Decomposing lexical and compositional syntax and semantics with deep language models

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Abstract

The activations of language transformers like GPT2 have been shown to linearly map onto brain activity during speech comprehension. However, the nature of these activations remains largely unknown and presumably conflate distinct linguistic classes. Here, we propose a taxonomy to factorize the high-dimensional activations of language models into four combinatorial classes: lexical, compositional, syntactic, and semantic representations. We then introduce a statistical method to decompose, through the lens of GPT2's activations, the brain activity of 345 subjects recorded with functional magnetic resonance imaging (fMRI) during the listening of 4.6 hours of narrated text. The results highlight two findings. First, compositional representations recruit a more widespread cortical network than lexical ones, and encompass the bilateral temporal, parietal and prefrontal cortices. Second, contrary to previous claims, syntax and semantics are not associated with separated modules, but, instead, appear to share a common and distributed neural substrate. Overall, this study introduces a general framework to isolate the distributed representations of linguistic constructs generated in naturalistic settings.

1. Linguistic representations in brains and deep networks.

Within less than three years, transformers (Devlin et al., 2019; Radford et al., 2019) have enabled remarkable progress in natural language processing. Pretraining these architectures on millions of texts to predict words from their context greatly facilitates translation, text synthesis (Lample & Conneau, 2019) and the retrieval of world-knowledge (Brown et al., 2020).

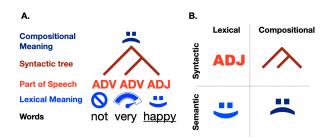


Figure 1. **Taxonomy A.** To understand the meaning of a phrase, one must combine the meaning of each word using the rules of syntax. For example, the meaning of the phrase "not very happy" is (roughly) "sad", and can be found by recursively combining the two adverbs and the adjective. **B.** We aim to decompose lexical features (what relates to the word level) from the compositional features (what relates to a combination of words) both for syntactic representations (e.g. Part-of-speech versus syntactic tree) and for semantic representations (e.g. the set of word meaning versus the meaning of their combination).

Interestingly, the activations of language transformers tend to linearly map onto those of the human brain, when presented with the same sentences (Toneva & Wehbe, 2019; Abnar et al., 2019; Schrimpf et al., 2020a; Caucheteux & King, 2020). This linear mapping suggests that, in spite of their vast learning ¹ and architectural differences ², the brain and language transformers converge to similar linguistic representations.

However, the nature of these shared representations is largely unknown. Three factors explain this gap-of-knowledge. First, linguistic theories are generally described and interpreted in terms of combinatorial *symbols* (discrete words, syntactic trees, etc). In contrast, brain and language transformers generate high-dimensional *vectors* (a.k.a "distributed" representations). While these formats are formally equivalent (Smolensky, 1990), interpreting vectorial representations in language models and in the brain remains

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¹The brain learns continuously from a small set of situated sentences, whereas transformers learn from large sets of pure texts.

²The brain is a single-stream recurrent architecture, whereas the transformer is a multi-stream feedforward architecture.

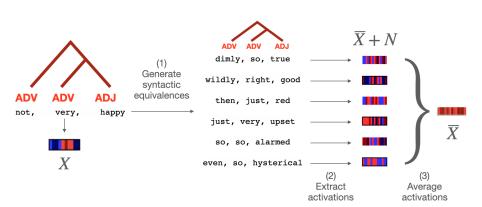


Figure 2. Method to isolate syntactic representations in GPT2's word and compositional embbeddings. To isolate the syntactic representations of a sequence of words e.g. w ="not very happy", we (1) generate sentences with the same syntactic structure as w (e.g "dimly so true"), then (2) extract the corresponding GPT2 activations (from layer 9), and finally (3) average these activation vectors across the generated sentences. The resulting vector \overline{X} is an approximation of the syntactic representations of X in GPT2.

challenging.

Second, the representations of deep learning models have been interpreted independently of brain imaging. For example, deep neural networks have been shown to encode lexical analogies in their word embeddings (Mikolov et al., 2013), as well as singular/plural relationships (Lakretz et al., 2019), long-distance dependency information (Jawahar et al., 2019), and syntactic trees in their middle layers (Manning et al., 2020). Similarly, the human brain responses to language have been decomposed into a cascade of representations, which maps speech and reading input into phonetic (or orthographic), morphemic, lexical, and syntactic representations (Hickok & Poeppel, 2007; Dehaene & Cohen, 2011; Pallier et al., 2011; Friederici, 2011; Mesgarani et al., 2014; Huth et al., 2016a; Nelson et al., 2017; Gwilliams et al., 2020). However, we do not know whether all or any of these representations effectively drive the linear mapping between language models and the brain

Third, the mapping between language transformers and the brain has been mainly investigated with speech and/or narratives (Schrimpf et al., 2020b; Toneva & Wehbe, 2019; Abnar et al., 2019; Reddy & Wehbe, 2020) (although see (Caucheteux & King, 2020)). These uncontrolled conditions potentially confound various features such as phonological variations, sentiment contours, semantic contents, and syntactic properties (e.g. stressful texts may tend to be read more quickly, and make use of smaller constituency trees). In sum, the linear correspondence observed between language models and the brain may be driven by a variety of factors.

Here, we aim to decompose the similarity between the brain and high-performance language transformers like GPT2 (Radford et al., 2019), in light of four distinct linguistic classes, namely lexical, compositional, syntactic and semantic representations. To this end, we propose an operational taxonomy to separate them in vector systems. We then de-

scribe a statistical procedure to estimate distributed syntactic representations. Finally, we assess the linear mapping between i) the factorized activations of GPT2 and ii) the brain signals of 345 subjects listening to the same narratives (4.6 hours of audio stimulus in total) as recorded with functional magnetic resonance imaging (fMRI).

2. An operational taxonomy.

The notions of lexicon, composition, syntax and semantics are notoriously debated in linguistics. Without pretending to solve this issue, we propose *operational* definitions designed to decompose these four classes within vectorial systems.

