Speech prosody enhances the neural processing of syntax

AUTHORS
Giulio Degano[1], Peter W. Donhauser[4], Laura Gwilliams[5], Paola Merlo[6], Narly Golestani[1,2,3,4].

1. Department of Psychology, Faculty of Psychology and Educational Sciences, University of Geneva, Geneva, Switzerland.
2. Brain and Language Lab, Cognitive Science Hub, University of Vienna.
3. Dept of Behavioral and Cognitive Biology, Faculty of Life Sciences, University of Vienna.
4. Ernst Strüngmann Institute for Neuroscience in Cooperation with Max Planck Society, Frankfurt am Main, Germany.
5. Department of Psychology, Stanford University, California, USA
6. Department of Linguistics, University of Geneva, Geneva, Switzerland.
7. University Centre for Informatics, University of Geneva, Geneva, Switzerland.

Abstract

Human language relies on hierarchically structured syntax to facilitate efficient and robust communication. The correct processing of syntactic information is essential for successful communication between speakers. As an abstract level of language, syntax has often been studied separately from the physical form of the speech signal, thus often masking the interactions that can promote better syntactic processing in the human brain. We analyzed a MEG dataset to investigate how acoustic cues, specifically prosody, interact with syntactic operations. We examined whether prosody enhances the cortical encoding of syntactic representations. We decoded left-sided dependencies directly from brain activity and evaluated possible modulations of the decoding by the presence of prosodic boundaries. Our findings demonstrate that prosodic boundary presence improves the representation of left-sided dependencies, indicating the facilitative role of prosodic cues in processing abstract linguistic features. This study gives neurobiological evidence for the boosting of syntactic processing via interaction with prosody.

Introduction

Human language is based on hierarchically structured syntax, allowing for robust and efficient communication. This structure has an important role in speech comprehension, as it lays down a set of rules, our syntax, over which infinite number of utterances can be created. Thus, the correct processing of syntactic information becomes fundamental for successful communication across speakers. Aside from syntactic rules, different abstract sources of information can change the way these utterances are processed (i.e. semantic content, context, predictions based on statistics, etc), but research in the last twenty years has shown that syntax can be also tightly linked to a more physical aspect of speech: prosodic information [1,2].

The suprasegmental information carried by prosody has multiple acoustic markers that can be used to orient the interpretation of a sentence. These acoustic markers can include variation in pitch or in the energy of the speech signal as well as lengthening of syllables or the insertion of long pauses. For example, the sentence “Johnny the little boy is playing” can be parsed with two different syntactic structures based on the temporal location of the acoustic cues. The lengthening of the syllable *boy* and the placement of an additional pause after it can differentiate between two syntactic structures: one where the sentence is directed at someone called ‘Johnny’ (i.e., “Jonny, the little boy is playing”), and one where ‘Johnny’ is the subject of the verb phrase (i.e. “Johnny, the little boy, is playing”) and the noun phrase ‘the little boy’, is an apposition. This example shows how prosodic boundaries can dramatically change how words need to be grouped together in order to successfully communicate concepts. This particular feature of prosodic boundaries can be seen as one of the most evident connections between prosody and syntax as it highlights, for example, a close correspondence with grammatical phrase boundaries[1,2]. Indeed, the redundancy between these two linguistic features might be integral for facilitating the mapping of the incoming speech signal onto a syntactic structure, and disambiguating between two alternative parses.

The link between prosody and syntax has also extensively been explored in the context of developmental studies, where it has been proposed that prosody assists the acquisition of the first language; this phenomenon is known as prosodic bootstrapping [3,4]. This theoretical framework proposes that infants use prosodic information in the speech signal to help them infer syntactic rules and structures, and thus acquire their first language [4]. Indeed, prosody has been shown to help infants learn syntactic constituency [5], interpret syntactic adjacency [6], and segment continuous speech [7]. Importantly, prosodic bootstrapping has also been shown to occur in different languages, such as English, French, and Italian [8] and in bilingual infants [9]. The significant role of prosody in ontogeny is consistent with its posited role as a precursor of language [10], coming from work showing that newborn babies can already distinguish languages coming from the same rhythmic class as their environmental language from those coming from different rhythmic classes [10,11]. In turn, such a developmentally early sensitivity to prosody likely arises from prenatal processing and learning [12,13], thanks to an auditory system that is established and functional in the last 4-6 weeks of gestation [14–16]. Indeed, prenatal exposure to speech and other acoustic signals is more faithful to slower-changing acoustic information such as that contained in prosody, due to low low-pass filtering of sound by the amniotic fluid [17–20].

Although the results in children show that syntactic learning becomes less reliant on prosody later in life [21,22], there is evidence of a continuous interaction between these two features even in adults. This is likely due to the fact that prosodic signals can be a reliable acoustic and perceptual scaffold for the online processing of syntactic features [23]. Indeed, it has been shown that prosodic cues such as pitch variation and syllable duration can assist syntax learning more than transitional probabilities [24]. Prosody also helps the initial parsing of sentences [25,26], morphosyntactic dependency learning [7], and speech segmentation [7], in adults.

Biological evidence for a prosody-syntax interaction further supports the importance of prosody for more reliable syntactic parsing. Brain imaging research using electroencephalography (EEG) has shown that changes in pause, pitch, loudness, or

duration that mark boundaries between phrases, known as prosodic boundaries [7], affect neural markers of syntactic disambiguation. For example, it has been found that manipulation of the placement of prosodic boundary modulates the evoked responses to the stimuli such as to assist syntactic disambiguation [27,28] and processing of garden path sentences [29–31]. Conversely, research has also shown the influence of syntactic predictions on prosodic processing. For instance, it has been shown that a neural marker of prosodic processing - the closure positive shift [32] – can be elicited by biases generated from initial syntactic parsing preferences, even in the absence of explicit acoustic cues [33]. It is thus possible to hypothesize that the regular interaction between and co-occurrence of these two linguistic features has driven the brain into expecting syntax and prosody to be coherent even if one of the two is not explicitly present, or when they don't co-occur. In line with this, a recent study has demonstrated that the cortical tracking of naturalistic speech is enhanced when overt and covert prosodic boundaries are aligned with the syntactic structure compared to when they are misaligned [34].

Very few fMRI studies have been done on the interaction between prosody and other, more abstract levels of linguistic information. Seminal studies on the processing of linguistic prosody per se involved comparing different types of filtered speech. These studies showed mixed results in terms of hemispheric lateralization, with some having identified right [35,36] but also some left [37] hemispheric involvement of temporal and frontal-opercular regions in relation to the modulation of pitch (i.e. intonation) during speech processing. The lateralization likely depends on which information is being extracted from the signal or on the control condition [38–41]. The processing of higher-level linguistic features such as syntax is known to be more left-lateralized involving regions such as the inferior frontal gyrus (IFG), and middle temporal gyrus [42–44]. The few studies that have focused on the question of prosody-syntax *interactions* using fMRI showed, for example, that in tonal languages (here: Mandarin), there are shared activations in the left but not right inferior frontal gyrus IFG between intonational (question vs. answer) and phonologically relevant tonal (word category) processing [45]. Another investigation similarly reported a role of the left IFG in processing

linguistically relevant intonational cues; this region's activation was modulated when those cues played a crucial role in sentence comprehension [41].

Although research has shown neural evidence for prosody-syntax interactions, more work is needed to fill the knowledge gap regarding how the brain processes these two linguistic features jointly in more *naturalistic* processing contexts. Most of the studies to date, especially those having used EEG, have exploited neural signals or activity emerging from the violation or disambiguation of prosodic or syntactic signals. In the context of EEG studies, this has allowed us to assess the neural markers of time-locked analyses [46], but has limited implications regarding the neural processing of syntactic and prosodic information during naturalistic speech perception. Moreover, controlled studies that make use of expectations or violations can be highly affected by error detection or other processes that are not central to syntactic judgments, again making it difficult to draw conclusions regarding the processing of prosody-syntax interactions per se [30].

