational integration of noisy evidence and prior semantic expectations in sentence interpretation. Proceedings of the National Academy of Sciences, 110(20), 8051–8056.

Gibson, E., Piantadosi, S. T., Brink, K., Bergen, L., Lim, E., & Saxe, R. (2013). A noisy-channel account of crosslinguistic word-order variation. Psychological Science, 24(7), 1079–1088.

Gibson, E., Sandberg, C., Fedorenko, E., Bergen, L., & Kiran, S. (2016). A rational inference approach to aphasic language comprehension. Aphasiology, 30(11), 1341–1360.

Gibson, E., Tan, C., Futrell, R., Mahowald, K., Konieczny, L., Hemforth, B., & Fedorenko, E. (2017). Don’t underestimate the benefits of being misunderstood. Psychological Science, 28(6), 703–712.

Gil, D. (2013). Riau Indonesian: A language without nouns and verbs. In J. Rijkhoff & E. van Lier (Eds.), Flexible Word Classes (pp. 89–130). Oxford University Press.

Goldin-Meadow, S., So, W. C., Özyürek, A., & Mylander, C. (2008). The natural order of events: How speakers of different languages represent events nonverbally. Proceedings of the National Academy of Sciences, 105(27), 9163-9168.

Greenberg, J. H. (1963). Some universals of grammar with particular reference to the order of meaningful elements. Universals of Language, 73–113.

Grodzinsky, Y., & Santi, A. (2008). The battle for Broca’s region. Trends in Cognitive Sciences, 12(12), 474–480.

Hall, M. L., Ferreira, V. S., & Mayberry, R. I. (2014). Investigating constituent order change with elicited pantomime: A functional account of SVO emergence. Cognitive Science, 38(5), 943–972.
Haspelmath, M. (2019). Differential place marking and differential object marking. *STUF-Language Typology and Universals*, 72(3), 313–334.

Hessel, J., & Schofield, A. (2021). How effective is BERT without word ordering? Implications for language understanding and data privacy. *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, 204–211. https://doi.org/10.18653/v1/2021.acl-short.27

Hick, W. E. (1952). On the rate of gain of information. *Quarterly Journal of Experimental Psychology, 4*(1), 11–26. https://doi.org/10.1080/17470215208416600

Hockett, C. F. (1960). The origin of speech. *Scientific American, 203*, 88–96.

Hyman, R. (1953). Stimulus information as a determinant of reaction time. *Journal of Experimental Psychology, 53*, 188–196.

Ioannidis, J. P., Munafo, M. R., Fusar-Poli, P., Nosek, B. A., & David, S. P. (2014). Publication and other reporting biases in cognitive sciences: Detection, prevalence, and prevention. *Trends in Cognitive Sciences, 18*(5), 235–241.

Jackendoff, R., & Wittenberg, E. (2017). Linear grammar as a possible stepping-stone in the evolution of language. *Psychonomic Bulletin & Review, 24*(1), 219–224.

Jaeger, T. F. (2010). Redundancy and reduction: Speakers manage syntactic information density. *Cognitive Psychology, 61*(1), 23–62.

Keller, T. A., Carpenter, P. A., & Just, M. A. (2001). The Neural Bases of Sentence Comprehension: A fMRI Examination of Syntactic and Lexical Processing. *Cerebral Cortex, 11*(3), 223–237. https://doi.org/10.1093/cercor/11.3.223

Kim, A., & Osterhout, L. (2005). The independence of combinatorial semantic processing: Evidence from event-related potentials. *Journal of Memory and Language, 52*(2), 205–225.

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *ArXiv Preprint ArXiv:1412.6980.*

Kiparsky, P. (1997). The rise of positional licensing. In A. von Kemenade & N. Vincent (Eds.), *Parameters of morphosyntactic change* (pp. 460–494). Cambridge University Press.

