The emergence of number and syntax units in LSTM language models

Anonymous NAACL submission

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 number information is managed by very few "grandmother cells" in a localist fashion. Importantly, the behaviour of the number cells is partially controlled by other units that are independently shown to track the syntactic structure of sentences. 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

[1-6]

Studies showing that LSTMs trained on language modeling do well on the agreement task: (**?**; **?**), to a lesser extent: (**?**; **?**). Studies conjecturing this is just heuristics: (**?**; **?**). Grandma cells: (**?**).

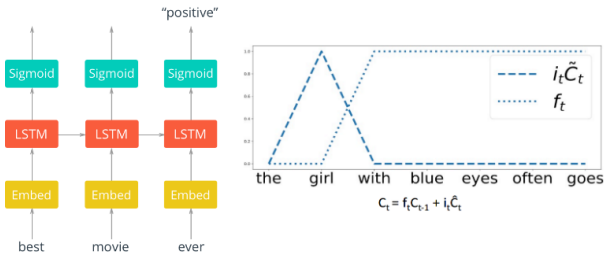

Figure 1: Caption.

2 Related literature

2.1 Interpreting LSTM networks

Short survey of works that: - Interpret neural networks in general (e.g., CNNs in vision) - Interpret LSTMs (e.g. Karpathy's) - Interpret LSTM language models

Besides **?**), remember to discuss **?**), as they find a "sentiment" grandma cell. **?**) found a character-level RNN to track morpheme boundaries in a localist fashion, through a single cell.

Radford:etal:2017,

2.2 Subject-verb agreement in English

- Subject-verb agreement from psycholinguistics (e.g., Miller and Bock, Franck and Rizzi) - SV agreemnt in LSTMs (**?**; **?**; **?**; **?**; **?**; **?**) - Relate to Nelson et. al 2017 PNAS, an intracranial study that identifies electrodes whose high-gamma activity correlates with syntactic tree-depth (numnber of open nodes)

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
SubjRel	the boy that avoids the girl greets the guy
ObjRel	the boy that the girl avoids greets the guy
ObjRel0	the boy the girl avoids greets the guy

Table 1: NA tasks illustrated by representative singular sentences.

3 Data

3.1 Number-agreement tasks

We generated number-agreement tasks (NA-tasks) with fixed syntactic structures and varied lexical material that probe subject-verb number agreement in increasingly challenging setups. The different structures are illustrated in Table 1 by examples where all forms are in the singular. Distinct sentences were randomly generated by selecting (different) 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 varied their number, resulting in four conditions. For example, the NounPP sentence in the table illustrates the SS (singular-singular) condition. The corresponding sentences in the other conditions are: "the boy near the cars greets the guy" (SP), "the boys near the car greet the guy" (PS), and "the boys near the cars greet the guy" (PP).

Possibly move this to Models or Results section. For each NA-task, model performance was evaluated for each of its conditions separately, by computing its accuracy in predicting the correct form of the main verb. Specifically, for each sentence from a condition, the model was presented with all words up to the one immediately preceding the main verb. If the model assigned higher likelihood to the correct form of the verb than to its counterpart with the wrong number, then the trial was marked as a hit.

Yair: consider move these explanations about contrasts to the results section: ~~Note that 2Adv features the same subject-verb distance as NamePP, but without gender-carrying words acting as possible distractors in the middle. Similarly, CoAdv can serve as a distractor-free control for NounPP.~~

Task sata-set sizes across conditions ranged from 600 (Simple) to 18k sentences (relatives), based on the possibilities for variation allowed by the combinatorics given each structure.[1]

Finally, we also used the naturalistic, corpus-derived agreement test set of **?**), in the version made available by **?**).

3.2 Number of open nodes

4 The models

The recurrent models that are the focus of our studies are LSTM models (**?**). To inspect the internal dynamics of these models, we use additional linear models trained to predict information from the hidden state activations of the language models. (DH: Or something like this. I'd put (**?**) and (**?**), but @yair perhaps we have also some neuroscience ref? Would you mind calling it diagnostic classifiers?) In this section, we describe how we train the language models we study, as well as our diagnostic classifier protocol.

4.1 LSTM language model

Following (**?**), we study LSTM language models with two layers containing 650 nodes and an embedding size of 650. We consider the pretrained model that was made available by (**?**), as well as 3 (?) additional models that were trained following the same protocol, but with a different seed and/or different dropout rate.