First, we use the standard definition of a representation as the linearly-extractible information in a vector of activations, with the rationale that a single artificial or biological neuron can read-out this information (Kriegeskorte et al., 2008). In this view, a system Ψ_1 is said to share the representation of a system Ψ_2 if there exists a linear mapping from X to Y, where $X=\Psi_1(w)$ and $Y=\Psi_2(w)$ are the activations elicited by the words w in each system.

Second, we define *lexical* representations as the representations that are context-invariant. This definition follows the standard notion of (non-contextualized) word-embeddings, which associate a unique vector to each word of a dictionary \mathcal{V} .

By contrast, we define *compositional* representations as the "contextualized" representations generated by a system combining multiples words: $\Psi(w_1 \dots w_M)$. For clarity, we restrict the term "compositional" to its strict sense: i.e. to the set of representations that cannot be accounted for by lexical representations, and thus by a linear combination of word-embeddings.

Third, we define syntactic representations as the set of representations associated with the structure of sentences. Linguistic theories have proposed symbolic representations of

such structures (e.g part-of-speech, dependency and constituency trees, see Figure 1). Here, we introduce a vectorial representation of syntax through the length of deep neural transformers, following the idea that transformers linearly encode syntactic properties (Jawahar et al., 2019) such as syntactic distances (Manning et al., 2020). We will build those representations out of the average of the activations elicited by a set of synthetic sentences that share the same syntactic properties (see section 3).

Finally, even though a variety of meaningful features appeared to be captured by both word embeddings (Mikolov et al., 2013) and contexualized embeddings (Radford et al., 2019), meaning and semantics remain difficult to formally define (Jackendoff, 2002). To decompose syntax and semantics in distributed representations, we thus propose to define semantic representations as the representations of a language system that are not syntactic.

According to these definitions, lexical and compositional classes thus fully decompose both syntax and semantics (and vice versa). For example, lexico-syntactic representations refer to the functional categories of words: i.e. partof-speech (i.e. verb, noun, adjective, etc.). By contrast, compositional syntax refers to the representations that link words with one another, typically referred to as dependency (or constituency) trees. Similarly, in the phrase "not very happy" (Figure 1), the lexical meaning of words (i.e. the linear combination of each of the three words) can be distinguished from their compositional meaning (i.e. \approx sad). This meaning of the composition need not represent syntax, in that it could have been (approximately) generated with another sentence (e.g. "glum", "down in the dumps", etc.). Critically, both transformers and the brain may generate distributed representations of syntax that have not been theorized yet – e.g. temporary structures that allow building the syntactic tree of a sentence.

3. Statistical method to isolate distributed representations of syntax

Here, we introduce a method to isolate distributed representations of syntax. We assume that a system $\Psi (\Psi : \mathcal{V}^M \to \mathbb{R}^{d \times M}, \mathcal{V}$ a vocabulary of words), takes sequences of M words as inputs and generates activations that encode syntactic properties (among other properties).

Let w be a sentence of M words ($w \in \mathcal{V}^M$, e.g "the cat is on the mat"), and Ω_w be the set of sentences that have the same syntax as w. The syntactic representation of w is, by construction, also the syntactic representations of all sentences $w' \in \Omega_w$. If this common syntactic representation is denoted $\overline{\psi} \in \mathbb{R}^d$, we have:

$$\forall w' \in \Omega_w, \quad \Psi(w') = \overline{\psi} + z_{w'}$$

with $z_{w'}$ a random perturbation of distribution \mathbb{P}_w , that corresponds to the non-syntactic part of the randomized activations $\Psi(w')$. If the density of \mathbb{P}_w is well-defined and centered around 0, then:

$$\mathbb{E}\big[\Psi(w')\big] = \overline{\psi} ,$$

where w' is sampled uniformly in Ω_w . Thus, $\overline{\psi}$ (the syntactic representation of w) can be approximated through:

$$\overline{\Psi}_k = \frac{1}{k} \sum_{i=1}^k \left(\overline{\psi} + z_{w_i} \right) \xrightarrow[k \to \infty]{l.l.n} \overline{\psi}$$

with $(z_{w_1}, \ldots, z_{w_k})$ *i.i.d* samples from \mathbb{P}_w .

In practice, to approximate $\overline{\psi}$, we generate k=10 versions of each story w with the same syntactic structure $(|\Omega_w| = k = 10$, see below). We then extract the corresponding GPT2 activations (layer 9) $\Psi(w)$, and average the activations across the generated texts of Ω_w (cf. Figure 2). To generate Ω_w , i.e the texts that respect the syntactic structure of the story w, we first (i) split the story into sentences, (ii) extract their syntactic graphs (dependency tags) using Gector (Omelianchuk et al., 2020), a state-of-the-art dependency parser, (iii) uniformly sample words from \approx 58K words of Wikipedia (combined with the transcripts of the fMRI audio corpus) with the same dependency tags as the ones of the sentences $(k' \gg k)$, with k' the number of samplings per word), and (iv) apply grammatical checks to filter the sentences that did not match to the target syntax (cf. section 6).

4. Mapping representations onto fMRI signals

We aim to map the activations of two systems Ψ_1 , a neural network, and Ψ_2 , the brain, input with the same sequence words $w=(w_1,\ldots,w_M)$. Let $X=\Psi_1(w)\in\mathbb{R}^{M\times d}$ be a vector of Ψ_1 activations elicited by w (M vectors of dimension d, one per input word), and $Y=\Psi_2(w)\in\mathbb{R}^N$ the observable brain response of one voxel, at each of the N fMRI recorded time sample (TR=2 s). For simplicity, we consider the analysis for one particular fMRI voxel, the same analysis can be repeated to map X with every voxel in the brain.