Koplenig, A., Meyer, P., Wolfer, S., & Müller-Spitzer, C. (2017). The statistical trade-off between word order and word structure–Large-scale evidence for the principle of least effort. *PloS One, 12*(3), e0173614.

Kuperberg, G. R., Kreher, D. A., Sitnikova, T., Caplan, D. N., & Holcomb, P. J. (2007). The role of animacy and thematic relationships in processing active English sentences: Evidence from event-related potentials. *Brain and Language, 100*(3), 223–237.
Lachman, R. (1973). Uncertainty effects on time to access the internal lexicon. *Journal of Experimental Psychology, 99*(2), 199.

Levshina, N. (2020). Efficient trade-offs as explanations in functional linguistics: Some problems and an alternative proposal. *Revista Da Abralin, 19*(3), 50–78.

Levshina, N. (2021). Cross-Linguistic Trade-Offs and Causal Relationships Between Cues to Grammatical Subject and Object, and the Problem of Efficiency-Related Explanations. *Frontiers in Psychology, 12*, 2791.

Levy, R. (2008). A noisy-channel model of rational human sentence comprehension under uncertain input. *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, 234–243.

Luzzatti, C., Toraldo, A., Guasti, M. T., Ghirardi, G., Lorenzi, L., & Guarnaschelli, C. (2001). Comprehension of reversible active and passive sentences in agrammatism. *Aphasiology, 15*(5), 419–441.

MacDonald, M. C. (2013). How language production shapes language form and comprehension. *Frontiers in Psychology, 4*, 226.

MacWhinney, B. (1977). Starting points. *Language, 53*, 152–168.

Marslen-Wilson, W., & Tyler, L. K. (1980). The temporal structure of spoken language understanding. *Cognition, 8*(1), 1–71.

Martin, N., Kohen, F. P., Kalinyak-Fliszar, M., & Guerrero, M. (2013). Comprehension of sentences with reversible semantic roles is sensitive to phonological STM capacity.

McFadden, T. (2003). On morphological case and word-order freedom. *Proceedings of the Berkeley Linguistics Society*.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, 3111–3119.

Mollica, F., & Piantadosi, S. T. (2019). Humans store about 1.5 megabytes of information during language acquisition. *Royal Society Open Science, 6*(3), 181393.

Nair, V., & Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. *Icml*.

Nivre, J., De Marneffe, M.-C., Ginter, F., Goldberg, Y., Hajic, J., Manning, C. D., McDonald, R., Petrov, S., Pyysalo, S., Silveira, N., & others. (2016). Universal dependencies v1: A multilingual treebank collection. *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16)*, 1659–1666.
Noble, C. H., Rowland, C. F., & Pine, J. M. (2011). Comprehension of argument structure and semantic roles: Evidence from English-learning children and the forced-choice pointing paradigm. *Cognitive Science, 35*(5), 963–982.

Nowak, M. A., & Sigmund, K. (2005). Evolution of indirect reciprocity. *Nature, 437*(7063), 1291–1298.

Osgood, C. E. (2013). *Lectures on language performance* (Vol. 7). Springer Science & Business Media.

Palmer, M., Titov, I., & Wu, S. (2013). Semantic Role Labeling. *NAACL HLT 2013 Tutorial Abstracts, 10–12. https://aclanthology.org/N13-4004*

Papadimitriou, I., Chi, E. A., Futrell, R., & Mahowald, K. (2021). Deep Subjecthood: Higher-Order Grammatical Features in Multilingual BERT. *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, 2522–2532. https://aclanthology.org/2021.eacl-main.215*

Pennington, J., Socher, R., & Manning, C. D. (2014). GloVe: Global Vectors for Word Representation. *Empirical Methods in Natural Language Processing (EMNLP), 1532–1543. http://www.aclweb.org/anthology/D14-1162*

Pereira, F., Gershman, S., Ritter, S., & Botvinick, M. (2016). A comparative evaluation of off-the-shelf distributed semantic representations for modelling behavioural data. *Cognitive Neuropsychology, 33*(3–4), 175–190.