This leaves us with 4 (?) models that . . . (DH: One sentence describing the number of modes that we used and how they differed. Here also name the models. I believe this can be very short, for details we can refer to the code/appendix, we shouldn't waste our space

[1] We uploaded the data-set generation script as supplementary material.

here with too much information unimportant to the story. E.g., LSTM equations, the exact training data... these details can be found in earlier papers.)

The models we consider were comparable in terms of perplexity on a heldout dataset (with perplexities of W, X, Y and Z, respectively) but differ in their accuracy on the *agreement task* ... (DH: I have to find these numbers, then I'll finish this subsection.)

4.2 Regression model

- Explain that the model was used to predict the depth of the syntactic tree from network activity

4.2.1 Model description

- Describe the Features: network activity (hidden/cell activity) - Describe the label: Tree depth (refer to the section describing the synthetic data) - Describe the model: A Ridge/LASSO model.

4.2.2 Model training and evalution

- Model training: nested 5-fold CV procedure. Train/val/test. Optimal regularization size was estimated from the validation set (report optimal lamda - figures in FAIRNS.pdf on slack) - model evaluation: R-squared on test set. Report resulting values (text+figures in FAIRNS.pdf).

5 Results

To successfully perform the NA-task, it seems that the LSTM-LM should encode and store at least two types of informations: (1) the grammatical number of the subject; and (2) the syntactic structure of the sentence. The latter information is important for knowing at which time point the network should output and update the stored number information. This section describes the detailed mechanism by which units in the network encode and store these types of information, and the interaction between these units. Section 5.1 identifies and describes 'number units', units in the network that specializes in encoding and storing the grammatical number of the subject for short- and long-range dependencies; Section 5.2 describes 'syntax units', units whose activity correlates with the depth of the syntactic tree; Then, section 5.3 explores the interactions among syntax and number units, required for accomplishing the NA-task. Finally, section 5.4 looks into the dynamics of these units during the processing of complex syntactic structures with single or double relative clauses.

5.1 Long-range number-units

To accomplish the NA-task, the LSTM network should encode and store the grammatical number of the subject up to one step before the verb, when prediction of the verb form (singular or plural) occurs. In some cases, this may be quite challenging, in particular in the case of a long-range dependency between subject and verb, and in particular, when another noun with an opposite number appears before the verb (cite). This section explores the underlying mechanism that enables the network to encode and store number information in various syntactic constructions, including ones with an interfering noun. Subsection 5.1.1 describes an ablation study, which reveals *long-range number units (LR-number units)* that can store and carry number information from subject to verb, also across interfering nouns. Subsection 5.1.2 describes the intricate gate and state dynamics of LR-number units during the processing of sentences with long-range dependencies. Section 5.1.3 describes a different type of number units that encode grammatical number for only short-range dependencies, such as in the case of a verb immediately following a subject. Finally, subsection 5.1.4 looks into the structure of the efferent weights of number units, by which number information is propagated to the output layer.

5.1.1 Local vs. distributed code - an ablation study

Generally, 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 number information. 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 on the NA-task, compared to when ablating other units. To test this, we conducted ablation experiments in which each time a single unit of the network is ablated and the resulting model is then evaluated on several NA-tasks. Each NA-task contained sentences with a fixed syntactic structure, such as "Det Noun Adv Verb" or "Det Noun P Det Noun Verb", and each task was composed of several conditions depending on the possible assignments of grammatical number to the noun(s) in the sentence (see section 3.1 for details about all NA-tasks). In addition, we also evaluated each ablated model on the Linzen task (cite). Tables 1 summarizes the results from all ablation experiments, showing units whose ablation resulted in a performance decrease of more than 10% (TODO: choose a non-arbitrary threshold by looking at the distribution). For each NA-task, the performance of the full, non-ablated, model is also reported.

NA task	C	770	776	988	1283	Full
Simple	S	-	-	-	-	100
Adv	S	-	-	-	-	100
2Adv	S	-	-	-	-	99.8
Co-Adv	S	-	-	84.0	84.0	98.8
namePP	SS	-	-	-	-	98.9
nounPP	SS	-	-	-	-	97.5
nounPP	SP	-	-	58.8	-	88.5
subjrel	SS	-	-	88.0	-	97.0
subjrel	SP	-	-	-	-	58.8
objrel	SS	-	-	-	-	64.7
objrel	SP	-	-	-	-	45.7
Simple	P	-	-	-	-	100
Adv	P	-	-	-	-	99.6
2Adv	P	-	-	-	-	99
Co-Adv	P	-	78.9	-	-	99.7
namePP	PS	-	57.6	-	-	66.8
nounPP	PS	85.2	49.7	-	-	93.2
nounPP	PP	-	81.7	-	-	98.3
subjrel	PS	85.8	58.6	-	-	87.8
subjrel	PP	-	88.1	-	-	99.3
objrel	PS	-	-	-	-	69.0
objrel	PP	-	-	-	-	81.0
Linzen	-	?	?	?	?	?