To assess the mapping between X and Y, we evaluate a linear spatio- (f) temporal (g) encoding model trained to predict the i^{th} fMRI volume given the network's activations X, on a given interval $I \subset [1 \dots N]$:

$$\mathcal{R}(X): f \mapsto \mathcal{L}\left(f \circ g(X)_{i \in I}, \overline{(Y_i)}_{i \in I}\right)$$
 (1)

Specifically, given a story w of M words ($w = (w_1, \ldots, w_M) = (\text{the, cat, is, on, the, mat, } \ldots \text{end})$, we

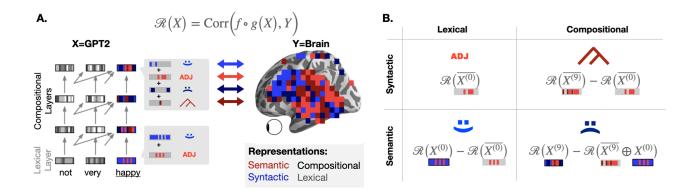


Figure 3. Method to decompose the brain activations A. The human brain and modern language models like GPT2, both generate distributed representations, which are thus difficult to link with the symbolic properties proposed by linguistic theories. We introduce a method to decompose the representations of GPT2, and the corresponding activations X onto the brain activations Y, elicited by the same sequence of words (e.g. "not very happy") with a spatio-temporal estimator $f \circ g$. This mapping is evaluated through cross-validation, with a Pearson correlation between the predicted and the actual brain signals $\mathcal{R}(X)$. B. Comparison used to decompose the brain score $\mathcal{R}(X)$ into the four linguistic components. $X^{(l)}$ refers to the the l^{th} layer's activations of GPT2 input with the sentences heard by the subjects; $\overline{X^{(l)}}$ refers to the average l^{th} layer's activations of GPT2 input with the shuffled sentences; \oplus indicates a feature concatenation, — indicates a subtraction between scores. Colored elements are purely illustrative.

first extract the corresponding brain measurements Y of length N time samples. To maximize signal-to-noise ratio, we average the responses across the subjects that listened to that story:

$$\overline{Y} = \left(\frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} Y_i^{(s)}\right)_{i \in I}$$

with $Y^{(s)}=(Y_1^{(s)},\ldots,Y_N^{(s)})$, the N fMRI scans of one subject $s\in\mathcal{S}$, elicited by the story w.

The sampling frequency of fMRI is typically lower than word rate. Furthermore, fMRI signals are associated with delayed time responses that can span several seconds. Following others (Huth et al., 2016a; Deniz et al., 2019; Shain et al., 2020), we thus align the word-times features X, of length M, to the dynamics of the fMRI signals by applying a finite impulse response (FIR) model g.

Specifically, for each fMRI time sample $i \in [1...N]$, g_i combines word features within each acquisition interval as follows:

$$g_{i}: \mathbb{R}^{M \times d} \to \mathbb{R}^{5d}$$

$$u \mapsto \left[\widetilde{u_{i}}, \widetilde{u_{i-1}}, \dots, \widetilde{u_{i-4}}\right]$$

$$\widetilde{u_{i}} = \sum_{\substack{m \in [1...M] \\ \mathcal{T}(m) = i}} u_{m}$$

with

$$\begin{split} \mathcal{T}: \llbracket 1 \dots M \rrbracket &\to \llbracket 1 \dots N \rrbracket \\ m \mapsto i \quad / \quad |t_{y_i} - t_{x_j}| = \min_{k \in \llbracket 1 \dots N \rrbracket} |t_{y_k} - t_{x_m}| \end{split}$$

with \tilde{u} the summed activations of words between successive fMRI time samples, u the five lags of FIR features, (t_{x_1},\ldots,t_{x_M}) the timings of the M words onsets, and (t_{y_1},\ldots,t_{y_N}) the timings of the N fMRI measurements.

Finally we learn a "spatial" mapping $f \in \mathbb{R}^d$ from the zero-mean unit-variance of X to the zero-mean unit-variance fMRI recordings Y with a ℓ_2 -regularized "ridge" regression:

$$\underset{f}{\operatorname{argmin}} \sum_{i \in I_{\text{train}}} \left(\overline{Y_i} - f^T g(X)_i \right)^2 + \lambda ||f||^2$$

with λ the regularization parameter.

We summarize the mapping with a Pearson correlation score evaluated on left out data:

$$\mathcal{R} = \operatorname{corr}\left(f \circ g(X), \overline{Y}\right) .$$
 (2)

This correlation score measures the linear mapping between the brain and the activation space X. We will refer to this score as the *brain score* of an activation space X.

5. Decomposing the activations of the brain and neural language models

Here, we use the definitions and methods introduced in sections 2, 3 and 4 to decompose the representations of

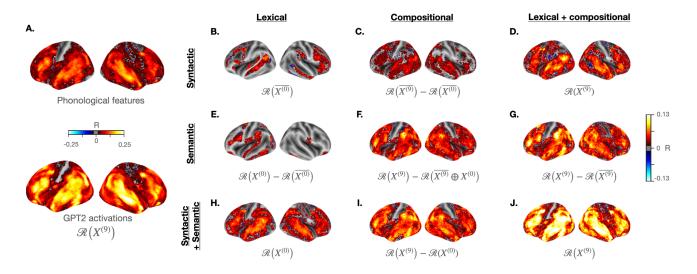


Figure 4. Results Decomposition of the brain scores of 345 subjects listening to narratives into their phonological (A) syntactic (B-D), semantic (E-G), lexical (B-H), compositional (C-I) components and their combinations (nine combinations in total). A Comparison between the brain scores of three phonological features (word rate, phone rate, and phone categories, on the top) and the brain scores of the activations extracted from the 9th layer of GPT2, when input with the same narratives (on the bottom). B-J. Brain scores decomposed into different sub-processes. To focus on language – and not low-level speech – processing, we display the *gain* in brain scores compared to the phonological features. For simplicity, the $\mathcal R$ values reported refers to this gain. Brain scores were computed for each fMRI voxel (averaged across subjects), on 100 splits of ≈ 2.5 min of audio stimulus. Non-significant brain regions are not displayed (.05 threshold), as assessed with a two-sided Wilcoxon test across splits, corrected for multiple comparison across the 75 regions of interest (cf. section 6).

two systems: a deep neural network that encode linguistic properties, and the average brain of 385 subjects listening to narratives.