In contrast to what can be assessed with well-controlled experimental paradigms, human communication is based on a very complex, multidimensional signal that spans different sensory modalities. Hence the use of tightly controlled experiments and reductionist, task-based paradigms fall short of an ecological characterization of the neural processes underlying naturalistic language processing [47]. The importance of the generalization of neuroscience research has gained attention in recent years, and the last decade has seen increased use of narratives in experimental designs, to simulate natural speech perception. For this, brain activity is measured during passive listening, to closely simulate the way that speech is processed in day-to-day contexts. In such studies, control over the effect(s) of interest can be applied *after* data collection, at the data analysis stage, thus increasing the flexibility and ecological validity of the experiment [48]. A driving force underlying this paradigm change is the increasingly flexible and powerful computational tools that are now becoming available to model the multidimensional, hierarchical, and interactive nature of human speech. Indeed, the use of machine learning techniques to statistically assess (and control for) different linguistic features has led to a new line of research that

takes advantage of state-of-the-art (linear or nonlinear) computational models of cognitive or neural function [49]. Importantly, such model-based encoding and decoding approaches allow results to be interpretable in light of proposed underlying cognitive and/or neural mechanisms [50] . Recent studies have already shown promising results in using linearized modeling approaches for pinpointing the neural signatures underlying the processing of semantics [51–53], syntax [54–56], phonetics [57,58] and acoustics [59–61]. These computational models of the different levels of the linguistic hierarchy have however often been investigated in isolation, and very few studies have looked at their possible interactions [52].

In the present study, we made use of naturalistic stimuli together with model-based decoding [49] to fill a crucial knowledge gap in how the cortical representation of syntax can be modulated by prosody in order to facilitate speech processing and overcome structural ambiguity. We used state-of-the-art machine learning techniques to compute the syntactic dependency structure serving to express functional relationships between words, and the prosodic boundaries of a speech corpus (TED talks).

While formally equally expressive [62], dependency grammars differ from phrase structure grammars because they do not posit unobserved constituents and create hierarchical syntactic representations entirely based on dependencies between words. In this respect then, dependencies are a more parsimonious representation, as they introduce only a minimal set of assumptions. Moreover, previous work has shown that after controlling for structural distance (which does not distinguish phrasal from dependency information), phrase structural predictors do not significantly contribute to an explanation of activity in the temporal lobe [63]. In fact, while dependency structures have been less explored than phrase structure grammar in neuroimaging, recent research has revealed the cognitive significance of looking at some of the operations underpinning the functional relationships among the words of a sentence, particularly left-side dependencies [64]. In this latter study, neural activation underlying two syntactic features that operationalize phrase and dependency structures were compared: closed phrase structures and left dependencies. Importantly, the left dependencies not only activated highly important areas of the language network such as

the left anterior temporal lobe, but it was even found that left inferior frontal activation was more specific to dependency than to phrase structure. These results thus corroborated the existence of a cortical network that supports the representation of the incremental build-up of dependency relations. Finally, the relevance of left dependencies for more complex syntactic operations is confirmed by many pieces of work in psycholinguistics based on dependency relations [65] and by work showing the interchangeability between dependency and phrase structure grammar [66–68].

Here, we first tested whether the strength of the prosodic boundaries present in the speech data was modulated as a function of left-side dependency when producing natural speech (TED talks). Then, in an existing magnetoencephalography (MEG) dataset of participants listening to the same TED talks, we investigated whether the neural encoding mirrors the prosodic-syntactic interaction we identified in the speech signal. Such a finding would provide biological evidence for ‘prosodic boosting’ of syntactic encoding in the adult brain, reflecting a neural mechanism that allows prosodic cues to increase the robustness of syntactic representations, and thus of successful speech comprehension.

Results

Stimulus spectrogram analysis

We first analyzed the TED talks spectrograms, to understand if the speakers used different prosodic cues in correspondence with the syntactic dependency structure of their utterances. Since the prosodic boundary strength is characterized by positive values as well as by a skewed distribution, we used a gamma mixture to model the strength distribution. The gamma-mixture model was fitted to the prosodic boundary strength distributions across all 4 TED talks. This analysis revealed two latent gamma distributions: Γ_1 with shape of 1.144 and rate of 2.807 and Γ_2 with shape of 13.964 and rate of 10.697. The gamma-mixture analysis resulted in a boundary between Γ_1 and Γ_2 at 1.01 prosodic boundary strength

(dimensionless quantity), thus dividing the words of the TEDLium corpora into high and low prosodic boundary strength content items (left panel, Fig. 2).

This binarization of the dataset allowed us to uncover the distribution of words with versus without syntactic left dependencies within these two latent prosody distributions. We found that in the presence of weak prosodic boundary strength, the percentage of words without a left dependency (54.63%) was greater than the one with a left dependency (45.37), whereas when the speakers used a strong prosodic boundary strength this pattern was reversed (31.25% for words without a left dependency and 68.75% for words with a left dependency) (right panel, Fig. 2). We then tested for differences in the proportion of words with versus without left dependencies across the two prosodic boundary strength categories, using chi-squared tests. Importantly, given the large number of words, we compared the strength of these effects with two different Pearson's chi-squared tests, simulating a power of 80% and effect size equal to a frequency shift at 5%. Both simulations were adjusted to the sample size of the prosodic category on which they were computed. This step generated a chi-squared test for the weak prosodic boundary strength cluster with degree-of-freedom (df) of 1 and non-central parameter (ncp) of 44.06, and a chi-squared test for the strong prosodic boundary strength cluster with df of 1 and ncp of 10.88. We found that while in the weak prosodic boundary strength cluster, the difference in the proportion of left dependencies was below a 5% frequency shift (p-value of our samples = $7.914e^{-10}$ > p-value of test distribution = $6.233\ e^{-14}$), the cluster with high prosodic boundary strength showed a strong bias towards words with left dependencies (p-value of our samples = $7.914e^{-10}$ < p-value of test distribution = $6.233\ e^{-14}$). These results suggest that the 4 speakers used stronger prosodic boundaries when producing words that had left syntactic dependencies.

These results allowed the formation of three different combinations of words that could then be evaluated in the brain decoding. The first one comprised a group of words

with a weak prosody boundary, called here ‘neutral’, that had either the presence or absence of a left dependency. A second group included words without a left dependency and a weak prosodic boundary, as well as words with a left dependency and a strong prosodic boundary, called here ‘coherent’ as it included the most statistically probable combination based on the stimuli analysis. Vice versa, the third and final group was composed of words with a left dependency and a weak prosodic boundary and words without left dependency and a strong prosodic boundary. This latter combination was called ‘incoherent’, since it had the least probable association of prosody and syntax given our analysis of the speech data. Crucially, the choice of the three sets allowed us to assess (1) the contribution of prosodic boundary strength into the encoding syntactic operation in the brain and (2) if the interaction between syntax and prosody that was seen in the stimuli was also mirrored within the cortical representation of the participants (see neural analysis).

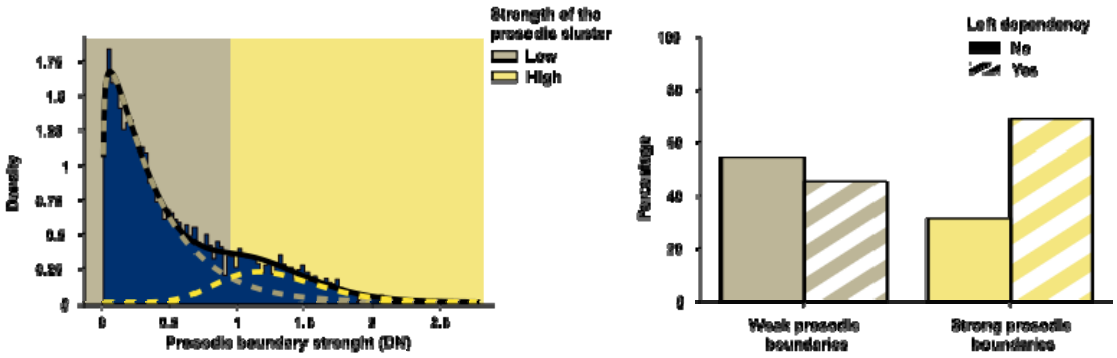

Figure 2. Results of the stimulus analysis. The left panel shows the two-Gamma Mixture Model that was used to binarize the words according to high or low prosodic boundary strength. The beige line indicates the probability distribution of words with a weak PB, while the yellow line represents the probability distribution of words with a strong prosodic boundary. The right panel shows the frequencies of words with and without a left dependency in the two prosody clusters.