Table 2: Ablation experiments results: Percentage of correct subject-verb agreements in all NA-tasks (section 3.1). Full - non-ablated model, C - condition, S - singular, P - plural. For task with two nouns, SS - singular-singular, SP - singular-plural, PS - plural-singular, PP - plural-plural. Red: singular number units, Blue: Plural number units.

The discussion of Table 2 should lead more clearly to the following discussion in which we focus on 776 and 988. We should say at a certain point that the 770 and 1283 might be complementary cells, but clearly the main job of tracking LR number is left to 776 and 988.

It's still unclear to me that the relative clause results really fit here.

We first highlight several aspects of the behavioral results of the full network (table 1 - right column) before describing in more details the ablation results. First, some NA-tasks and conditions are clearly more difficult for the network than others. For example, performance on the simple NA-task is better than that on the nounPP NA-task, which in turn is better than that of the objrel task. This matches previously reported results in humans and LSTM-LMs (cite). Second, having an interfering noun before the verb, with an opposite number than that of the subject, is clearly a more challenging task for the network - we find that for the nounPP, subjrel and objrel tasks: $ACC_{SP} > ACC_{SS}$ and $ACC_{PS} > ACC_{PP}$. We return to this point in section 5.4. Finally, for long-range dependencies, reliably encoding that the subject is singular is in most cases more difficult than plural. For example, in all the above tasks: $ACC_{SS} < ACC_{PP}$ and $ACC_{SP} < ACC_{PS}$. Interestingly, this singular-plural asymmetry has been reported also in humans (cite). We elaborate on this point in the discussion section.

We next describe several important aspects of the ablation-experiment results. First, in all NA-tasks, only four units from the entire network (1300 LSTM units in total) had a significant effect on task performance. This result suggests a local coding scheme for long-range grammatical-number information

(TODO: quantify a 'significant' reduction, and perhaps link to the emergence of local coding in neural-network simulations (Bowers) and to findings about grandmother neurons in humans (e.g., Fried)). Second, we note that all number units emerged at the second layer of the network. This seems appropriate if number information needs to be directly projected to the output layer for correct verb-form prediction. In section 5.1.4 we further explore the projection weights from number units. Third, for simple, 1Adv and 2Adv NA-tasks, none of the units had a significant effect on task performance. This suggests that for short-range dependencies number information may be also encoded elsewhere in the network, perhaps via a more distributed code. We therefore make a distinction between long-range (LR) and short-range (SR) number units in what follows. We return to this point in section 5.1.3 (TODO: complete the identification of short-range number units from the resulting weights of the classifier in the generalization-across-time experiment). Fourth, LR-number units can be further divided into two types, depending on the grammatical number of the subject. Units 770 and 776 had a significant effect only when the first noun was plural, but not singular, and vice versa for units 988 and 1283 (blue and red in table 1, respectively). We therefore refer to the former as *plural units* and to the latter as *singular units*. Finally, we note that two of the number units (776 & 988) had an exceptional effect on network performance in both nounPP-SP&PS conditions. These two conditions are in particular revealing since they involve both a long-range dependency (over a prepositional phrase) and an interfering noun before the verb, while performance of the non-ablated network is still relatively high (88.5%&93.2%, respectively) in contrast to these conditions in subjrel and objrel. Ablating one of these two units brought the network from high performance on the NA-task to around chance-level performance (58.8%&49.7%, respectively). In the next section, we therefore focus on these two units when exemplifying gate and state dynamics of number units.