To this end, we (i) compute the activations of the neural language model elicited by the same narratives as the subjects (ii) factorize its activations into linguistic components, (iii) map with supervised learning the factorized components onto brain activity, and finally (iv) decompose the brain activations by evaluating this mapping.

Deep language models are composed of stacked modules called "layers" ($l \in [1 \dots L]$), stacked over a (non contextualized) word embedding layer (l=0). Each layer can be written as a non-linear system $\Psi^{(l)}$ that transforms a sequence of words w (e.g. "not", "very", "happy") into a vectorial representation of the same length,

$$\Psi^{(l)}: \mathcal{V}^M \to \mathbb{R}^{M \times d}$$
$$w \mapsto \Psi^{(l)}(w) = [\Psi^{(l)}(w)_1, \dots, \Psi^{(l)}(w)_M]$$

with \mathcal{V} the set of vocabulary words, M the length of the sequence, and d the dimensionality of the output representation taken at each word.

We denote $X^{(l)}$ the activations of $\Psi^{(l)}$ elicited by w, and $\overline{X^{(l)}}$ the syntactic representations extracted from $X^{(l)}$ using the method introduced in section 3. Following the definitions of section 2, we can decompose the activations X of

 Ψ into their:

- lexical representations: $X^{(0)}$, the word embedding of the network.
- (strictly) compositional representations: $X^{(l)} X^{(0)}$ with l > 0, i.e. the compositional representations $X^{(l)}$, when removing the lexical components.
- syntactic representations: $\overline{X^{(l)}}$, that can be extracted for any layer $l \in [0 \dots L]$. The lexical syntactic representations $\overline{X^{(0)}}$ is equivalent to the part-of-speech of the word. Compositional syntactic representations can be extracted from any layer l>0 that encode syntactic information.
- semantic representations: $X^{(l)} \overline{X^{(l)}}$, as the residuals of syntactic representations. They can be defined at both the lexical $X^{(0)} \overline{X^{(0)}}$ and compositional level (l>0).

Finally, following section 4, we can compute the brain scores of the corresponding representations to decompose brain activity into:

- lexical representations: $\mathcal{R}(X^{(0)})$
- compositional representations: $\mathcal{R}(X^{(l)}), l > 0$

- (strictly) compositional representations: $\mathcal{R}(X^{(l)}) \mathcal{R}(X^{(0)})$, with l > 0, i.e. the compositional representations when removing the brain activity accounted by lexical activations.
- syntactic representations: $\mathcal{R}(\overline{X^{(l)}}), l \in [0 \dots L]$
- semantic representations: $\mathcal{R}(X^{(l)}) \mathcal{R}(\overline{X^{(l)}})$, i.e. the residual brain scores of syntactic representations, for any layer $l \in [0 \dots L]$

6. Experiments

Here, we apply the general statistical method described above to decompose the activations of two nonlinear systems, GPT2 (Ψ_1) and the brain activity of 345 subjects listening to narratives (Ψ_2) .

Functional MRI dataset. We analyse the publicly available "Narratives" dataset (Nastase et al., 2020) comprised of the fMRI measurements of 345 unique subjects listening to narratives. The narratives consist of 27 English spoken stories, ranging from ≈ 3 minutes to ≈ 56 minutes, for a total of ≈ 4.6 hours of unique stimuli. The original paper included two fMRI preprocessing pipelines, one with spatial smoothing and the other without. All our analyses are tested on the unsmoothed fMRI. X pairs of (subject, scans) were excluded because of noisy stimuli or fMRI recordings, resulting in 617 unique (story, subject) pairs and a total of ≈ 4 hours of unique audio stimuli.

For each story, text-level, word-level and phoneme-level transcripts were provided in the Narratives database, thanks to Gentle ³, a forced-alignment algorithm. The phoneme and word-level transcripts do not include punctuation marks.

Neural language models activations. GPT2 is a high-performing causal (i.e. left to right) language model trained to predict a word given its previous context (Radford et al., 2019), and known to generate brain-like representations (Goldstein et al., 2021; Caucheteux & King, 2020; Affolter et al., 2020; Schrimpf et al., 2020a). It is comprised of 12 Transformer (contextual) layers ($l \in [1\dots 12]$) stacked over a (non-contextual) embedding layer (l = 0), each of dimensionality 768, with 1.5 billion parameters in total. We used the pretrained GPT-2, trained on a dataset of 8 million web pages (Wolf et al., 2020).

In practice, to extract the activations elicited by the 27 stories, we proceed as follows: we first format and lower cased the texts (replacing special punctuation marks such as "—" and duplicated marks "?." by dots), then apply the tokenizer provided by Huggingface to convert the transcript into either word-level or sub-word-level tokens called "Byte Pair

Encoding" (BPE) (Sennrich et al., 2016). Here, more than 99.5% of BPE-level tokens were complete words. The tokens are then split into sections of 256 tokens (this length is constrained by GPT2's architecture) and input to the model one story at a time. The activations of each layer are finally extracted, resulting in 12 vectors of 768 activations for each token of each story transcript (i.e. one for each of the 12 layers).

Generating syntactically equivalent narratives. To isolate the syntactic representations of GPT2 (section 3), we generate, for each story w, k=10 texts of the same syntactic structure (cf Figure 2). To this end, we proceed as follows:

- The transcript is formatted as described in the previous paragraph, split into sentences and tokenized using the large English tokenizer provided by spaCy (Honnibal et al., 2020).
- Then, we use Supar, a state-of-the art dependency parser (Zhang et al., 2020) to extract the dependency structure of each sentence and the part-of-speech.
- For each word of a sentence, we sample from k'=100 to k'=1,000 words of the same part-of-speech and dependency tag out of a subset of $\approx 58,000$ Wikipedia words combined with the transcripts of the stimulus. At this stage, k' versions of the initial transcript were generated.
- The reconstructed sentences are not always grammatically correct. We thus automatically correct incorrect sentences with Gector (Omelianchuk et al., 2020), and filter out those sentences that do not have the same length or part-of speech as the initial sentence.
- Some of the generated sentences may end up with a distinct syntactic tree than the original sentence, because semantics can disambiguate syntax (e.g. "I shot an elephant in my pyjamas"). To assess the syntactic similarity between the original and the generated sentences, we computed their respective syntactic trees and computed the Pearson correlation between the words' pairwise distances, following (Manning et al., 2020)'s method and selected the sentences whose syntactic trees are the most similar. 95% of the generated sentences had a syntactic tree that correlated with the original sentence's above R=90%.

