The emergence of number and syntax units in LSTM language models

Yair Lakretz
Cognitive Neuroimaging Unit
NeuroSpin center
91191, Gif-sur-Yvette, France
yair.lakretz@gmail.com

German Kruszewski
Facebook AI Research
Paris, France
germank@gmail.com

Theo Desbordes
Facebook AI Research
Paris, France
tdesbordes@fb.com

Dieuwke Hupkes
ILLC, University of Amsterdam
Amsterdam, Netherlands
d.hupkes@uva.nl

Stanislas Dehaene
Cognitive Neuroimaging Unit
NeuroSpin center
91191, Gif-sur-Yvette, France
stanislas.dehaene@gmail.com

Marco Baroni
Facebook AI Research
Paris, France
mbaroni@fb.com

Abstract

Recent work has shown that LSTMs trained on a generic language modeling objective capture syntax-sensitive generalizations such as long-distance number agreement. We have however no mechanistic understanding of how they accomplish this remarkable feat. Some have conjectured it depends on heuristics that do not truly take hierarchical structure into account. We present here a detailed study of the inner mechanics of number tracking in LSTMs at the single neuron level. We discover that long-distance number information is largely managed by two "number units". Importantly, the behaviour of these units is partially controlled by other units independently shown to track syntactic structure. We conclude that LSTMs are, to some extent, implementing genuinely syntactic processing mechanisms, paving the way to a more general understanding of grammatical encoding in LSTMs.

1 Introduction

In the last years, recurrent neural networks (RNNs), and particularly long-short-term-memory (LSTM) architectures (Hochreiter and Schmidhuber, 1997), have been successfully applied to a variety of NLP tasks. This has spurred interest in whether these generic sequence-processing devices are discovering genuine structural properties of language in their training data, or whether their success can be explained by opportunistic surface-pattern-based heuristics.

Until now, this debate has mostly relied on "behavioural" evidence: The LSTM had been treated as a black box, and its capacities had been indirectly inferred by its performance on linguistic tasks. In this study, we took a complementary approach inspired by neuroscience: We thoroughly investigated the inner dynamics of an LSTM language model performing a number agreement task, striving to achieve a mechanistic understanding of how it accomplishes it. We found that the LSTM had specialized two "grandmother" cells (Bowers, 2009) to carry number features from the subject to the verb across the intervening material.[1] Interestingly, the LSTM also

[1] In the neuroscientific literature, "grandmother" cells are (sets of) neurons coding for specific information, e.g., about your grandmother, in a non-distributed manner.

possesses a more distributed mechanism to predict number when subject and verb are close, with the grandmother number cells only playing a crucial role in more difficult long-distance cases. Crucially, we independently identified a set of cells tracking syntactic structure, and found that one of them encodes the presence of an embedded phrase separating the main subject-verb dependency, and has strong efferent connections to the long-distance number cells, suggesting that the network relies on genuine syntactic information to regulate agreement-feature percolation.

Our analysis thus provides direct evidence for the claim that LSTMs trained on unannotated corpus data, despite lacking significant linguistic priors, learn to perform structure-dependent linguistic operations. In turn, this suggests that raw linguistic input and generic memory mechanisms, such as those implemented in LSTMs, may suffice to trigger the induction of non-trivial grammatical rules.

2 Related work

Starting with the seminal work of Linzen et al. (2016), a long-distance number agreement task has emerged as a standard way to probe the syntactic capabilities of neural language models. In the number agreement task, a model is asked to predict the verb in a sentence where the subject and main verb are separated by one or more intervening nouns ("the **boy** near the *cars* **greets**…") and evaluated based on how often it predicts the right verb form.

Following mixed initial results by Linzen and colleagues and Bernardy and Lappin (2017), Gulordava et al. (2018) and Kuncoro et al. (2018b) have robustly established that LSTM language models achieve near-human performance on the agreement task. While Gulordava and colleagues provided some evidence that the LSTMs are relying on genuine syntactic generalizations, Kuncoro et al. (2018a) and Linzen and Leonard (2018) suggested that the LSTM achievements can, at least in part, be accounted by superficial heuristics (e.g., "percolate the number of the first noun in a sentence"). Other recent work has extended syntax probing to other phenomena such as negative polarity items and island constraints (Chowdhury and Zamparelli, 2018; Jumelet and Hupkes, 2018; Marvin and Linzen, 2018; Wilcox et al., 2018).

While Linzen et al. (2016) presented intriguing qualitative data showing cells that track grammatical number in a network directly trained on the agreement task, most of the following work focused on testing the network output behaviour, rather than on understanding how the latter follows from the inner representations of the network. Another research line studied linguistic processing in neural networks through 'diagnostic classifiers', that is, classifiers trained to predict a certain property from network activations (e.g., Gelderloos and Chrupała, 2016; Adi et al., 2017; Alain and Bengio, 2017; Hupkes et al., 2018). This approach may give insight into which information is encoded by the network in different layers or at different time points, but it only provides indirect evidence about the specific mechanics of linguistic processing in the network.