5.1.2 Visualizing gate and cell-state dynamics

Results from the ablation study suggest that there's a small set of units that encodes number information for long-range dependencies, in particular, we find that in some conditions two units can bring the network from relatively high performance to around chance-level performance on the NA-task (section 5.1.1). However, it remains unclear what is the exact mechanism underlying successful trials in the NA-task, and what goes wrong in unsuccessful ones. To better understand this, we now looks into gate and state dynamics of these units during the processing of sentences from the nounPP NA-task. **Why do we focus on nounPP: because it is the minimal case with the four conditions, but without the complications of tracking another agreement relation as in the relatives.**

To anticipate the results and facilitate their interpretations, we begin by discussing what could be a solution to the NA-task implemented by number units in their gate and state activity. We recall that the update rule of the LSTM cell has two terms (equation 1.x). In the first term $f_t * C_{t-1}$, the forget gate controls whether to keep the previous content C_{t-1} stored in the cell ($f_t = 1$ - perfect remembering), or forget it ($f_t = 0$ - complete forgetting). In the second term $i_t * \tilde{C}_t$, the input gate controls whether the information currently presented to the network could be updated onto the cell state: $i_t = 1$ - full access, $i_t = 0$ - no access. Therefore, to produce correct number agreement, it seems that number units should at least have the following three properties: (1) The grammatical number of the subject should first be encoded by $\tilde{C}_{t_{subject}}$, encoding singular and plural with *different* values. (2) To grant the encoded grammatical number $\tilde{C}_{t_{subject}}$ access to the cell, the input gate should be open at the time when the subject is presented: $i_{t_{subject}} > 0$, and ideally $i_{t_{subject}} = 1$. In addition, to protect the stored grammatical number from interfering information updating onto the cell, such as in the case of an interfering noun, the input gate should be

closed during all successive time steps until the verb: $i_t = 0, t < t_{verb}$; (3) Finally, to successfully store number information in the cell for a long-range dependency, the forget gate should be in a remembering state, starting one time step after the subject: $f_t = 1, t > t_{subject}$. In addition, to clean up the cell from previously stored information, the forget gate should reset when the subject is presented: $f_{t_{subject}} = 0$. Figure 1B summarizes these three presumably desired properties.

Figure 2 presents the actual gate and state dynamics of units 776 and 988 during the processing of sentences from the nounPP NA-task. For each unit, we draw the dynamics of the suggestion $\tilde{C}_t$ (panels A-B), input-gate (panels C-D), forget-gate (panels E-F) and the cell variable (G-H). For each of these cases, the four condition (SS, SP, PS and PP) are described in separate curves. Error-bars represent standard deviation across 1000 sentences in each condition.

We describe the results along the order of the properties discussed above. First, the values of the cell suggestions $\tilde{C}_t$ of both units seem to obey the first property. For the singular unit 988, we find that singular nouns are encoded with negative values $\tilde{C}_{t_{subject}} = -1$, and plurals with positive $\tilde{C}_{t_{subject}} = 1$ (panel A), and similarly for unit 776 (panel B). This shows that singular and plural nouns are indeed encoded differently by these units, in accordance with the results of the ablation study that suggested the labeling of units 988 and 776 as singular and plural units, respectively.

Second, input-gate dynamics of both number units seem to correspond to the second property described above. Input-gate activity spikes around the subject and stays approximately zero for subsequent time steps until the verb. One difference with respect to the desired property is the non-zero activity of the input gate at the time step immediately following the subject. This may be due to various reasons and requires further research. One possible explanation for this is that the network has developed this behavior as a heuristic to deal with compound nouns, given that for compound nouns the relevant number information resides at the second noun, whereas in the case of simple nouns there's anyway no risk of encountering an interfering noun immediately after the subject (TODO: discuss this part in the meeting to see if it makes sense to all. If yes, perhaps we could easily check this in an experiment.). Finally, note that for unit 988, the input gate is only open when the subject is singular, whereas for unit 776 it is only open when the subject is plural. This too is consistent with the labeling of these units as singular and plural.

Third, forget-gate dynamics of both number units also seem to correspond to the above properties. In both units, forget-gate activity starts at value around zero $f_{t_{subject}=0}$ and then goes abruptly towards its maximal value at the next step $t_{subject}+1$, then stably staying at this level until after the verb $t_{verb}+1$. Note that for all four conditions (SS, SP, PS and PP), the forget-gate exhibits similar dynamics, being indifferent to the grammatical number of the subject. This seems appropriate for whether the second noun is singular or plural given that the network cannot know in advance whether an interfering noun will appear, and it should anyway store number information for long-range dependencies also in the absence of any upcoming noun (TODO: explain or leave as an open question the reason for which we observe the same dynamics whether the first noun is singular or plural). Last, we note that in all cases the forget-gate activity resets at $t_{verb}+1$. This seems appropriate, given that at this point the subject's number is no more useful, and the cell would be better free up to encode new number information.