Phonological features. To focus on lexical and supralexical language processing – as opposed to low-level speech processing, we extract three potential phonological confounds: the phone rate (the number of phones between two fMRI measurements, of dimension 1), the word rate (the

³https://github.com/lowerquality/gentle

number of words between two fMRI measurements) and the phones themselves. Using Gentle phoneme annotations, 117 unique phones (with unique stress and tones) were found in total, resulting in a one-hot encoded feature of the same dimension.

Text-to-speech alignment. In the three previous paragraphs, we generate phoneme-level, BPE-level and word-level features for each story. In order to be mapped to brain activity, these features were time-aligned to the audio files and then summed between successive fMRI measurements. The speech-to-text time alignment is provided at the word level, following Gentle tokenization. In other words, we assign each phoneme and word to the time onset of its closest Gentle token.

Mapping the activations of GPT2 and fMRI. As described in equation (1), we evaluate the mapping between the activations $X^{(l)} \in \mathbb{R}^{M \times d_x}$ extracted from the layer lof GPT2, and the fMRI signals $Y \in \mathbb{R}^{N \times d_y}$ by fitting a linear spatio- (f) temporal (g) encoding model. $f \circ g$ was fitted on $I_{\rm train} = 99\%$ of the dataset, and evaluated on $I_{\rm test}=1\%$ of the left out-data (2.5 min of audio), using L, a Pearson R correlation between predicted and actual brain signals on I_{test} . In practice, we used the scikit-learn implementation of the linear ridge regression (Pedregosa et al., 2011a), with penalization parameters chosen among 10 values log-spaced between 10^{-1} and 10^{8} and q was a finite impulse response (FIR) model with 5 delays, following (Huth et al., 2016b). X and Y were normalized (mean=0, std=1) across scans for each story, using a robust scaler clipping below and above the 0.01^{st} and 99.99^{th} percentiles, respectively. We repeated the procedure 100 times with a 100-fold cross-validation, using scikit-learn 'KFold' without shuffling (Pedregosa et al., 2011b).

Cross-validation and significance. We assessed the significance of our results across test folds (k=100). To this end, we first average the brain scores within each brain region, as defined by the Destrieux Atlas parcellation (Destrieux et al., 2010)). Then, we apply a Wilcoxon two-sided signed-rank test across folds to evaluate whether this average brain score is significantly different from zero. The p-values of the 75 brain regions were corrected for multiple comparison using a False Discovery Rate, (Benjamini/Hochberg) as implemented in MNE-Python (Gramfort et al., 2013). Nonsignificant p-values (0.05 threshold) are masked in Figure 4.

7. Results

The brain scores corresponding to the lexical $(\mathcal{R}(X^{(0)}))$, compositional $(\mathcal{R}(X^{(9)}))$, syntactic $(\mathcal{R}(\overline{X^{(9)}}))$ and semantic representations $(\mathcal{R}(X^{(9)}) - \mathcal{R}(\overline{X^{(9)}}))$ of GPT2 are dis-

played in Figure 4 (Non-significant scores after correction for multiple comparison across regions are masked). We focus on GPT2's ninth layer because this intermediate layers have been shown to better encode syntactic properties than input and output layers (Jawahar et al., 2019).

Phonological features. First, to isolate the sublexical speech representations, we compute the brain scores using a concatenation of three sets of features, i.e., word rate, phone rate, and phone categories. These features lead to significant brain scores across the expected language networks and mainly peak within the bilateral superior temporal lobe, the temporo-parietal junction, the lateral intra-parietal sulcus, the infero-frontal cortex as well as in the right motor cortex (Figure 4A).

To strictly focus on lexical and compositional representations, we now focus on the *gain* in brain scores obtained over those of sublexical features. For simplicity, the \mathcal{R} values reported below refer to this gain (i.e. to the increase of brain scores obtained with each feature set, as compared to the scores obtained with phonological features).

Lexical features. The lexical representations of the brain can be investigated through the lens of a word-embedding (Huth et al., 2016a; Mitchell et al., 2008). GPT2's word embedding $X^{(0)}$ results in lexical brain scores significantly higher than sublexical features' in most of the language network (Huth et al., 2016a; Caucheteux & King, 2020): i.e. within the bilateral superior temporal lobe, and the inferofrontal cortex, as well as in the primary motor areas (Figure 4 H).

Lexical syntax. Do these brain scores result from semantic and/or syntactic representations? To tackle this issue, we compute brain scores from the word embeddings $(\overline{X^{(0)}})$ input with the shuffled sentences: i.e. word sequences sharing the same syntax as the original sentence (Figure 4B). The results reveal significant brain scores (as compared to sublexical ones) mainly in the left superior temporal sulcus, the left planum temporale, as well as in the infero- and orbito-frontal cortex.

Lexical semantics. To identify the representations of lexical semantics, we compare the brain score obtained with the word embedding to those obtained with the lexical syntax $(\mathcal{R}(X^{(0)}) - \mathcal{R}(\overline{X^{(0)}}))$ in Figure 4E). The resulting brain scores were significant mainly in the left hemisphere, and peaked in the superior temporal gyrus, the infero-frontal cortex and in the supra-marginal cortex as well as in the precuneus and the tranverse temporal gyrus. These results are more modest than we anticipated given past work (Huth et al., 2016a).

Compositional representations. Recent studies have shown that the contextual (i.e. deep) layers of language models better predict brain activity than word embedding (Jain & Huth, 2018; Jat et al., 2019; Toneva & Wehbe, 2019; Caucheteux & King, 2020). We replicate this result with a representative contextual layer of GPT2 (layer 9 out of 12, Figure 4J): $\mathcal{R}(X^{(9)})$ almost doubles the brain scores obtained with the word embedding $\mathcal{R}(X^{(0)})$ in the bilateral temporal, infero-frontal and infero-parietal cortices.