Neural analysis

Our analysis of brain activity involved the multivariate decoding of syntactic information from brain activity using a combination of the mne-Python software and custom code.

The MEG data was divided into smaller trials based on word offsets, and a logistic classifier was trained to map brain activity to the presence or absence of left dependencies. Two types of classifications were performed: one using a classical multivariate pattern analysis (MVPA) thus concatenating MEG data across time and channels (Fig. 3), and another performing a temporal classification over the epoched data (Fig. 4). Importantly, the decoder was trained only on neutral combinations to evaluate the neural processing of syntactic information within a weak prosodic context, thus avoiding any inherent bias that was present in the stimuli. By generalizing the performance of the model across the neutral, coherent, and incoherent conditions, it was then possible to quantify and assess differences in the strength of syntactic representations in the brain under various prosodic conditions.

MVPA decoding

First, we tested whether the neural encoding of left dependencies was modulated by prosodic strength, in line with our stimulus analysis. Specifically, we test the hypothesis that syntactic dependency classification performance is highest in the “coherent” condition, where the presence of left dependency is coupled with strong prosodic cues. In the MVPA analysis of the pre-offset time windows (Fig. 3), we found that the classification performance of all the conditions was greater than chance (Coherent: acc. 0.526, C.I. [-0.009, 0.022], pVal < 0.001; Incoherent: acc. 0.507, C.I. [-0.006, 0.017], pVal = 0.02; Neutral: acc. 0.508, C.I. [-0.011, 0.017], pVal = 0.046). The coherent decoding was also found to be better in both neutral and incoherent conditions (Max>Inv: pVal = 0.002; Max>Train: pVal < 0.001). We also show similar results in the post-offset time window, where the coherent and neutral separability decoding was greater than chance (Coherent: acc. 0.536, C.I. [-0.011, 0.023], pVal < 0.001; Inchoerent: acc. 0.51, C.I. [-0.015, 0.028], pVal = 0.084; Neutral: acc. 0.522, C.I. [-0.01, 0.021], pVal < 0.001), again with the coherent

performance being better than the other test sets (Max > Inv: pVal = 0.009; Max > Train: pVal = 0.011).

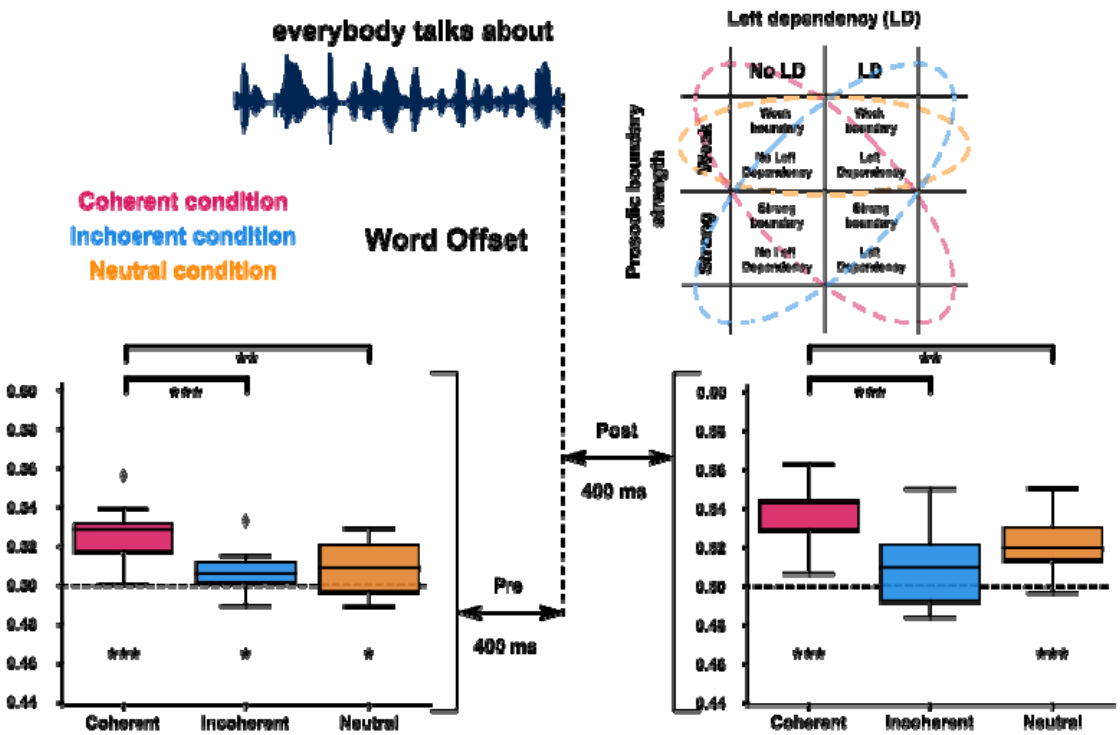

Figure 3. Results of the MVPA. We decoded the presence of left dependencies using the MEG activity within 400 ms time windows before and after stimulus offset, for the three generalizations sets (coherent in red, incoherent in blue and neutral in orange). The left panel corresponds to the decoding in the pre-stimulus offset time window, where we found that all three sets were decodable above chance. The right panel shows the decoding results for the post-stimulus offset window, where we found successful classification for the coherent and neutral sets. In both pre- and post-offset data, the different test sets were also compared to one another; in both cases, the coherent condition was found to be the set with the highest decodability. (*) pval<0.05; (**) pval<0.01; (***) pval<0.001.

Temporal decoding

The results of the temporal decoding analysis likewise showed significant encoding of syntactic dependencies in all three test sets (Fig. 4, upper row). The permutation test in the coherent condition revealed a cluster that spanned across both pre and post-word offsets, with a peak in the range around 0 and 200ms (Cluster 1 [-0.185, 0.411]sec, pVal = 0.001). In the incoherent condition, we found significant clusters only in the pre-offset period, between -300ms and 0 (Cluster 1 [-0.305, -0.225]sec, pVal = 0.02; Cluster 2 [-0.211,-0.004]sec, pVal = 0.002). Finally, in the neutral condition, we found a similar but weaker trend compared to the coherent one, with significant clusters spanning both pre and post-offset time windows

(Cluster 1 [-0.111, 0.056]sec, pVal = 0.004; Cluster 2 [0.136, 0.310]sec, pVal = 0.005).

In both contrasts comparing tests sets, we found that the presence of prosodic content boosted the strength of the syntactic classification (lower row, Fig. 4). The cluster-permutation test comparing coherent with the neutral condition showed significant clusters in the post-offset period (Cluster 1 [-0.065, 0.377]sec, pVal 0.001), as did the test comparing coherent with incoherent trials (Cluster 1 [0.036, 0.103]sec, pVal = 0.044; Cluster 2 [0.145,0.411]sec, pVal = 0.001). This demonstrates a coherence between patterns observed in the neural encoding of the syntax-prosody interaction and in those detected in the speech stimuli themselves.