Other studies are closer to our approach in that they attempt to attribute function to specific network cells, often by means of visualization (Karpathy et al., 2016; Li et al., 2016; Tang et al., 2017). Radford et al. (2017), for example, detected a "sentiment" grandmother cell in a language-model-trained network. Kementchedjhieva and Lopez (2018) recently found a character-level RNN to track morpheme boundaries in a single cell. We are however not aware of others studies systematically characterizing the processing of a linguistic phenomenon at the level of RNN cell dynamics, as is the attempt in the study hereby presented.

3 Setup

Language model We study the pretrained LSTM language model made available by Gulordava et al. (2018). This model is composed of a 650-dimensional embedding layer, two 650-dimensional hidden layers, and an output layer with vocabulary size 50,000. The model was trained on Wikipedia data, without fine-tuning for number agreement, and obtained perplexity close to state of the art in the experiments of Gulordava et al.[2]

Number-agreement tasks We complement analysis of the naturalistic, corpus-derived number-agreement test set of Linzen et al. (2016), in the version made available by Gulordava et al. (2018), with synthetically generated data-sets.

[2]Key findings reported below were also replicated with the same model trained with different initialization seeds and variations with different hyper-parameters.

Simple	the **boy** **greets** the guy
Adv	the **boy** probably **greets** the guy
2Adv	the **boy** most probably **greets** the guy
CoAdv	the **boy** openly and deliberately **greets** the guy
NamePP	the **boy** near Pat **greets** the guy
NounPP	the **boy** near the car **greets** the guy
NounPPAdv	the **boy** near the car kindly **greets** the guy

Table 1: NA tasks illustrated by representative singular sentences.

Each synthetic number-agreement task (NA-task) instantiates a fixed syntactic structure with varied lexical material, in order to probe subject-verb number agreement in controlled and increasingly challenging setups.[3] The different structures are illustrated in Table 1, where all forms are in the singular. Distinct sentences were randomly generated by selecting words from pools of 20 subject/object nouns, 15 verbs, 10 adverbs, 5 prepositions, 10 proper nouns and 10 location nouns. The items were selected so that their combination would not lead to semantic anomalies. For each NA-task, we generated singular and plural versions of each sentence. We refer to each such version as a *condition*. For NA-tasks that have other nouns occurring between subject and main verb, we also systematically vary their number, resulting in two *congruent* and two *incongruent* conditions. For example, the NounPP sentence in the table illustrates the congruent SS (singular-singular) condition and the corresponding sentence in the incongruent PS (plural-singular) condition is: "the *boys* near the *car greet* the guy". For all NA-tasks, each condition consisted of 600 sentences

Syntactic depth data-set We probed the implicit syntax-parsing abilities of the model by testing whether its representations predict the syntactic depth of the words they process. Following Nelson et al. (2017), this was operationalized as predicting the number of open syntactic nodes at each word, given the canonical syntactic parse of a sentence. We generated a data-set of sentences with unambiguous but varied syntactic structures and annotated them with the number of open nodes at each word. For example: "Ten_1 really_2 ecstatic_3 cousins_3 of_4 four_5 teachers_6 are_2 quickly_3 laughing_4", where indexes show the corresponding number of open nodes. Since syntactic depth is naturally correlated with the position of a word in a sentence, we used a data-point sampling strategy to de-correlate these factors. For each length between 2 and 25 words, we randomly generated 300 sentences. From this set, we randomly picked examples uniformly covering all possible position-depth combinations within the 7-12 position and 3-8 depth ranges. The final data-set contains 4,033 positions from 1,303 sentences.[4]

4 Experiments

To successfully perform the NA-task, the LSTM should: (1) encode and store the grammatical number of the subject; and (2) track the main subject-verb syntactic dependency. The latter information is important for identifying the time period during which subject number should be stored, output and then updated by the network. This section describes the 'neural circuit' that encodes and processes this information in the LSTM.

4.1 Long-range number units

We first tested the performance of the LSTM on the Linzen's data and on the NA-tasks in Table 1. Following Linzen et al. (2016) and later work, we computed the likelihood that the LSTM assigns to the main verb of each sentence given the preceding context and compared it to the likelihood it assigns to the wrong verb inflection. Accuracy in a given condition was measured as the proportion of sentences in this condition for which the model assigned a higher likelihood to the correct verb form than to the wrong one.

Network performance is reported in Table 2 (right column – 'Full'). We first note that our results on the Linzen NA-task confirm those reported in Gulordava et al. (2018). For the other NA-tasks, results show that some tasks and conditions are more difficult than others. For example, performance on the Simple (0-distance) NA-task is better than that on the Co-Adv NA-task, which in turn is better than that of the nounPP tasks. Second, as expected, incongruent conditions (the number-mismatch conditions of namePP, nounPP and nounPPAdv) reduce network performance.