Finally, cell activity should reflect the dynamics of the suggestion, input and forget gates. Indeed, the cell value becomes non-zero at $t_{subject}$ and preserves this value until $t_{verb}-1$ when verb-form prediction occurs (Panels G-H). Note that this is the case only for the relevant conditions: in conditions SS and SP, unit 987 encodes singular as $C_t = -1$ and is approximately zero during sentence processing in the other two conditions (PP and PS). Similarly, unit 776 encodes plural with a non-zero, negative, value only in the relevant conditions (PP and PS) but not in the

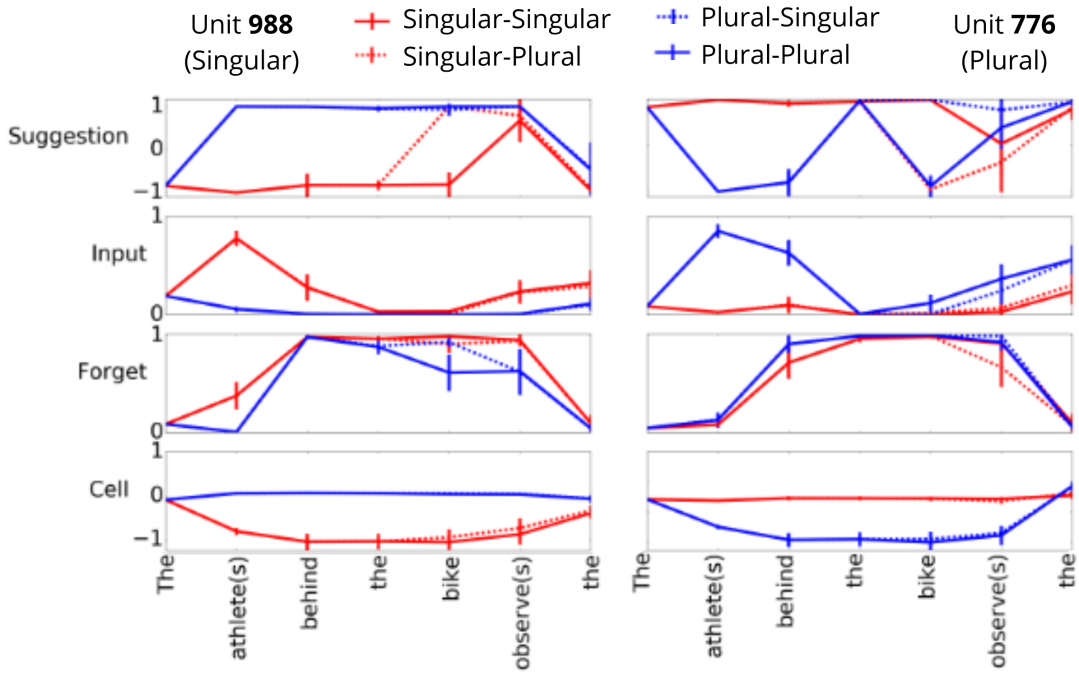

Figure 2: Cell and gate activations during processing of a sentence with a prepositional phrase between subject and verb. (A) Cell activity C_t for the two number units 775 and 987 and output activity h_t for the syntax unit 1149, for all four combinations of grammatical numbers of the two nouns. Note that the cell activity of units 775/987 is non-zero only when the first noun is plural/singular, respectively. (B) Corresponding forget-gate activity for the same number units. Note that gate activity is indifferent of the grammatical number of both nouns and that its value is close to one during the PP until after the verb. (C) Input-gate activity of the same units. Note that the gate value of unit 775/987 spikes around the first noun only when it is plural/singular. **Change bike to bike(s) in caption? Also, I think the NLP audience will understand $\tilde{C}$ and C better than Suggestion and Cell. Also, do we really need $\tilde{C}$? Isn't the important information already there in the C plot?**

irrelevant ones (SS and SP). Note that for the irrelevant conditions, cell activity is kept approximately zero thanks to the clear-up of the cell: $f_{t_{subject}} = 0$ and $i_{t_{subject}} = 0$, and the following input- and forget-gate dynamics.

Taken together, these results describe the intricate mechanism underlying subject-verb agreement in LSTM number units. They also clarify why ablating either one of these two units may bring the network close to chance level on the NA-task. Without the stored information in the cell of a number unit the network hopelessly tries to solve the task.