Compositional syntax. Do these gains in brain score reflect compositional semantics and/or compositional syntax? To tackle this issue, we compare the brain scores obtained with the ninth layer of GPT2 input with the shuffled sentences $\mathcal{R}(\overline{X}^{(9)})$, to the the brain scores obtained with the first layer of GPT2, input with those same shuffled sentences $\mathcal{R}(\overline{X}^{(9)})$. The results show that the representations of compositional syntax are distributed over the bilateral temporal and infero-frontal cortices pars opercularis, and actually extend to a relatively large set of brain areas. Overall, these results, although correlational, thus favor a distributed (Fedorenko et al., 2012) rather than a modular (Pallier et al., 2011; Friederici et al., 2000) view of syntax: both lexical and compositional syntactic effects do not appear to be confined within a single brain area.

Compositional semantics. Finally, we estimate the brain representations of compositional semantics by comparing the brain scores obtained with the syntactic representations $\mathcal{R}(\overline{X^{(9)}})$ to those obtained with the "normal" activations $\mathcal{R}(X^{(9)})$, i.e. GPT2's activations obtained with the very sentences that subjects heard. Again, the resulting effects proved to be remarkably distributed, and peaked in the supramarginal, and infero-frontal cortex pars triangularis (Figure 4G). These brain scores appear to result from strictly compositional semantics: these effects remain significant even when we subtract away the contribution of lexical semantics (Figure 4E).

8. Discussion

In the present study, we introduce a simple taxonomy and its associated method to decompose the distributed representations of language in brains and deep language models.

Our taxonomy capitalizes on classic linguistic proposals (Lycan, 2018; Givón, 2001; Chomsky, 2014) to offer precise definitions of lexicality, compositionality, syntax and semantics. These definitions, however, are far from perfect. First, compositionality is often associated with specific properties that are not presently considered (e.g. systematicity and generalizability (Szabó, 2004; Hupkes et al., 2019; Baroni, 2020)). Furthermore, we here define semantics as the *residual* representations of any text embedding once

syntactic representations have been removed. This proposal is very coarse: semantics is generally defined as the study of meaning (which is itself not very easy to define). Yet, some language features like emotional value and textual style may arguably not "mean" anything, in that they do not necessarily refer to a state of the world. In spite of this limit, the advantage of our framework is that it makes *precise* and *quantifiable* predictions to investigate distributed linguistic representations.

The present study follows suit with past research on naturalistic / poorly-controlled linguistic stimuli (Mesgarani et al., 2014; Huth et al., 2016b; Brennan, 2016; Brennan & Hale, 2019; Stehwien et al., 2020; Gwilliams et al., 2020). This approach diverges with and complements previous practices (Hamilton & Huth, 2020), consisting of carefully designed stimuli, typically matched for word length, word frequency (Kutas & Hillyard, 1980) and/or constituent size (Pallier et al., 2011; Ding et al., 2016), which becomes exponentially difficult when the number of variables to control increases. This change of practice has been empowered by the rise of high-performing language models: previous research lacked a method to make single trial/single sentence predictions and could thus only compare the average activations across blocks of similarly constructed sentences. By contrast, modern language models offer the possibility to predict the repesentations of individual words and sentences (Hale et al., 2018; Toneva & Wehbe, 2019; Caucheteux & King, 2020; Schrimpf et al., 2020a; Heilbron et al., 2020). Consequently, carefully-controlled experimental designs can now be relaxed to naturalistic settings, and allow one to refine her tests and hypotheses without having to conduct new (and arguably artificial e.g. Jabberwocky (Pallier et al., 2011; Fedorenko et al., 2012)) experiments.

The main drawback of such an uncontrolled setting is undoubtedly signal-to-noise ratio: like any bias/variance trade-off, relaxing the set of hypotheses that one can test in a given dataset reduces the probability of a successful test. To accodomate this issue, we here opted to analyze the average brain signal across subjects. Even then, prediction scores remain far from 100%. Furthermore, the brain bases of language processing are notoriously variable across individuals (Fedorenko et al., 2010). Future works thus remain necessary to take into the functional and anatomical variability across subjects.

Thanks to machine learning, our method sheds new light on the neural bases of language in general, and of syntactic processes in particular. First, it supplements previous work on the neural basis of lexical (Friederici et al., 2000; Mitchell et al., 2008) and compositional representations of language (Pallier et al., 2011; Nelson et al., 2017; Fedorenko et al., 2012; Brennan & Pylkkänen, 2017): syntactic processes, in particular, appear to be linked to a remarkably

wide-spread *distribution* of activation in the language networks. This result favours a distributed (Fedorenko et al., 2012) as opposed to a modular (Pallier et al., 2011) view of syntactic processes. Second, our study highlights the remarkably-large recruitment of compositional semantics – an observation that strengthens and extends what had already been reported at the lexical level (Huth et al., 2016a). Overall, these results thus reinforce the idea that speech comprehension results from a the coordination of a huge cortical network. While its rules remain unknown, the functional similarity between the brain and deep networks offers a new and powerful mean to understand the laws of language.

References

- Abnar, S., Beinborn, L., Choenni, R., and Zuidema, W. Blackbox meets blackbox: Representational Similarity and Stability Analysis of Neural Language Models and Brains. *arXiv*:1906.01539 [cs, q-bio], June 2019. arXiv: 1906.01539.
- Affolter, N., Egressy, B., Pascual, D., and Wattenhofer, R. Brain2word: Decoding brain activity for language generation. *arXiv preprint arXiv:2009.04765*, 2020.
- Baroni, M. Linguistic generalization and compositionality in modern artificial neural networks. *Philosophical Transactions of the Royal Society B*, 375(1791):20190307, 2020.
- Brennan, J. Naturalistic sentence comprehension in the brain. *Language and Linguistics Compass*, 10(7):299–313, 2016.
- Brennan, J. R. and Hale, J. T. Hierarchical structure guides rapid linguistic predictions during naturalistic listening. *PloS one*, 14(1):e0207741, 2019.
- Brennan, J. R. and Pylkkänen, L. Meg evidence for incremental sentence composition in the anterior temporal lobe. *Cognitive science*, 41:1515–1531, 2017.
- Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., and Amodei, D. Language Models are Few-Shot Learners. *arXiv:2005.14165 [cs]*, July 2020. arXiv: 2005.14165.
- Caucheteux, C. and King, J.-R. Language processing in brains and deep neural networks: computational convergence and its limits. *BioRxiv*, 2020.
- Chomsky, N. The minimalist program. MIT press, 2014.