[3] We exclude, for the time being, agreement across a relative clause, as it comes with the further complication of accounting for the extra agreement process taking place inside the relative clause.

[4] All our data-sets are available at: https://github.com/FAIRNS/Number_and_syntax_units_in_LSTM_LMs.

NA task	C	Ablated		Full
		776	988	
Simple	S	-	-	100
Adv	S	-	-	100
2Adv	S	-	-	99.9
CoAdv	S	-	82	98.7
namePP	SS	-	-	99.3
nounPP	SS	-	-	99.2
nounPP	SP	-	54.2	87.2
nounPPAdv	SS	-	-	99.5
nounPPAdv	SP	-	54.0	91.2
Simple	P	-	-	100
Adv	P	-	-	99.6
2Adv	P	-	-	99.3
CoAdv	P	79.2	-	99.3
namePP	PS	39.9	-	68.9
nounPP	PS	48.0	-	92.0
nounPP	PP	78.3	-	99.0
nounPPAdv	PS	63.7	-	99.2
nounPPAdv	PP	-	-	99.8
Linzen	**-**	75.3	-	93.9

Table 2: Ablation-experiments results: Percentage accuracy in all NA-tasks. Full: non-ablated model, C: condition, S: singular, P: plural. Red: Singular subject, Blue: Plural subject. Performance reduction less than 10% is denoted by '-'.

Third, for long-range dependencies, reliably encoding singular subject across an interfering noun is more difficult than a plural subject: for both nounPP and nounPPAdv, PS is easier than SP. A possible explanation for this finding is that in English the plural form is almost always more frequent than the singular one, as the latter only marks third person singular, whereas the former is identical to the infinitive and other forms. Thus, if the network reverts to unigram probabilities, it will tend to prefer the plural.

Looking for number units through ablation Number information may be stored in the network in either a local, sparse, or a distributed way, depending on the fraction of active units that carry it. We hypothesized that if the network uses a local or sparse coding, meaning that there's a small set of units that encode number information, then ablating these units would lead to a drastic decrease in performance in the NA-tasks. To test this, we ablated each unit of the network, one at a time, by fixing its activation to zero, and tested on the NA-tasks.

Two units were found to have exceptional effect on network performance (Table 2, 776 and 988 columns).[5] Ablating them reduced network performance by more than 10% across various conditions, and, importantly, they were the only units whose ablation consistently brought network performance to around chance level in the more difficult incongruent conditions of the namePP, nounPP and nounPPAdv tasks.

Moreover, the ablation effect depended on the grammatical number of the subject: ablating 776 significantly reduced network performance only if the subject was plural (P, PS or PP conditions) and 988 only if the subject was singular (S, SP or SS conditions). In what follows, we will therefore refer to these units as the 'plural' and 'singular' units, respectively, or long-range (LR) number units when referring to both. Finally, we note that although the Linzen NA-task contained mixed stimuli from many types of conditions, the plural unit was found to have a substantial effect on average on network performance. The singular unit didn't show a similar effect in this case, which highlights the importance of using carefully crafted stimuli, as in the nounPP and nounPPAdv tasks, for understanding network dynamics. Taken together, these results suggest a highly local coding scheme of grammatical number when processing long-range dependencies.

Visualizing gate and cell-state dynamics To understand the functioning of the number units, we now look into their gate and state dynamics during sentence processing. We focus on the nounPP NA-task, which is the simplest NA-task that includes a long-range dependency with an interfering noun, in both SP and PS conditions.

Recall the standard LSTM memory update and output rules (Hochreiter and Schmidhuber, 1997):

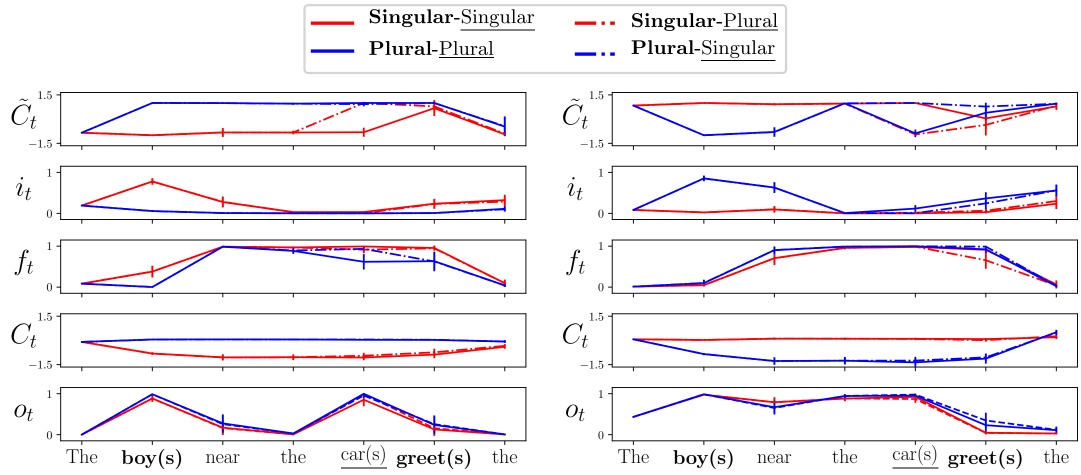
$$C_t = f_t \circ C_{t-1} + i_t \circ \widetilde{C}_t \quad (1)$$

$$h_t = o_t \circ \tanh(C_t), \quad (2)$$

where $f_t, i_t, o_t \in (0,1)$ are gating scalars computed by the network, and $\widetilde{C}_t \in (-1,1)$ is an update candidate for cell value.