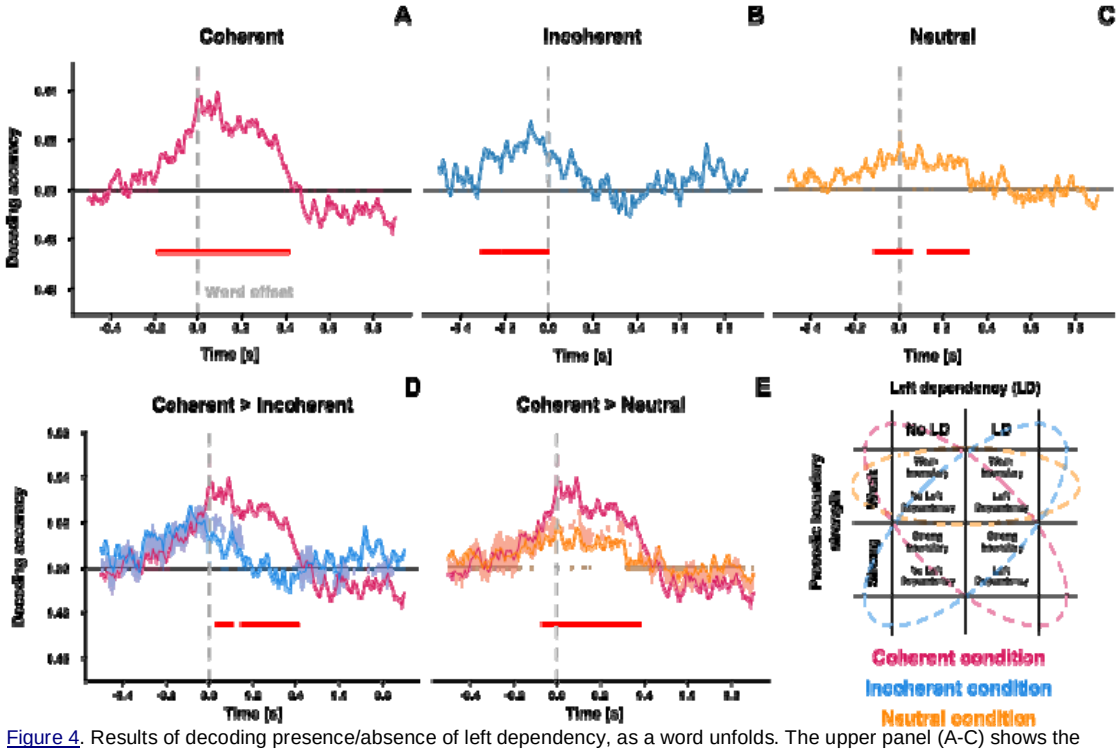

Figure 4. Results of decoding presence/absence of left dependency, as a word unfolds. The upper panel (A-C) shows the temporal classification accuracy in the coherent (red - A), Incoherent (blue - B) and neutral (yellow - C) sets. All three test sets performed above chance, but both decoding accuracy and the significant time windows differed across these sets. The performance of test sets was then directly compared (D and E), to identify the time windows during which the coherent set performed better than the incoherent and neutral ones. We found that in the post-stimulus time window of 100-400 ms, the decoding of syntactic dependencies in coherent condition (i.e. containing trials that had a combination of prosodic and syntactic features that was consistent with the pattern that was most frequently detected in the stimuli) was significantly stronger than for left dependencies with weak or mismatched prosodic boundary strength.\ Horizontal red lines represent significant results under cluster-based permutation tests.

Discussion

The purpose of this study was to shed light on the interaction between the processing of prosody and syntactic dependencies in the adult brain. We aimed at uncovering their relation within utterances produced by different TED talk speakers and within the neural representation of syntactic dependencies. We tested the hypothesis that the brain processes syntactic dependencies differently depending on the prosodic structure of the sentences; this would lend support to the idea that prosodic information is used by the brain to facilitate, and disambiguate, the representation of syntactic relationships during speech processing.

In our stimulus analysis, we showed that speakers modulate their speech output depending on the intended syntactic structure. More specifically, we showed that stronger prosodic boundaries were more likely to be placed on words that had a syntactic left dependency relation. Conversely, the speech utterances had a relatively weaker if not absent prosodic boundary for words that did not have a preceding functional relationship. These results are in line with known linguistic relationships between prosody and syntax in speech, based on evidence that the placement of stress or boundaries in intonational phrases can reflect the syntactic structure of the sentence [1,2]. Our findings support the presence of an interaction between the closure of functional relationships between words and prosodic cues, likely reflecting a mechanism whereby speakers, whether consciously or not, modulate their speech output to help the listener focus on the more salient syntactic relationships between words in order to facilitate comprehension.

Previous such evidence for prosody-syntax relationships has, however, not been investigated in speech corpora using fully automated, large-scale language models for the extraction of prosodic and syntactic features like the ones adopted here [69,70]. Instead, most of the research exploiting these powerful language parsers has been used for the extraction of prosodic and syntactic regularities from large amounts of data to produce better text-to-speech generators [71,72] or to improve the quality of syntactic parsing [73]. Deep learning

approaches can indeed be useful as they indirectly demonstrate a statistical relationship between prosody and syntax, but only a few of these studies have shown links that are linguistically interpretable [74]. Here, we used data-driven language models to allow the automated extraction of well-characterized linguistic features from a continuous, naturalistic speech signal, and as such our work contributes to a more focused and quantitative analysis of the interface between prosody and syntax than has been demonstrated to date.

In the MEG data analysis, we asked whether the neural processing of syntactic information is modulated by prosody, when listening to the same TED talks. We first trained a decoding model that was free of prosodic biases to learn the mapping of the syntactic dependency information in the neural data. Then, during generalization testing, we contrasted the decoding performance across words belonging to different combinations of prosodic and syntactic information. Two decoding methods were used to assess the relationship. Using MVPA, we tested time windows before and after the offset of each word to see if the neural processing of syntactic information may have differed across different prosody-syntax combinations. The second method made use of temporal decoding, to give us a finer-grained and continuous view of the dynamics of potential left dependency and prosodic boundary interactions. Both the MVPA and the temporal decoding analyses revealed that prosodic boundary strength was associated with better classification of the presence or absence of left dependencies, suggesting that the presence of prosodic cues leads to enhanced syntactic processing. Critically, we found this enhancement to underlie coherent rather than incoherent conditions, that is, for words with but not for those without a left dependency. This neural boosting of syntactic processing by prosody aligns with our observation that words with more left dependencies are produced with stronger prosodic boundary cues in the speech signal itself. To further validate the specificity of this effect, we additionally analyzed the temporal decoding within the 4 classes separately (see Supplementary materials). Results confirmed that the high decoding accuracy of the coherent condition is driven by words having high prosodic boundary strength and left dependencies.

Our finding aligns with previous work showing the relevance of prosody in the modulating brain markers of sentence structures and syntactic operations [27,29–31,33,75], but our work further shows that prosody results in a syntactic representational gain in the neural signal. Such a finding is not achievable with classical disambiguation studies. Our result is highly important, especially in the context of linguistic information theory, which posits that language structure is organized such as to optimize efficiency at the service of communication and learning [76]. Specifically, our findings suggest that the temporal co-occurrence or alignment of prosodic cues, grounded in the acoustic signal, and of higher-level, abstract linguistic features can enhance, or boost the neural processing of higher-level linguistic operations. This finding is relevant for evolutionary theories of language, as it could suggest that prosodic cues might have either co-evolved with or even preceded the evolution of syntax, to assist the structuring of human speech. In this context, theorists have already proposed that, as early forms of communication gradually transformed from protolanguages to complex hierarchical structures, prosody likely served as a foundational element in influencing the evolution of complex grammatical systems [77,78].

Our temporal decoding analysis revealed interesting qualitative patterns before and after word offsets. In all conditions, decoding performance was above chance even before word offsets. This suggests the presence of predictive mechanisms, whereby the brain is anticipating the closure of functional relationships between words before the words are completely heard. In the coherent condition, significant decoding lasts up to 400ms *after* word offsets, suggesting an additive contribution of acoustic cues (i.e. presence of prosodic boundary strength) to the higher order processing underlying speech comprehension following syntactic closures [75]. In other words, the presence of prosodic information appears to promote longer-lasting neural processing of syntax, possibly arising from reverberating top-down and bottom-up processing during comprehension. Interestingly, the brain decoding of the words that contained mismatching syntax-prosody combinations (i.e. left dependency but weak prosodic boundary strength, or no left dependency and strong prosodic boundary strength) (i.e. incoherent conditions) showed above-chance performance until word offset,

but not afterward. We speculate that this shorter-lasting neural signature of syntactic processing may be due to possible interference arising from syntax-prosodic combinations that are divergent from the statistical regularities to which our brain is normally exposed. Similar results have also been found in ERPs studies, where it has been shown that superfluous prosodic breaks (i.e. ones that don't coincide with syntactic breaks) disrupt sentence processing (i.e. comprehension) more than missing prosodic breaks (i.e. absence of prosodic break at the position of syntactic break) [29,30].