- Dehaene, S. and Cohen, L. The unique role of the visual word form area in reading. *Trends in Cognitive Sciences*, 15(6):254–262, June 2011. ISSN 1879-307X. doi: 10. 1016/j.tics.2011.04.003.
- Deniz, F., Nunez-Elizalde, A. O., Huth, A. G., and Gallant, J. L. The Representation of Semantic Information Across Human Cerebral Cortex During Listening Versus Reading Is Invariant to Stimulus Modality. *Journal of Neuroscience*, 39(39):7722–7736, September 2019. ISSN 0270-6474, 1529-2401. doi: 10.1523/JNEUROSCI. 0675-19.2019. Publisher: Society for Neuroscience Section: Research Articles.
- Destrieux, C., Fischl, B., Dale, A., and Halgren, E. Automatic parcellation of human cortical gyri and sulci using standard anatomical nomenclature. *NeuroImage*, 53(1):1–15, October 2010. ISSN 1053-8119. doi: 10.1016/j.neuroimage.2010.06.010.
- Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv:1810.04805 [cs]*, May 2019. arXiv: 1810.04805.
- Ding, N., Melloni, L., Zhang, H., Tian, X., and Poeppel, D. Cortical tracking of hierarchical linguistic structures in connected speech. *Nature neuroscience*, 19(1):158–164, 2016.
- Fedorenko, E., Hsieh, P.-J., Nieto-Castañón, A., Whitfield-Gabrieli, S., and Kanwisher, N. New method for fmri investigations of language: defining rois functionally in individual subjects. *Journal of neurophysiology*, 104(2): 1177–1194, 2010.
- Fedorenko, E., Nieto-Castanon, A., and Kanwisher, N. Lexical and syntactic representations in the brain: an fmri investigation with multi-voxel pattern analyses. *Neuropsychologia*, 50(4):499–513, 2012.
- Friederici, A. D. The Brain Basis of Language Processing: From Structure to Function. *Physiological Reviews*, 91 (4):1357–1392, October 2011. ISSN 0031-9333, 1522-1210. doi: 10.1152/physrev.00006.2011.
- Friederici, A. D., Opitz, B., and Von Cramon, D. Y. Segregating semantic and syntactic aspects of processing in the human brain: an fmri investigation of different word types. *Cerebral cortex*, 10(7):698–705, 2000.
- Givón, T. *Syntax: an introduction*, volume 1. John Benjamins Publishing, 2001.
- Goldstein, A., Zada, Z., Buchnik, E., Schain, M., Price, A., Aubrey, B., Nastase, S. A., Feder, A., Emanuel, D., Cohen, A., et al. Thinking ahead: prediction in context as a keystone of language in humans and machines. *bioRxiv*, pp. 2020–12, 2021.

- Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., and Hämäläinen, M. MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7, 2013. ISSN 1662-453X. doi: 10.3389/fnins.2013.00267. Publisher: Frontiers.
- Gwilliams, L., King, J.-R., Marantz, A., and Poeppel, D. Neural dynamics of phoneme sequencing in real speech jointly encode order and invariant content. *bioRxiv*, 2020.
- Hale, J., Dyer, C., Kuncoro, A., and Brennan, J. R. Finding syntax in human encephalography with beam search. *arXiv* preprint arXiv:1806.04127, 2018.
- Hamilton, L. S. and Huth, A. G. The revolution will not be controlled: natural stimuli in speech neuroscience. *Language, Cognition and Neuroscience*, 35(5):573–582, 2020.
- Heilbron, M., Armeni, K., Schoffelen, J.-M., Hagoort, P., and de Lange, F. P. A hierarchy of linguistic predictions during natural language comprehension. *bioRxiv*, 2020.
- Hickok, G. and Poeppel, D. The cortical organization of speech processing. *Nature Reviews Neuroscience*, 8(5): 393–402, May 2007. ISSN 1471-0048. doi: 10.1038/nrn2113. Number: 5 Publisher: Nature Publishing Group.
- Honnibal, M., Montani, I., Van Landeghem, S., and Boyd, A. spaCy: Industrial-strength Natural Language Processing in Python, 2020. URL https://doi.org/10.5281/zenodo.1212303.
- Hupkes, D., Dankers, V., Mul, M., and Bruni, E. The compositionality of neural networks: integrating symbolism and connectionism. *arXiv preprint arXiv:1908.08351*, 2019.
- Huth, A. G., De Heer, W. A., Griffiths, T. L., Theunissen, F. E., and Gallant, J. L. Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature*, 532 (7600):453–458, 2016a.
- Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E., and Gallant, J. L. Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature*, 532 (7600):453–458, April 2016b. ISSN 0028-0836, 1476-4687. doi: 10.1038/nature17637.
- Jackendoff, R. Foundations of Language: Brain, Meaning, Grammar, Evolution. Oxford University Press, 2002.ISBN 978-0-19-171325-5. Publication Title: Foundations of Language.
- Jain, S. and Huth, A. G. Incorporating context into language encoding models for fmri. *BioRxiv*, pp. 327601, 2018.