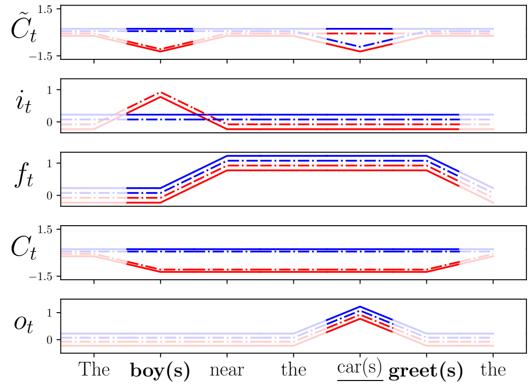
Consider now how a number unit may reliably encode and store subject number across interfering nouns. Figure 1c exemplifies this for a singular unit, showing the desired gate and cell dynamics.

[5] Units 1-650 belong to the first layer, 651-1300 to the second. All units detected by our analyses come from the latter.

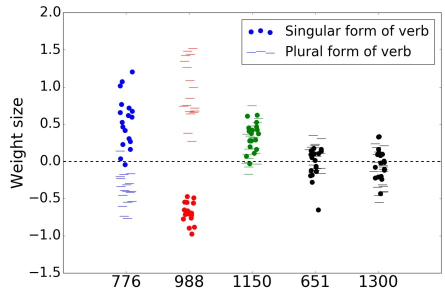


(a) 988 (singular)

(b) 776 (plural)



(c) Prediction (singular)



(d) Efferent weights of the LR-units (776 and 988), the syntax unit (1150 ; section 4.3) and two arbitrary units (651 and 1300).

Figure 1: (a) to (c) – Cell and gate activations during processing of sentences with a prepositional phrase between subject and verb. Values in (a) and (b) are averaged across all condition sentences, with error bars showing standard deviations. (d) – Efferent weights of specific units at the output layer to singular and plural verb forms.

The four conditions are represented with separated curves - red for singular subject, blue for plural, and dashed lines for incongruent conditions. Gate and cell activity at time points unrelated to solving the NA-task are masked with white, as we do not make precise predictions for them.

The update rule of the LSTM cell has two terms (Eq. 1).[6] In the first, $f_t \circ C_{t-1}$, the forget gate controls whether to keep the previous cell content ($f_t = 1$: perfect remembering) or forget it ($f_t = 0$: complete forgetting). In the second, $i_t \circ \tilde{C}_t$, the input gate controls whether the information currently presented to the network, as encoded by $\tilde{C}_t$, should be written onto the cell ($i_t = 1$: full access) or not ($i_t = 0$). The singular unit can thus use these gates to reliably store number information across long-range dependencies. Specifically, the unit can (enumeration follows the same order as the panels in Figure 1c): (1) encode subject number via $\tilde{C}_{t_{subject}}$ with different values for singular and plural; (2) open the input gate *only* when a singular subject is presented ($i_{t_{subject}} = 1$ in red curves *only*) and protect it from interfering nouns ($i_t = 0, t_{subject} < t < t_{verb}$); (3) at the same time, clear the cell from previously stored information ($f_{t_{subject}} = 0$) and then store subject number across the entire dependency ($f_t = 1, t_{subject} < t < t_{verb}$); (4) this will result in stable encoding of subject number in the cell C_t throughout the dependency; (5) finally, output subject number at the right moment, when predicting the verb form ($o_{t_{verb}-1} = 1$) (Eq. 2).

Figures 1a and 1b present the actual gate and cell dynamics of the singular and plural units. Both units follow the general solution for reliable

[6]We abuse notation here, using the symbols denoting whole layers in equations (1) and (2) to denote the components of single cells.

number storage described above. Note that for $\tilde{C}_t$ and i_t, and as a result also for C_t, the plural unit 'mirrors' the singular unit with respect to subject number (red curves of PP and PS vs. blue curves of SS and SP). This is in accordance with the results of the ablation experiments, which showed that ablating these units had an effect that depended on the grammatical number of the subject (Table 2). This provides complementary support for the identification of these units as 'singular' and 'plural'.