Pylkkänen, L. (2019). The neural basis of combinatory syntax and semantics. *Science, 366*(6461), 62–66.

Ravishankar, V., Kulmizev, A., Abdou, M., Søgaard, A., & Nivre, J. (2021). Attention Can Reflect Syntactic Structure (If You Let It). *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, 3031–3045. https://aclanthology.org/2021.eacl-main.264*

Richardson, F. M., Thomas, M. S., & Price, C. J. (2010). Neuronal activation for semantically reversible sentences. *Journal of Cognitive Neuroscience, 22*(6), 1283–1298.

Ryskin, R., Stearns, L., Bergen, L., Eddy, M., Fedorenko, E., & Gibson, E. (2020). The P600 ERP component as an index of rational error correction within a noisy-channel framework of human communication. *BioRxiv*.

Schouwstra, M., & de Swart, H. (2014). The semantic origins of word order. *Cognition, 131*(3), 431–436.

Schwartz, M. F., Saffran, E. M., & Marin, O. S. M. (1980). The word order problem in agrammatism 1: Comprehension. *Brain and Language, 10*(2), 249–262. https://doi.org/10.1016/0093-934x(80)90055-3
Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*, 623–656.

Shannon, C. E. (1951). Prediction and Entropy of Printed English. *Bell System Technical Journal, 30*(1), 50–64.

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, 0956797611417632.

Sinclair, H., & Bronckart, J.-P. (1972). SVO A linguistic universal? A study in developmental psycholinguistics. *Journal of Experimental Child Psychology, 14*(3), 329–348.

Sinha, K., Jia, R., Hupkes, D., Pineau, J., Williams, A., & Kiela, D. (2021). Masked language modeling and the distributional hypothesis: Order word matters pre-training for little. *ArXiv Preprint ArXiv:2104.06644*.

Sinnemäki, K. (2008). Complexity trade-offs in core argument marking. *Language Complexity: Typology, Contact, Change, 67*, 88.

Sommerfeld, R. D., Krambeck, H.-J., Semmann, D., & Milinski, M. (2007). Gossip as an alternative for direct observation in games of indirect reciprocity. *Proceedings of the National Academy of Sciences, 104*(44), 17435–17440.

Stromswold, K., Caplan, D., Alpert, N., & Rauch, S. (1996). Localization of syntactic comprehension by positron emission tomography. *Brain and Language, 52*(3), 452–473. https://doi.org/10.1006/brln.1996.0024

Thothathiri, M., Kimberg, D. Y., & Schwartz, M. F. (2012). The neural basis of reversible sentence comprehension: Evidence from voxel-based lesion symptom mapping in aphasia. *Journal of Cognitive Neuroscience, 24*(1), 212–222.

Torrance, M., Nottbusch, G., Alves, R. A., Arfé, B., Chanquoy, L., Chukharev-Hudilainen, E., Dimakos, I., Fidalgo, R., Hyönpä, J., Jóhannesson, Ö. I., & others. (2018). Timed written picture naming in 14 European languages. *Behavior Research Methods, 50*(2), 744–758.

Tyler, L. K., Marslen-Wilson, W. D., Randall, B., Wright, P., Devereux, B. J., Zhuang, J., Papoutsi, M., & Stamatakis, E. A. (2011). Left inferior frontal cortex and syntax: Function, structure and behaviour in patients with left hemisphere damage. *Brain, 134*, 415–431. https://doi.org/10.1093/brain/awq369

Ullman, M. T. (2016). The Declarative/Procedural Model. In *Neurobiology of Language* (pp. 953–968). Elsevier. https://doi.org/10.1016/B978-0-12-407794-2.00076-6

Wit, E., & Gillette, M. (1999). What is linguistic redundancy. *University of Chicago.*