- Jat, S., Tang, H., Talukdar, P., and Mitchell, T. Relating simple sentence representations in deep neural networks and the brain. *arXiv preprint arXiv:1906.11861*, 2019.
- Jawahar, G., Sagot, B., and Seddah, D. What Does BERT Learn about the Structure of Language? In *Proceedings* of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 3651–3657, Florence, Italy, 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1356.
- Kriegeskorte, N., Mur, M., and Bandettini, P. A. Representational similarity analysis connecting the branches of systems neuroscience. *Frontiers in Systems Neuroscience*, 2, 2008. ISSN 1662-5137. doi: 10.3389/neuro.06.004.2008. Publisher: Frontiers.
- Kutas, M. and Hillyard, S. A. Reading senseless sentences: Brain potentials reflect semantic incongruity. *Science*, 207(4427):203–205, 1980.
- Lakretz, Y., Kruszewski, G., Desbordes, T., Hupkes, D., Dehaene, S., and Baroni, M. The emergence of number and syntax units in LSTM language models. arXiv:1903.07435 [cs], April 2019. arXiv: 1903.07435.
- Lample, G. and Conneau, A. Cross-lingual Language Model Pretraining. *arXiv:1901.07291 [cs]*, January 2019. arXiv: 1901.07291.
- Lycan, W. G. *Philosophy of language: A contemporary introduction.* Routledge, 2018.
- Manning, C. D., Clark, K., Hewitt, J., Khandelwal, U., and Levy, O. Emergent linguistic structure in artificial neural networks trained by self-supervision. *Proceedings of the National Academy of Sciences*, pp. 201907367, June 2020. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas. 1907367117.
- Mesgarani, N., Cheung, C., Johnson, K., and Chang, E. F. Phonetic feature encoding in human superior temporal gyrus. *Science*, 343(6174):1006–1010, 2014.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. Distributed Representations of Words and Phrases and their Compositionality. In Burges, C. J. C., Bottou, L., Welling, M., Ghahramani, Z., and Weinberger, K. Q. (eds.), *Advances in Neural Information Processing Systems* 26, pp. 3111–3119. Curran Associates, Inc., 2013.
- Mitchell, T. M., Shinkareva, S. V., Carlson, A., Chang, K.-M., Malave, V. L., Mason, R. A., and Just, M. A. Predicting human brain activity associated with the meanings of nouns. *science*, 320(5880):1191–1195, 2008.

- Nastase, S. A., Liu, Y.-F., Hillman, H., Zadbood, A., Hasenfratz, L., Keshavarzian, N., Chen, J., Honey, C. J., Yeshurun, Y., Regev, M., Nguyen, M., Chang, C. H. C., Baldassano, C., Lositsky, O., Simony, E., Chow, M. A., Leong, Y. C., Brooks, P. P., Micciche, E., Choe, G., Goldstein, A., Vanderwal, T., Halchenko, Y. O., Norman, K. A., and Hasson, U. Narratives: fMRI data for evaluating models of naturalistic language comprehension. preprint, Neuroscience, December 2020.
- Nelson, M. J., El Karoui, I., Giber, K., Yang, X., Cohen, L., Koopman, H., Cash, S. S., Naccache, L., Hale, J. T., Pallier, C., and Dehaene, S. Neurophysiological dynamics of phrase-structure building during sentence processing. *Proceedings of the National Academy of Sciences*, 114 (18):E3669–E3678, May 2017. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.1701590114.
- Omelianchuk, K., Atrasevych, V., Chernodub, A., and Skurzhanskyi, O. GECToR Grammatical Error Correction: Tag, Not Rewrite. *arXiv:2005.12592 [cs]*, May 2020. arXiv: 2005.12592.
- Pallier, C., Devauchelle, A.-D., and Dehaene, S. Cortical representation of the constituent structure of sentences. *Proceedings of the National Academy of Sciences*, 108 (6):2522–2527, 2011.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011a.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011b.
- Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.
- Reddy, A. J. and Wehbe, L. Syntactic representations in the human brain: beyond effort-based metrics. *bioRxiv*, 2020.
- Schrimpf, M., Blank, I. A., Tuckute, G., Kauf, C., Hosseini, E. A., Kanwisher, N. G., Tenenbaum, J. B., and Fedorenko, E. The neural architecture of language: Integrative reverse-engineering converges on a model for predictive processing. *bioRxiv*, 2020a.
- Schrimpf, M., Blank, I. A., Tuckute, G., Kauf, C., Hosseini, E. A., Kanwisher, N. G., Tenenbaum, J. B., and

- Fedorenko, E. Artificial Neural Networks Accurately Predict Language Processing in the Brain. *bioRxiv*, pp. 2020.06.26.174482, June 2020b. Publisher: Cold Spring Harbor Laboratory Section: New Results.
- Sennrich, R., Haddow, B., and Birch, A. Neural Machine Translation of Rare Words with Subword Units. *arXiv*:1508.07909 [cs], June 2016. arXiv: 1508.07909.
- Shain, C., Blank, I. A., van Schijndel, M., Schuler, W., and Fedorenko, E. fMRI reveals language-specific predictive coding during naturalistic sentence comprehension. *Neuropsychologia*, 138:107307, February 2020. ISSN 0028-3932. doi: 10.1016/j.neuropsychologia.2019.107307.
- Smolensky, P. Tensor product variable binding and the representation of symbolic structures in connectionist systems. *Artificial Intelligence*, 46(1):159–216, November 1990. ISSN 0004-3702. doi: 10.1016/0004-3702(90)90007-M.
- Stehwien, S., Henke, L., Hale, J., Brennan, J., and Meyer, L. The little prince in 26 languages: Towards a multilingual neuro-cognitive corpus. In *Proceedings of the Second Workshop on Linguistic and Neurocognitive Resources*, pp. 43–49, 2020.
- Szabó, Z. G. Compositionality. 2004.
- Toneva, M. and Wehbe, L. Interpreting and improving natural-language processing (in machines) with natural language-processing (in the brain). *arXiv* preprint *arXiv*:1905.11833, 2019.
- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C.,
 Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M.,
 Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite,
 Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., Drame, M.,
 Lhoest, Q., and Rush, A. M. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 38–45, Online, October 2020. Association for Computational Linguistics.
- Zhang, Y., Li, Z., and Min, Z. Efficient second-order TreeCRF for neural dependency parsing. In *Proceedings of ACL*, pp. 3295–3305, 2020. URL https://www.aclweb.org/anthology/2020.acl-main.302.