A single divergence between the solution depicted in Figure 1c and the actual dynamics of the number units is that input gate activity is smaller, but not zero, at the time step immediately following the subject. One speculative explanation is that this might be useful to process compound nouns. In these cases, subject number information is stored with the second noun, whereas in the case of simple nouns there is no 'risk' of encountering an interfering noun immediately after the subject, making the delay in closing the gate safe.

The singular and plural units had emerged at the second layer of the network. This seems appropriate since number information needs to be directly projected to the output layer for correct verb-form prediction. Moreover, number-unit output should be projected differently to singular and plural verb forms in the output layer, only increasing activity in output units representing the suitable form. For example, for the singular unit, since singular subjects are encoded with a negative value ($C_{t_{verb}-1} < -1$ in figure 1a), the more negative its efferent weights to singular verb forms in the output layer, the higher the probabilities of these verb forms would be. Figure 1d shows the efferent weights of the LR-number units to all verbs in our data-sets. We found that, indeed, the efferent weights to the singular and plural verb forms are segregated from each other, with weight signs that correspond to the negative encoding of subject number used by both singular and plural units. Two other arbitrary units, 651 and 1300 , and the syntax unit 1150 to be described below (Section 4.3) do not have segregated efferent weights to verb forms, as expected.

4.2 Short-range number information

Performance on the easier NA-tasks (Simple, Adv, 2Adv) was not impaired by single-unit ablations. This suggests that number may be encoded also

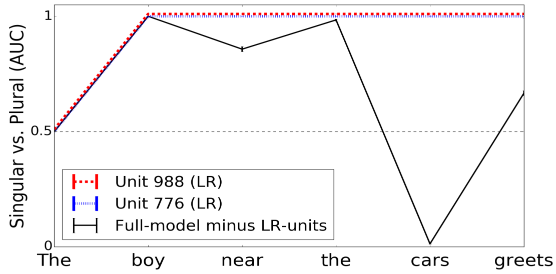
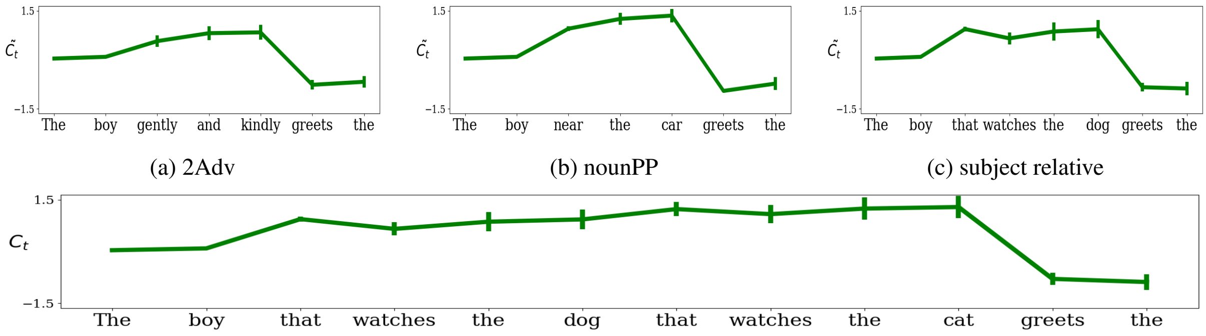


Figure 2: Generalization across time of subject-number prediction. Error bars represent standard deviations across cross-validation splits.

elsewhere in the network, perhaps via a more distributed code. To verify this, we tested whether subject number can be decoded from the whole pattern of activities in the network (excluding the two LR-number units) and whether this decoding is stable across time (see Giulianelli et al., 2018, for similar observations and related methods). We expected this distributed activity to track number in a small time window after the subject, but, unlike the LR-number units, to be affected by incongruent intervening nouns.

We trained a linear model to predict the grammatical number of the subject from network activity in response to the presentation of the subject, and tested its prediction on test sets from all time points (King and Dehaene, 2014), in incongruent conditions only of the nounPP task. We used Area under of Curve (AUC) to evaluate model performance. Figure 2 shows decoding across time of subject number from cell activity of each number unit separately and from cell activity of the entire network without these two units ('Full model minus LR-units'). Results show that number information can be efficiently decoded from other units in the network, and that this information can be carried for several time steps (relatively high AUC up to the second determiner). However, the way in which these units encode number is sensitive to the last encountered noun, with AUC decreasing to zero around the second noun ('cars'), whereas test performance of the models trained on cell activity of the LR-number units is consistently high. This confirms that number prediction is supported both by the LR-number units, and by distributed activation patterns of other short-range (SR) number units. The latter, however, are not syntax-sensitive, and simply encode the number of the last noun encountered.



(a) 2Adv (b) nounPP (c) subject relative

(d) Two embeddings with subject relatives

Figure 3: Cell activity of syntax unit 1150 while processing various syntactic structures. Values averaged across all stimuli in an NA-task, with error bars representing standard deviations. Relative clause NA-task stimuli were specifically generated for this visualization.