Our decoding analysis of MEG data limits our ability to localize brain regions involved in the prosody-syntax interface. Previous studies looking at the brain networks modulated by linguistic prosody per se have shown the involvement of regions within the ventral and dorsal pathways spanning the superior temporal lobe and sulcus, premotor cortex, posterior temporal lobe and IFG, often biased towards the right hemisphere [38,79] but found also in the left, or bilaterally [80–82]. Interestingly, two of these areas – the posterior temporal lobe and IFG – have historically been considered to also play a crucial role as hubs for syntactic processing [83–85]. It can be thus hypothesized that the posterior temporal lobe and the inferior frontal gyrus (IFG) may be possible loci for the interface between prosody and syntax. Indeed, recent findings seem to indicate the involvement of the left IFG in cases where intonation is used to establish sentence structure [41,86]. Further investigation on the role of linguistic prosody, especially in interaction with syntax, remains to be conducted. This work could for example employ functional connectivity analyses, to shed light on how the respective networks interact to support synergistic interaction between different levels of (para-)linguistic processing. This research ought ideally to also integrate more complex models that can disentangle the amount of information conveyed by prosody and its potential to benefit the structuring of human speech. For example, extending our computational approach to data with higher spatial resolution, such as fMRI, could uncover the neural architecture that exploits prosodic information to enhance the cortical representation of syntactic structures.

Methods

MEG data acquisition and preprocessing

We made use of an existing MEG dataset obtained from 11 participants in previously published work (20-34 years; 5 female) [57]. The MEG signals were recorded using a 275-channel VSM/CTF system, with a sampling rate of 2400 Hz and low-pass filtered at 660 Hz. Eye movements and blinks were recorded using 2 bipolar electro-oculographic (EOG) channels.

Independent component analysis was used to remove artifacts due to eye movement and heartbeats. The MEG signal from each channel was subsequently visually inspected to remove those containing excessive broadband power spectra. For the coregistration between anatomical data and the MEG channels, the head shape of each participant was digitized using Polhemus Isotrak (Polhemus Inc., USA), based on T1-weighted structural MRI data (1.5 T, 240 x 240 mm field of view, 1 mm isotropic, sagittal orientation).

Forward modeling was computed on the MEG data using the overlapping-sphere model [87]. Noise normalized minimum norm operator was used to estimate the inverse solution [88]. Further, singular value decomposition was performed on the resolution matrices defining the source space. For each session and subject, this operation produced a set of M singular vectors reflecting an orthogonal space on which the coregistered data was projected. By taking the 99% cut-off of the singular value spectrum, we defined a low-dimensional space X_c over which the decoding analysis was computed. For further details regarding the data preparation, see [57].

Speech stimuli

The speech stimuli used during the MEG acquisition comprised of 4 different talks (Daniel Kahneman, James Cameron, Jane McGonigal, and Tom Wujec), extracted from the TEDLium corpus [89]. Seven audio files were created by splitting three TED talks into two

parts, while one was kept intact. Audio files lasted 509 secs on average, and only one was played during each block of MEG acquisition. There were 7 blocks in total, with an average length of 8.49 min [+/- sd of 1.24 mins] (see supplementary material for more information).

The speech stimuli were forced-aligned to the TED talk text, extracted from the online transcripts using the Montreal forced aligner (MFA, [90]. The automatic alignment was implemented with the LibriSpeech corpora [91], available as an MFA model. The output of the alignment was examined, and corrected manually using the Praat software [92].

Further stimulus adjustments were done to optimize the following MEG analysis (see Decoding section). First, out-of-dictionary tokens were labeled as <unk> and removed from the set. Second, to avoid positional confounds due to end-of-sentence effects, the last word of each sentence was also removed.

The complete preprocessing of the TED talks produced a stimulus set consisting of 1723 unique words that were subsequently used in the stimulus and MEG data analysis.

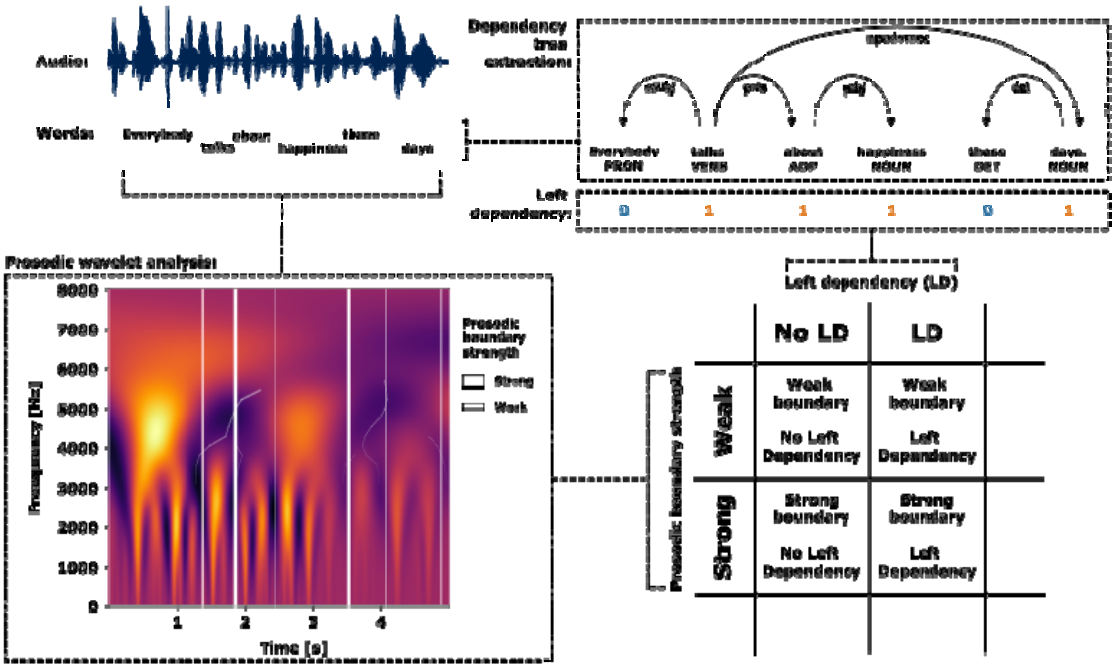

Figure 1. Pipeline for the extraction of the syntactic and prosodic features from the stimuli. Top right corner shows that we first extracted the dependency trees from the text annotation using Spacy. We then marked each word in the text based on the presence (1 - orange) or absence (0 - blue) of left dependency relations. Bottom left corner shows that we computed a wavelet analysis of the stimulus acoustics to extract the prosodic boundaries (PB - red lines). Prosodic boundaries varied in their strength, depending on the local spectral characteristics of the speech stimuli (thickness of the lines reflects stronger

boundaries). Finally, using gamma mixtures models we binarized the prosodic boundaries in two groups, to allow investigation of the prosody - syntax interaction in a 2x2 factorial design.

Prosodic and syntactic features in the speech stimuli

Two sets of features were extracted from the text and audio signal to characterize the syntactic and prosodic components, respectively (Fig. 1). The sentences obtained from the online transcriptions of the selected TED talks were tokenized, tagged with their Part-of-Speech label, and finally annotated with an automatic dependency parser. The complete annotation was performed using the pre-trained Spacy pipeline (en_core_web_trf, version 3.2.4, https://spacy.io/), with the RoBERTa transformer [70]. After the dependency parsing was computed, we first counted the number of left-side edges for each word in the dataset and assigned each word from the stimulus set to two different classes. One class represented the group of words that had a left dependency relation, and the other represented the group of words that didn't have a left dependency [64].

In the second step, we computed a spectro-temporal analysis of the audio files to extract the word duration, the energy, and the f_0 information. The time courses of these three features were then combined and analyzed via wavelet transform. The spectrogram obtained after this last step was used to evaluate the maps of minimal power around word offsets to assess the prosodic boundary strength associated with each word. This unsupervised modeling of prosodic information was computed using the Wavelet Prosodic Toolkit (https://github.com/asuni/wavelet_prosody_toolkit), which has been shown to perform as well as gold standard approaches for the annotation of prosodic boundaries [69]. Words that were automatically tagged with prosodic boundary strength equal to 0 were discarded from further analysis as they did not contain meaningful spectral content. The prosodic distribution of the data was subsequently modeled using a two-Gamma Mixture model to cluster the complete stimulus set into two latent distributions. This step allowed us to classify the prosodic content of each word within the binary categories of weak and strong prosodic boundary strength. The final feature matrix Y describing our stimuli was thus comprised of a syntactic feature

characterizing the words as having or not having a left dependency, and of a prosodic feature characterizing the words as having a weak or strong prosodic boundary strength (Fig. 1).