5.1.3 Predicting the verb form

For long-range dependencies, storing the number of the subject in the cell is necessary for correct prediction in the NA-task (except for cases of mere chance) but is not sufficient. Two more conditions need to be met: (1) the stored number should be output from the cell at the right moment $t_{verb} - 1$; and (2) The output from the number unit should increase activations only in units that represent the matching verb form in the output layer. For example, the output from unit 988 should be projected differently to singular and plural verb forms in the output layer, such that it will increase activity only in units representing the singular form. Given

that the encoding of singular by unit 988 is with a negative value $C_{t_{verb}-1} < -1$, and therefore $h_{t_{verb}-1} < -1$ (equation 1.x), this means that weights from unit 988 to units in the output layer that correspond to singular forms should be negative too, but not those projecting to plural forms.

To see whether number units meet the first condition, figure 3A shows the output-gate and hidden state dynamics of units 988 and 776. Indeed, the output gate opens at $t_{verb}-1$, reaching its almost maximal value (Panels A-B). This ensures that the stored number information is output from the cell and propagates to the output layer via h_t (equation 1.X) at the right moment (Panels C-D). Note also that for both units, output-gate dynamics are quite similar across all four conditions. This may seem sub-optimal, since one may expect that the network would learn to close the output gate for the irrelevant conditions (PS and PP for unit 987 and SS and SP for unit 776). However, as we saw, the cell value for these condition is anyway approximately zero and therefore an open output gate will have the same effect as closed one.

Next, to see whether number units meet the second condition, figure 3B presents the distribution of weight values from the two number units and from several other units to 36 units at the output layer - 18 corresponds to verbs in the singular form and 18 to verbs in the plural forms (TODO: extend to more/all verbs in the vocab). Clearly, for number units, weights to singular and plural forms have different values, but for other non-number units, there's no clear structure. Moreover, the weight values correspond to the encoding of singular/plural in the number unit. For example, weight values from unit 988 to singular forms are indeed negative, and those to plural forms are not. For all other units as well, the sign of $h_{t_{verb}-1}$ corresponds to the sign of the relevant weight values (panels A-B), such that their product is always positive. This ensures that number units increase activations only in the matching units in the output layer.

5.1.4 Short-range number units

I got lost in this discussion. Why does the continuous code requirement have to be met? The fundamental thing to be shown here should be that ablating *all* the candidate SR units (plus the LR units) and show they cause a large decrease in performance on the SR NA-tasks (controlling with random ablations of similar numbers of units). What's here now seems more like a *post-hoc* analysis of these units. We saw in section 5.3.1 that performance on several NA-tasks was not impaired after the ablation of any unit, nor by ablating the LR-number units 776 and 988, which suggested that number information may be encoded also elsewhere in the network, in other units. **Cite Dieuwke's paper on this.** We therefore start by defining requirements that a unit should meet to count as a (grammatical) *number unit*. For convenience, we focus on sentences that start by a subject and define two such requirements:

1. *Continuous code*: The grammatical-number of the subject should be decodable from unit's cell activity in a continuous manner. Continuity means that decoding performance is high for *all* subsequent time points and that the code for grammatical number is the same code as that used by the unit during the presentation of the subject. This excludes units for which grammatical code can be decoded from their activity at subsequent time points but that there is no consistent code, e.g., cell values for singular and plural flips from one time point to another. Units that meet this requirement for continuous code could be therefore interpreted as *storing* grammatical-number information.

2. *Number-segregated efferent weights*: The efferent weights of a number unit should be segregated for singular and plural forms of the verb. This is similarly to what was described above for the LR number units.