A full description of the SR-number units is beyond our scope. However, we note that 10 SR-number units in the second layer of the network were identified, which had efferent weights with a similar segregated structure as that of the LR units (Figure 1d). These units were indeed sensitive to the last encountered noun: subject number could be decoded from single-unit cell activity during its presentation (AUC>0.9), but activity 'swaps' once an interfering noun appears (i.e., AUC decreases to zero in a generalization-across-time analysis). Finally, to validate the role of SR-number units in encoding number for easier NA-tasks, we ablated both SR and LR number units (12 in total) or SR units only (10 in total) and evaluated network performance on these NA-tasks. Both experiments resulted in a significant reduction in task performance compared to 1,000 random equi-size ablations ($p < 0.01$ in all 'easier' tasks).

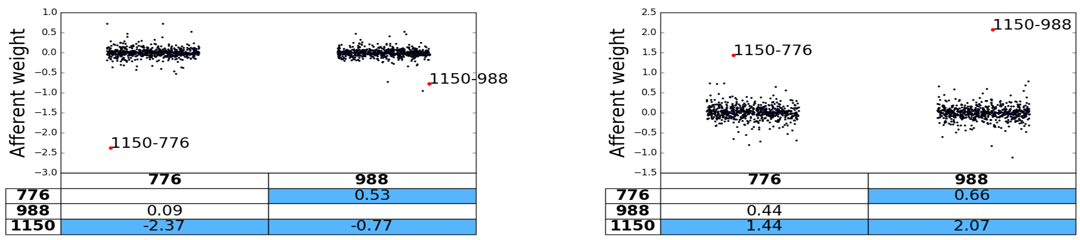
Intriguingly, we observed qualitatively that LR units are almost always making the right prediction, even when the network predicts the wrong number. The wrong outcome, in such cases, might be due to interference from the syntax-insensitive SR units. We leave the study of LR-SR unit interplay to future work.

4.3 Syntax units

We saw how the input and forget gates of the LR-number units control the flow of subject-number information. It remains unclear, however, how the dynamics of these gates are controlled by the network. We hypothesized that other units in the network may encode information about the syntactic structure of the sentence, and thus about the subject-verb dependency. These units could then control and coordinate the opening and closing of the input and forget gates of the number units.

To identify such 'syntax' units, we tested from which units syntactic information can be efficiently decoded. We used depth of the syntactic tree as a proxy for syntactic structure (Nelson et al., 2017) and trained an L2-regularized regression model to predict syntactic tree-depth from the hidden-state activity of all units. In all experiments, we used the data presented in Section 3 above and performed a nested 5-fold cross-validation procedure. Word frequency, which was added as a covariate to the model, had a negligible effect on the results. Syntactic tree-depth was found to be efficiently decodable from network activity ($R^2_{test-set} = 0.85 \pm 0.009$; covariate-corrected). A small subset of 'syntax' units had relatively high weights in the regression model (mean weight = 7.6×10^{-4}, SD=7.86×10^{-2}; cut-off for outlier weights was set to three SDs). Since the interpretation of the regression weights may depend on possible correlations among the features, we also tested the causal effect of these units on NA-task performance. Ablating the syntax units together resulted in significant performance reduction in NA-tasks that have an interfering noun: Linzen NA-task: $p = 0.024$, nounPPAdv-SP: $p = 0.011$, nounPPAdv-PS: $p = 0.034$, nounPP-SP: $p < 0.001$ and marginally significant in nounPP-PS: $p = 0.052$ (compared to 1000 random ablations of subsets of units of the same size).

To gain further insight regarding the functioning of the syntax units, we next visualized their gate and cell dynamics during sentence processing. We found that cell activity of unit 1150 , which also



(a) Input gate

(b) Forget gate

Figure 4: Connectivity among the syntax unit 1150 and LR-number units 776 and 988 . Projecting units are on the table rows. Blue background highlights outlier values ($|z - score| > 3$). Weights from the syntax unit are marked in red and are explicitly labeled in the plots, which show the overall distributions of afferent weights to each number unit.

had one of the highest weights in the regression model, was remarkably structured. The activity of this unit increases across the entire subject-verb dependency and drops abruptly right after. Figures 3a and 3b show cell activity of this unit during the processing of stimuli from the 2Adv and nounPP tasks. We found the same dynamics in cases where another verb occurs between subject and main verb, as in subject relatives (Figure 3c), and in exceptionally long-distance dependencies with two interfering nouns and verbs (Figure 3d). Taken together, these results suggest that unit 1150 consistently encodes subject-verb dependencies in a syntax-sensitive manner. Other syntax units did not show an easily interpretable dynamics and had no clear interactions with the number units in the analysis discussed next. This suggests that they perform different syntactic, or possibly other, functions.