Assessing the prosody-syntax interaction in the stimuli

To assess the interaction between prosodic and syntactic dependency information in the stimuli, we first separated all the words present in the dataset based on the weak or strong prosodic boundary strength content. We then compared these two groups regarding their percentage of words that did or did not have a left-side dependency relation. This allowed us to examine whether or not prosodic boundary strength was modulated in relation to syntactic dependencies during the production of the selected TED talks.

Model-based decoding of syntax in the MEG data

The multivariate decoding of syntactic information from brain activity was implemented using a combination of the mne-Python software (version 1.0, https://github.com/mne-tools/mne-python) and custom code. The low-dimensional MEG data X_c was separated into smaller trials by extracting the brain activity before and after each word offset. Trials with an inter-trial offset interval of less than 100 ms were discarded. Following that, a logistic classifier was trained to learn a linear mapping between the brain activity and the presence or absence of left dependencies. Two different types of classifications were computed. First, MEG data was concatenated across time and channels in the time windows pre-word and post-word offset to assess the general prosodic boosting, with the prediction that syntactic decoding performance would be modulated by prosodic boundary strength in a way that is coherent with the pattern obtained in the stimuli themselves. Second, a refined decoding analysis of each time point between 400ms pre-offset and 800ms post-offset was done, to assess finer temporal modulation patterns of the cortical processing of left dependencies.

Training and test data sets

The data to be used for training versus testing was selected based on the data-driven modeling computed on the word stimuli. Following the analysis of the stimuli (see 'Stimulus analysis' subsection of the Results), the training set was created by selecting only words having a weak prosodic boundary strength, including an equal number of words with and without left dependencies. This allowed us to obtain a classifier that was not influenced by the different levels of prosodic content, and that was syntactically balanced.

The model was assessed using three different test sets, each containing the same number of words from each left dependency category (i.e. with and without left dependencies) that were not overlapping across sets or repeating from the training sample. The first test set, similar to the training dataset, contained only words that had low prosodic boundary strength (*neutral*). The second set contained words having a left dependency and strong prosodic boundary strength, and words without a left dependency and weak prosodic boundary strength (*coherent*). The final set contained words having a left dependency but weak prosodic boundary strength, and words without a left dependency but with strong prosodic boundary strength (*incoherent*). The final training and testing sets were composed of 3740 words and 654 words respectively. These three different sets aim to characterize syntactic distributions (i.e. presence or absence of left dependencies) within different combinations of high and low prosodic boundary strength content. More specifically, we expected to find stronger syntactic encoding in the test set that was coherent with the results shown in the stimulus analysis (i.e. in the high separability set). Moreover, this procedure allowed us to quantify differences in the strength of syntactic encoding across the conditions, given that they were balanced such as each include the same number of stimuli with versus without left dependencies.

MVPA of pre and post-word offset

We used a logistic classifier (regularization parameter C = 1) to predict the presence of words with or without left dependencies. This linear mapping was tested by pooling all the brain activity timepoint x channel in two separate time windows: a 400 ms window before word offset and a 400 ms one after word offset. We hypothesized that the MVPA approach would also show that the encoding of left dependencies is modulated by the presence of prosodic information, i.e. that we'll find evidence for prosodic boosting of syntactic processing.

MVPA statistics

We evaluated the performance of the model by assessing the area under the curve (AUC) of the classification against chance (50%) on the test sets. The training and testing were repeated by performing 10-fold randomized cross-validation. The differences across the three conditions and against chance level were assessed in a second-level analysis via paired permutation testing with 2046 permutations (permutation_test of mlxtend package).

Temporal decoding

A single regularized logistic classifier was trained for each time point, and optimized via nested 5-fold cross-validation. The regularization parameter *C* was selected during nested cross-validation via a log-spaced grid search between 10^{-5} and 10^{5}.

The best temporal model obtained after the grid search was then tested by estimating the AUC of the classification (sklearn.metric.roc_auc_score) across each of the different conditions described above: neutral, incoherent and coherent.

The AUC results across these three test sets were used for two different contrasts to assess the effects of prosodic boundaries on the decodability of syntactic left dependencies from brain activity. In the first contrast, the coherent condition was tested against the neutral condition, while in the second we compared coherent against incoherent separability. Critically, while the first contrast allowed us to understand the effect of prosodic content on

left dependencies, the second verified that the prosodic boosting is specific to words with left dependencies.

Temporal decoding statistics

Similarly to the MVPA analysis, the temporal decoding results were evaluated using a cluster-based permutation test. The temporal decoding of the three test sets as well as of the two contrasts were extracted for each participant, and tested against chance (50%) in a second-level analysis. To do this we ran a non-parametric cluster-level paired t-test with 2046 permutations ($2^{\#ofSubjects}$) on the AUC time series obtained from each participant (mne.stats.permutation_cluster_1samp_test).

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Data availability

The decoding data files to reproduce the results using the Github code are available at figshare (https://figshare.com/s/0b2c756284f19ba9bd39). The raw data are available for research purposes only upon request from the corresponding author (giulio.degano@unige.ch) or Peter Donhauser (peter.donhauser@esi-frankfurt.de), because of constraints imposed by the ethics approval under which this study was conducted.

Code availability

The code for the stimulus analysis and results visualization is available at GitHub (https://github.com/gDegano/MEG_ProsodyEnhSyntax)

Author information

Authors and Affiliations

Department of Psychology, Faculty of Psychology and Educational Sciences, University of Geneva, Geneva, Switzerland.

Giulio Degano and Narly Golestani

Brain and Language Lab, Cognitive Science Hub, University of Vienna.

Narly Golestani

Dept of Behavioral and Cognitive Biology, Faculty of Life Sciences, University of Vienna.

Narly Golestani

Ernst Strüngmann Institute for Neuroscience in Cooperation with Max Planck Society, Frankfurt am Main, Germany.

Peter Donhauser

Department of Neurosurgery, University of California, San Francisco, California, USA

Laura Gwilliams

Department of Linguistics, University of Geneva, Geneva, Switzerland.

Paola Merlo

University Centre for Informatics, University of Geneva, Geneva, Switzerland.

Paola Merlo

Contributions

Conceptualization: G.D., N.G.; Methodology: G.D., L.G.; Software: G.D.; Formal analysis: G.D., N.G., L.G., P.M.; Investigation: G.D. N.G..; Resources: N.G.; Data curation: G.D. P.D..; Writing—original draft: G.D., N.G.; Writing—review and editing: G.D., N.G., L.G., P.D., P.M.; Visualization: G.D.; Supervision: N.G.; Funding acquisition: N.G.

Corresponding author

Correspondence to Giulio Degano

Ethics declarations

Competing interests

The authors declare no competing interests.

1. Elfner, E. The syntax-prosody interface: current theoretical approaches and outstanding questions. *Linguistics Vanguard* **4**, (2018).
2. Wagner, M. & Watson, D. G. Experimental and theoretical advances in prosody: A review. *Lang. Cogn. Process.* **25**, 905–945 (2010).
3. Morgan, J. L. & Demuth, K. *Signal to Syntax: Bootstrapping From Speech To Grammar in Early Acquisition*. (Psychology Press, 1996).
4. Christophe, A., Guasti, T. & Nespor, M. Reflections on phonological bootstrapping: Its role for lexical and syntactic acquisition. *Lang. Cogn. Process.* **12**, 585–612 (1997).
5. Hawthorne, K. & Gerken, L. From pauses to clauses: prosody facilitates learning of syntactic constituency. *Cognition* **133**, 420–428 (2014).
6. Massicotte-Laforge, S. & Shi, R. The role of prosody in infants' early syntactic analysis and grammatical categorization. *J. Acoust. Soc. Am.* **138**, EL441–6 (2015).