To quantify the first requirement, we use

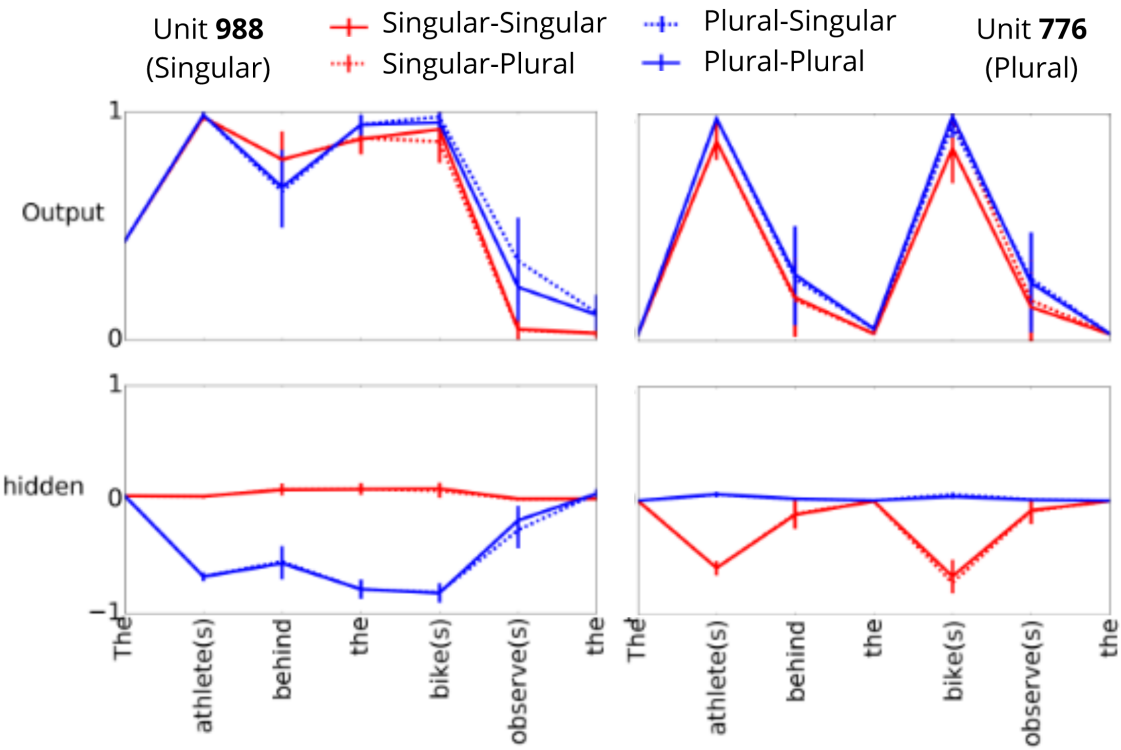

Figure 3: Hidden and output-gate activations during processing of a sentence with a prepositional phrase between subject and verb. **Do we need both? Isn't it a bit redundant? I mean, I see you can make the point of the output gate behaving in the same way in both cases, but that's perhaps a bit minor?**

a generalization across time (GAT) approach (cite). Specifically, for each unit, we trained a model to predict the grammatical number of the subject based on cell activity during the presentation of the subject but tested its prediction based on activity *from all time points*. We evaluate model performance using the Area under of Curve (AUC), and for each time point, we define 'high' performance as AUC values greater than 0.95. To quantify the second requirement, given two sets of weights to singular and plural verb forms W_S, W_P of unit u, with means $\bar{W_S}, \bar{W_P}$ and standard deviations σ_S, σ_P, we define a statistical distance: $d^u_{W_P,W_S} = \frac{|\bar{W_S} - \bar{W_P}|}{\sigma_S + \sigma_P}$. A unit is then said to have highly segregated weights if $d^u_{W_P,W_S}$ is at the top five percentile across all units. Units that meet Finally, as discussed in section 5.3.1, we distinguish between two types of units: (1) SR-units - units

Figure 4B presents shows the Area Under of Curve (AUC) for all units in the network that meet these two requirements.

5.2 Syntax units

In the previous section, a small number of units in the network was identified, which was found to store grammtical number for long-range dependecies also in the presence of interfering nouns. Remarkably, information about the two possible values of grammatical number, singluar and plural, is steadily carried by two specialized units in the network: unit 776 and 998. It remains unclear, however, how is the timing of storing and updating of number information in