4.4 Syntax-number units connections

We finally look at the connections that were learned by the LSTM between syntax unit 1150 , which appears to be more closely involved in tracking subject-verb agreement, and the LR number units, as well as at the connections between the LR-number units themselves. For each unit pair, there are 4 connection types, one for each component of the target cell (to the 3 gates and to the update candidate). We focus on input and forget gates, as they control the flow and storage of number information.

Figures 4a and 4b show the distributions of all afferent recurrent weights to the input and forget gates of the LR-number units, scaled by the maximal activity h_t of the pre-synaptic units during the nounPP task (this scaling evaluates the *effective* input to the units and did not change the conclusions described below). We found that the weights from the syntax unit to the forget gate of both 776 and 988 are exceptionally high in the positive direction compared to all other afferent connections in the network ($z - score = 8.1, 11.2$, respectively) and those to their input gates exceptionally negative ($z - score = -16.2, -7.2$). Since the cell activity of syntax unit 1150 is positive across the entire subject-verb dependency (e.g., Figure 3d), the connectivity from the syntax unit drives the number unit forget gates towards one ($W^f_{776,1150}h^{1150} \gg 0$ and $W^f_{988,1150}h^{1150} \gg 0$; $t_{subject} < t < t_{verb}$) and their input gates towards zero ($W^i_{776,1150}h^{1150} \ll 0$ and $W^i_{988,1150}h^{1150} \ll 0$). Looking at the right-hand-side of Eq. (1), this means that the first term becomes dominant and the second vanishes, suggesting that, across the entire dependency, the syntax unit conveys a 'remember flag' to the number units. Similarly, when the activity of the syntax unit becomes negative at the end of the dependency, it conveys an 'update flag'.

Last, we note that the reciprocal connectivity between the two LR-number units is always positive, to both input and forget gates (with $|z - score| > 3$ for the 776 -to-988 direction). Since their activity is negative throughout the subject-verb dependency (Figures 1a and 1b), this means that they are *mutually inhibiting*, thus steering towards an unequivocal signal about the grammatical number of the subject to the output layer.

5 Summary and discussion

We provided the first detailed description of the underlying mechanism by which an LSTM language-model performs long-distance number agreement. Strikingly, simply training an LSTM on a language-model objective on raw corpus data brought about single units carrying exceptionally specific linguistic information. Three of these units were found to form a highly interactive local network, which makes up the central part of a 'neural' circuit performing long-distance number agreement.

One of these units encodes and stores grammatical number information when the main subject of a sentence is singular, and it successfully carries this information across long-range dependencies. Another unit similarly encodes plurality. These number units show that a highly local encoding of linguistic features can emerge in LSTMs during language-model training, as was previously suggested by theoretical studies of artificial neural networks (e.g., Bowers, 2009) and in neuroscience (e.g., Kutter et al., 2018).

Our analysis also identified units whose activity correlates with syntactic complexity. These units, as a whole, affect performance on the agreement tasks. We further found that one of them encodes the main subject-verb dependency across various syntactic constructions. Moreover, the highest afferent weights to the forget and input gates of both LR-number units were from this unit. A natural interpretation is that this unit propagates syntax-based remember and update flags that control when the number units store and release information.

Finally, number is also redundantly encoded in a more distributed way, but the latter mechanism is unable to carry information across embedded syntactic structures. The computational burden of tracking number information thus gave rise to two types of units in the network, encoding similar information with distinct properties and dynamics.

The relationship we uncovered and characterized between syntax and number units suggests that agreement in an LSTM language-model cannot be entirely explained away by superficial heuristics, and the networks have, to some extent, learned to build and exploit structure-based syntactic representations, akin to those conjectured to support human-sentence processing.

In future work, we intend to explore how the encoding pattern we found varies across network architectures and hyperparameters, as well as across languages and domains. We also would like to investigate the timecourse of emergence of the found behaviour over training time.

More generally, we hope that our study will inspire more analyses of the inner dynamics of LSTMs and other sequence-processing networks, complementing the currently popular "black-box probing" approach. Besides bringing about a mechanistic understanding of language processing in artificial models, this could inform work on human-sentence processing. Indeed, our study yields particular testable predictions on brain dynamics, given that the computational burden of long-distance agreement remains the same for artificial and biological neural network, despite implementation differences and different data sizes required for language acquisition. We conjecture a similar distinction between SR and LR units to be found in the human brain, as well as an interaction between syntax-processing and feature-carrying units such as the LR units, and plan to test these in future work.

Acknowledgments

We would like to thank Kristina Gulordava, Jean-Remi King, Tal Linzen, Gabriella Vigliocco and Christophe Pallier for helpful feedback and comments on the work.

References

Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. 2017. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. In *Proceedings of ICLR Conference Track*, Toulon, France. Published online: https://openreview.net/group?id=ICLR.cc/2017/conference.

Guillaume Alain and Yoshua Bengio. 2017. Understanding intermediate layers using linear classifier probes. In *Proceedings of ICLR Conference Track*, Toulon, France.