7. Bion, R. A. H., Benavides-Varela, S. & Nespor, M. Acoustic markers of prominence influence infants' and adults' segmentation of speech sequences. *Lang. Speech* **54**, 123–140 (2011).
8. Millotte, S. *et al.* Phrasal prosody constrains word segmentation in French 16-month-olds. *J Port Linguist* **10**, 67–86 (2011).
9. Gervain, J. & Werker, J. F. Prosody cues word order in 7-month-old bilingual infants. *Nat. Commun.* **4**, 1490 (2013).
10. Mehler, J. *et al.* A precursor of language acquisition in young infants. *Cognition* **29**, 143–178 (1988).
11. Nazzi, T., Bertoncini, J. & Mehler, J. Language discrimination by newborns: toward an understanding of the role of rhythm. *J. Exp. Psychol. Hum. Percept. Perform.* **24**, 756–766 (1998).
12. Ghio, M., Cara, C. & Tettamanti, M. The prenatal brain readiness for speech processing: A review on foetal development of auditory and primordial language networks. *Neurosci. Biobehav. Rev.* **128**, 709–719 (2021).
13. Gervain, J. & Geffen, M. N. Efficient Neural Coding in Auditory and Speech Perception. *Trends Neurosci.* **42**, 56–65 (2019).
14. Jardri, R. *et al.* Fetal cortical activation to sound at 33 weeks of gestation: a functional MRI study. *Neuroimage* **42**, 10–18 (2008).
15. Chi, J. G., Dooling, E. C. & Gilles, F. H. Gyral development of the human brain. *Ann. Neurol.* **1**, 86–93 (1977).
16. Granier-Deferre, C., Ribeiro, A., Jacquet, A.-Y. & Bassereau, S. Near-term fetuses process temporal features of speech. *Dev. Sci.* **14**, 336–352 (2011).
17. Granier-Deferre, C., Ribeiro, A., Jacquet, A.-Y. & Bassereau, S. Near-term fetuses process temporal features of speech. *Dev. Sci.* **14**, 336–352 (2011).
18. Griffiths, S. K., Brown, W. S., Gerhardt, K. J., Abrams, R. M. & Morris, R. J. The perception of speech sounds recorded within the uterus of a pregnant sheep. *The Journal of the Acoustical Society of America* vol. 96 2055–2063 Preprint at

https://doi.org/10.1121/1.410147 (1994).

19. Querleu, D., Renard, X., Versyp, F., Paris-Delrue, L. & Crèpin, G. Fetal hearing. *Eur. J. Obstet. Gynecol. Reprod. Biol.* **28**, 191–212 (1988).
20. Richards, D. S., Frentzen, B., Gerhardt, K. J., McCann, M. E. & Abrams, R. M. Sound levels in the human uterus. *Obstet. Gynecol.* **80**, 186–190 (1992).
21. Jusczyk, P. W., Houston, D. M. & Newsome, M. The beginnings of word segmentation in english-learning infants. *Cogn. Psychol.* **39**, 159–207 (1999).
22. Ma, W., Golinkoff, R. M., Houston, D. & Hirsh-Pasek, K. Word Learning in Infant- and Adult-Directed Speech. *Lang. Learn. Dev.* **7**, 185–201 (2011).
23. Kreiner, H. & Eviatar, Z. The missing link in the embodiment of syntax: prosody. *Brain Lang.* **137**, 91–102 (2014).
24. Langus, A., Marchetto, E., Bion, R. A. H. & Nespor, M. Can prosody be used to discover hierarchical structure in continuous speech? *J. Mem. Lang.* **66**, 285–306 (2012).
25. Nakamura, C., Arai, M. & Mazuka, R. Immediate use of prosody and context in predicting a syntactic structure. *Cognition* **125**, 317–323 (2012).
26. Kjelgaard, M. M. & Speer, S. R. Prosodic Facilitation and Interference in the Resolution of Temporary Syntactic Closure Ambiguity. *J. Mem. Lang.* **40**, 153–194 (1999).
27. Bögels, S., Schriefers, H., Vonk, W., Chwilla, D. J. & Kerkhofs, R. The interplay between prosody and syntax in sentence processing: the case of subject- and object-control verbs. *J. Cogn. Neurosci.* **22**, 1036–1053 (2010).
28. Kerkhofs, R., Vonk, W., Schriefers, H. & Chwilla, D. J. Discourse, syntax, and prosody: the brain reveals an immediate interaction. *J. Cogn. Neurosci.* **19**, 1421–1434 (2007).
29. Pauker, E., Itzhak, I., Baum, S. R. & Steinhauer, K. Effects of cooperating and conflicting prosody in spoken English garden path sentences: ERP evidence for the boundary deletion hypothesis. *J. Cogn. Neurosci.* **23**, 2731–2751 (2011).
30. Bögels, S., Schriefers, H., Vonk, W., Chwilla, D. J. & Kerkhofs, R. Processing consequences of superfluous and missing prosodic breaks in auditory sentence comprehension. *Neuropsychologia* **51**, 2715–2728 (2013).

31. Honbolygó, F., Török, Á., Bánréti, Z., Hunyadi, L. & Csépe, V. ERP correlates of prosody and syntax interaction in case of embedded sentences. *J. Neurolinguistics* **37**, 22–33 (2016).
32. Steinhauer, K., Alter, K. & Friederici, A. D. Brain potentials indicate immediate use of prosodic cues in natural speech processing. *Nat. Neurosci.* **2**, 191–196 (1999).
33. Itzhak, I., Pauker, E., Drury, J. E., Baum, S. R. & Steinhauer, K. Event-related potentials show online influence of lexical biases on prosodic processing. *Neuroreport* **21**, 8–13 (2010).
34. Glushko, A., Poeppel, D. & Steinhauer, K. Overt and implicit prosody contribute to neurophysiological responses previously attributed to grammatical processing. *Sci. Rep.* **12**, 14759 (2022).
35. Meyer, M., Steinhauer, K., Alter, K., Friederici, A. D. & von Cramon, D. Y. Brain activity varies with modulation of dynamic pitch variance in sentence melody. *Brain Lang.* **89**, 277–289 (2004).
36. Plante, E., Creusere, M. & Sabin, C. Dissociating sentential prosody from sentence processing: activation interacts with task demands. *Neuroimage* **17**, 401–410 (2002).
37. Kreitewolf, J., Friederici, A. D. & von Kriegstein, K. Hemispheric lateralization of linguistic prosody recognition in comparison to speech and speaker recognition. *Neuroimage* **102 Pt 2**, 332–344 (2014).
38. Sammler, D., Grosbras, M.-H., Anwander, A., Bestelmeyer, P. E. G. & Belin, P. Dorsal and Ventral Pathways for Prosody. *Curr. Biol.* **25**, 3079–3085 (2015).
39. Wildgruber, D., Ackermann, H., Kreifelts, B. & Ethofer, T. Cerebral processing of linguistic and emotional prosody: fMRI studies. *Prog. Brain Res.* **156**, 249–268 (2006).
40. Chien, P.-J., Friederici, A. D., Hartwigsen, G. & Sammler, D. Neural correlates of intonation and lexical tone in tonal and non-tonal language speakers. *Hum. Brain Mapp.* **41**, 1842–1858 (2020).
41. van der Burght, C. L., Goucha, T., Friederici, A. D., Kreitewolf, J. & Hartwigsen, G. Intonation guides sentence processing in the left inferior frontal gyrus. *Cortex* **117**, 122–

134 (2019).

42. Hagoort, P. Nodes and networks in the neural architecture for language: Broca's region and beyond. *Curr. Opin. Neurobiol.* **28**, 136–141 (2014).
43. Matchin, W. & Hickok, G. The Cortical Organization of Syntax. *Cereb. Cortex* **30**, 1481–1498 (2020).
44. Friederici, A. D. *Language in Our Brain: The Origins of a Uniquely Human Capacity*. (MIT Press, 2017).
45. Chien, P.-J., Friederici, A. D., Hartwigsen, G. & Sammler, D. Neural correlates of intonation and lexical tone in tonal and non-tonal language speakers. *Hum. Brain Mapp.* **41**, 1842–1858 (2020).
46. Luck, S. J. *An Introduction to the Event-Related Potential Technique, second edition*. (MIT Press, 2014).
47. Nastase, S. A., Goldstein, A. & Hasson, U. Keep it real: rethinking the primacy of experimental control in cognitive neuroscience. *Neuroimage* **222**, 117254 (2020).
48. Hamilton, L. S. & Huth, A. G. The revolution will not be controlled: natural stimuli in speech neuroscience. *Lang Cogn Neurosci* **35**, 573–582 (2020).
49. Ivanova, A. A. *et al.* Beyond linear regression: mapping models in cognitive neuroscience should align with research goals. *arXiv [q-bio.NC]* (2022).
50. Bouton, S., Chambon, V., Golestani, N., Formisano, E. & Giraud, A.-L. Interpretability of statistical approaches in speech and language neuroscience. *PsyArXiv* (2019).
51. Broderick, M. P., Anderson, A. J. & Lalor, E. C. Semantic Context Enhances the Early Auditory Encoding of Natural Speech. *J. Neurosci.* **39**, 7564–7575 (2019).
52. de Heer, W. A., Huth, A. G., Griffiths, T. L., Gallant, J. L. & Theunissen, F. E. The Hierarchical Cortical Organization of Human Speech Processing. *J. Neurosci.* **37**, 6539–6557 (2017).
53. Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E. & Gallant, J. L. Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature* **532**, 453–458 (2016).

54. Pallier, C., Devauchelle, A.-D. & Dehaene, S. Cortical representation of the constituent structure of sentences. *Proc. Natl. Acad. Sci. U. S. A.* **108**, 2522–2527 (2011).

55. Brennan, J. *et al.* Syntactic structure building in the anterior temporal lobe during natural story listening. *Brain Lang.* **120**, 163–173 (2012).

56. Brennan, J. R., Dyer, C., Kuncoro, A. & Hale, J. T. Localizing syntactic predictions using recurrent neural network grammars. *Neuropsychologia* **146**, 107479 (2020).

57. Donhauser, P. W. & Baillet, S. Two Distinct Neural Timescales for Predictive Speech Processing. *Neuron* **105**, 385–393.e9 (2020).

58. Mesgarani, N., Cheung, C., Johnson, K. & Chang, E. F. Phonetic feature encoding in human superior temporal gyrus. *Science* **343**, 1006–1010 (2014).

59. Rutten, S., Santoro, R., Hervais-Adelman, A., Formisano, E. & Golestani, N. Cortical encoding of speech enhances task-relevant acoustic information. *Nat Hum Behav* **3**, 974–987 (2019).

60. Santoro, R. *et al.* Reconstructing the spectrotemporal modulations of real-life sounds from fMRI response patterns. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 4799–4804 (2017).

61. Tang, C., Hamilton, L. S. & Chang, E. F. Intonational speech prosody encoding in the human auditory cortex. *Science* **357**, 797–801 (2017).

62. Lombardo, V. & Lesmo, L. Formal aspects and parsing issues of dependency theory. in *COLING 1998 Volume 2: The 17th International Conference on Computational Linguistics* (1998).

63. Li, J. & Hale, J. Grammatical predictors for fMRI time-courses. in (Oxford University Press, 2019).

64. Lopopolo, A., van den Bosch, A., Petersson, K.-M. & Willems, R. M. Distinguishing syntactic operations in the brain: Dependency and phrase-structure parsing. *Neurobiology of Language* **2**, 152–175 (2021).

65. Gibson, E. Linguistic complexity: locality of syntactic dependencies. *Cognition* **68**, 1–76 (1998).

66. Xia, F. & Palmer, M. Converting Dependency Structures to Phrase Structures. in

Proceedings of the First International Conference on Human Language Technology Research (2001).

67. Johansson, R. & Nugues, P. Extended Constituent-to-Dependency Conversion for English. in *Proceedings of the 16th Nordic Conference of Computational Linguistics (NODALIDA 2007)* 105–112 (2007).
68. Wang, Z. & Zong, C. Phrase Structure Parsing with Dependency Structure. in *Coling 2010: Posters* 1292–1300 (2010).
69. Suni, A., Šimko, J., Aalto, D. & Vainio, M. Hierarchical representation and estimation of prosody using continuous wavelet transform. *Comput. Speech Lang.* **45**, 123–136 (2017).
70. Liu, Y. *et al.* RoBERTa: A Robustly Optimized BERT Pretraining Approach. *arXiv [cs.CL]* (2019).
71. Hodari, Z. *et al.* Camp: A Two-Stage Approach to Modelling Prosody in Context. in *ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* 6578–6582 (2021).
72. Tyagi, S., Nicolis, M., Rohnke, J., Drugman, T. & Lorenzo-Trueba, J. Dynamic Prosody Generation for Speech Synthesis using Linguistics-Driven Acoustic Embedding Selection. *arXiv [cs.CL]* (2019).
73. Tran, T. *et al.* Parsing Speech: a Neural Approach to Integrating Lexical and Acoustic-Prosodic Information. *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)* Preprint at https://doi.org/10.18653/v1/n18-1007 (2018).
74. Köhn, A., Baumann, T. & Dörfler, O. An Empirical Analysis of the Correlation of Syntax and Prosody. *arXiv [cs.CL]* (2018).
75. Bögels, S., Schriefers, H. & Vonk, W. Prosodic Breaks in Sentence Processing Investigated by Event□Related Potentials. *Language* (2010) doi:10.1111/j.1749-818X.2011.00291.x.

76. Gibson, E. *et al.* How Efficiency Shapes Human Language. *Trends Cogn. Sci.* **23**, 1087 (2019).

77. Brown, S. A Joint Prosodic Origin of Language and Music. *Front. Psychol.* **8**, 1894 (2017).

78. Benítez-Burraco, A. & Elvira-García, W. Human self-domestication and the evolution of prosody. *Lang. Linguist. Compass* **17**, e12485 (2023).

79. Meyer, M., Steinhauer, K., Alter, K., Friederici, A. D. & von Cramon, D. Y. Brain activity varies with modulation of dynamic pitch variance in sentence melody. *Brain Lang.* **89**, 277–289 (2004).

80. Doherty, C. P., West, W. C., Dilley, L. C., Shattuck-Hufnagel, S. & Caplan, D. Question/statement judgments: an fMRI study of intonation processing. *Hum. Brain Mapp.* **23**, 85–98 (2004).

81. Chien, P.-J., Friederici, A. D., Hartwigsen, G. & Sammler, D. Neural correlates of intonation and lexical tone in tonal and non-tonal language speakers. *Hum. Brain Mapp.* **41**, 1842–1858 (2020).

82. Wildgruber, D., Ackermann, H., Kreifelts, B. & Ethofer, T. Cerebral processing of linguistic and emotional prosody: fMRI studies. *Prog. Brain Res.* **156**, 249–268 (2006).

83. Friederici, A. D. *Language in Our Brain: The Origins of a Uniquely Human Capacity*. (MIT Press, 2017).

84. Matchin, W. & Hickok, G. The Cortical Organization of Syntax. *Cereb. Cortex* **30**, 1481–1498 (2020).

85. Hagoort, P. Nodes and networks in the neural architecture for language: Broca's region and beyond. *Curr. Opin. Neurobiol.* **28**, 136–141 (2014).

86. van der Burght, C. L., Numssen, O., Schlaak, B., Goucha, T. & Hartwigsen, G. Differential contributions of inferior frontal gyrus subregions to sentence processing guided by intonation. *Hum. Brain Mapp.* **44**, 585–598 (2023).

87. Huang, M. X., Mosher, J. C. & Leahy, R. M. A sensor-weighted overlapping-sphere head model and exhaustive head model comparison for MEG. *Phys. Med. Biol.* **44**, 423–440

(1999).

88. Dale, A. M. *et al.* Dynamic statistical parametric mapping: combining fMRI and MEG for high-resolution imaging of cortical activity. *Neuron* **26**, 55–67 (2000).
89. Rousseau, Deléglise & Esteve. TED-LIUM: an Automatic Speech Recognition dedicated corpus. *LREC Int. Conf. Lang. Resour. Eval.* (2014).
90. McAuliffe, M., Socolof, M., Mihuc, S., Wagner, M. & Sonderegger, M. Montreal Forced Aligner: Trainable Text-Speech Alignment Using Kaldi. *Interspeech 2017* Preprint at https://doi.org/10.21437/interspeech.2017-1386 (2017).
91. Panayotov, V., Chen, G., Povey, D. & Khudanpur, S. Librispeech: An ASR corpus based on public domain audio books. in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* 5206–5210 (2015).
92. Boersma, P. Praat, a system for doing phonetics by computer. *Glot. Int.* **5**, 341–345 (2001).