Jean-Philippe Bernardy and Shalom Lappin. 2017. Using deep neural networks to learn syntactic agreement. *Linguistic Issues in Language Technology*, 15(2):1–15.

Jeffrey Bowers. 2009. On the biological plausibility of grandmother cells: Implications for neural network theories in psychology and neuroscience. *Psychological Review*, 116(1):220–251.

Shammur Chowdhury and Roberto Zamparelli. 2018. RNN simulations of grammaticality judgments on long-distance dependencies. In *Proceedings of COLING*, pages 133–144, Santa Fe, NM.

Lieke Gelderloos and Grzegorz Chrupała. 2016. From phonemes to images: levels of representation in a recurrent neural model of visually-grounded language learning. In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 1309–1319.

Mario Giulianelli, Jack Harding, Florian Mohnert, Dieuwke Hupkes, and Willem Zuidema. 2018. Under the hood: Using diagnostic classifiers to investigate and improve how language models track agreement information. In *Proceedings of the EMNLP BlackboxNLP Workshop*, pages 240–248, Brussels, Belgium.

Kristina Gulordava, Piotr Bojanowski, Edouard Grave, Tal Linzen, and Marco Baroni. 2018. Colorless green recurrent networks dream hierarchically. In *Proceedings of NAACL*, pages 1195–1205, New Orleans, LA.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(8):1735–1780.

Dieuwke Hupkes, Sara Veldhoen, and Willem Zuidema. 2018. Visualisation and 'diagnostic classifiers' reveal how recurrent and recursive neural networks process hierarchical structure. *Journal of Artificial Intelligence Research*, 61:907–926.

Jaap Jumelet and Dieuwke Hupkes. 2018. Do language models understand anything? on the ability of lstms to understand negative polarity items. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 222–231.

Andrej Karpathy, Justin Johnson, and Fei-Fei Li. 2016. Visualizing and understanding recurrent networks. In *Proceedings of ICLR Workshop Track*, San Juan, Puerto Rico. Published online: https://openreview.net/group?id=ICLR.cc/2016/workshop.

Yova Kementchedjhieva and Adam Lopez. 2018. 'Indicatements' that character language models learn English morpho-syntactic units and regularities. In *Proceedings of the EMNLP Workshop on analyzing and interpreting neural networks for NLP*, Brussels, Belgium. In press.

Jean-Rémi King and Stanislas Dehaene. 2014. Characterizing the dynamics of mental representations: The temporal generalization method. *Trends in Cognitive Sciences*, 18(4):203–210.

Adhiguna Kuncoro, Chris Dyer, John Hale, and Phil Blunsom. 2018a. The perils of natural behavioral tests for unnatural models: The case of number agreement. Poster presented at the Learning Language in Humans and in Machines conference, online at: https://osf.io/view/L2HM/.

Adhiguna Kuncoro, Chris Dyer, John Hale, Dani Yogatama, Stephen Clark, and Phil Blunsom. 2018b. LSTMs can learn syntax-sensitive dependencies well, but modeling structure makes them better. In *Proceedings of ACL*, pages 1426–1436, Melbourne, Australia.

Esther Kutter, Jan Bostroem, Christian Elger, Florian Mormann, and Andreas Nieder. 2018. Single neurons in the human brain encode numbers. *Neuron*, 100(3):753–761.

Jiwei Li, Xinlei Chen, Eduard Hovy, and Dan Jurafsky. 2016. Visualizing and understanding neural models in NLP. In *Proceedings of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, pages 681–691.

Tal Linzen, Emmanuel Dupoux, and Yoav Goldberg. 2016. Assessing the ability of LSTMs to learn syntax-sensitive dependencies. *Transactions of the Association for Computational Linguistics*, 4:521–535.

Tal Linzen and Brian Leonard. 2018. Distinct patterns of syntactic agreement errors in recurrent networks and humans. In *Proceedings of CogSci*, pages 692–697, Austin, TX.

Rebecca Marvin and Tal Linzen. 2018. Targeted syntactic evaluation of language models. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202.

Matthew Nelson, Imen El Karoui, Kristof Giber, Xiaofang Yang, Laurent Cohen, Hilda Koopman, Sydney Cash, Lionel Naccache, John Hale, Christophe Pallier, and Stanislas Dehaene. 2017. Neurophysiological dynamics of phrase-structure building during sentence processing. *Proceedings of the National Academy of Sciences*, 114(18):E3669–E3678.

Alec Radford, Rafal Jozefowicz, and Ilya Sutskever. 2017. Learning to generate reviews and discovering sentiment. https://arxiv.org/abs/1704.01444.

Zhiyuan Tang, Ying Shi, Dong Wang, Yang Feng, and Shiyue Zhang. 2017. Memory visualization for gated recurrent neural networks in speech recognition. In *Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference on*, pages 2736–2740. IEEE.

Ethan Wilcox, Roger Levy, Takashi Morita, and Richard Futrell. 2018. What do RNN language models learn about filler–gap dependencies? In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 211–221.