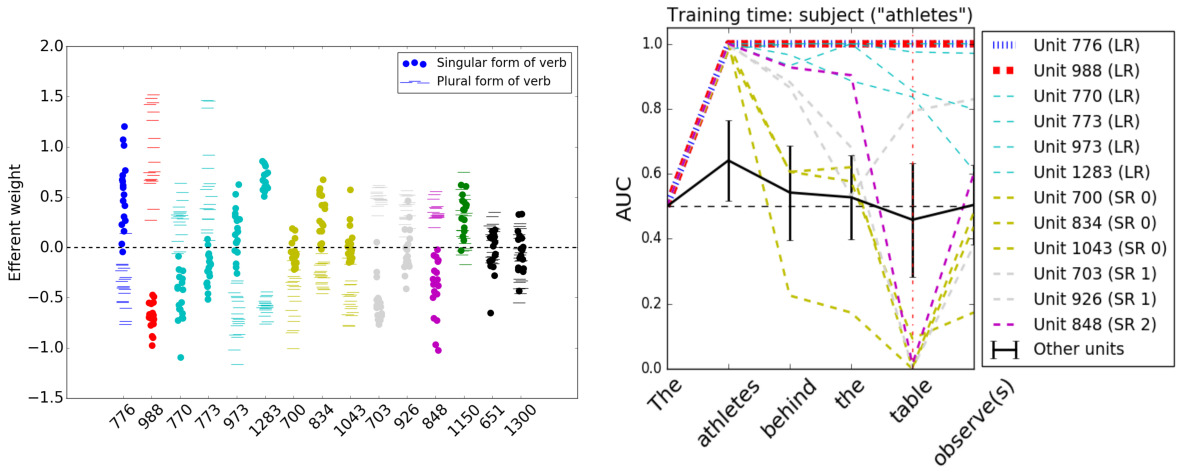

Figure 4: Connectivity structure to output layer. (A) Output activity h_t of all number units during the processing of a sentence with a PP between subject and verb. (B) Weight values from various units to output layer. Note that only for number units the output weights are clearly separated between singular and plural form of the verb, either positive or negative, compare to the syntax unit (1149) and two non-number units in the second layer. (C) Visualization of 18 verbs in their plural and singular forms (36 words in total) on the plane spanned by the two first principal components of their embeddings by the output weight matrix. A clear separation is observed between the singular and plural form along the first PC.

these units controlled by the network. In particular, given that the storage of information is controlled by the input and forget gates, how is the timing of these gates is controlled by the network. We therefore hypothesized that other units in the network may encode information about the syntactic structure of the sentence, which can be propagated to LR number units at moments required to accomplish the NA-task.

To identify such units, we tested whether there are units in the network from which syntactic information can be decoded. Given that ablation of single units in the network revealed number units only, we concluded that syntactic information may be encoded by the network in a more distributed way. We therefore tested decoding from the joint activity of a group of units in the network, using a regression model to predict syntactic information from the pattern of activity in the entire network. Specifically, the dependent variable of the model was syntactic complexity, which was quantified by counting the number of open nodes in the syntactic-tree, inspired by cite Nelso et. al 2017. In what follows, we refer to the number of open nodes in the syntactic tree as syntactic-tree depth. We then used the activity of all units in the network as predictors in the model, together with word frequency as a covariate. In additoin, to address possible co-linearities among unit activities, and to examine from which units syntactic-tree depth can be best predicted, we L1-regularized the regression model (section 4.2 for details section 4.2 should explain that the model was trained on the data from 3.2, word frequency, standarization of the values, etc.).

Figure 5A shows the resulting weights of all predictors in the model. We define as *outlier weights*, weights that are more than three standard-deviations away from the mean weight size add mean and std values. 17 outlier weights were found in the model ?add resulting unit numbers?, whose corresponding units may thus be carrying syntactic information, given their high weight in predicting syntactic complexity.

If these units indeed carry information about the sytactic structure of the sentence, ablating these units would lead to a reduction in network

performance on the NA-task We used Linzen for this. Do we want to also test of nounPP, etc?. To test this, we conductued an ablation study, in which groups of 17 random units are ablated, and the resulting network is then tested on the NA-task. We performed 1000 such random-ablation experiments, and another one in which we ablated the 17 units resulted from the regression model. Figure 5B presentes the null-distribution of network performance on the NA-task, generated from the 1000 random-ablation experiments. Reduction in network performance when ablating the 17 units from the regression model (black arrow) was found significant ($p - value = 0.024$). Taken together, these results suggest that the 17 units identified by the regression model carry syntactic information required for succesfully performaing the NA-task. In what follows, we therefore refer to these units as *syntax units*.

Next, we looked into the dynamics of these units by visualizing their gate and cell dynamics during the processing of sentences with various syntactic structures. In particular, we found that unit 1150, which resulted with the highest weight in the regression study, seems to have an interpretable dynamics during the processing of various types of sentences. Figure 2 & 3 shows the hidden and cell activity of this unit in the nounPP, subjrel, objrel and double-subjrel tasks. In all these cases, the value of the hidden variable of this unit follows the structure of the embedded phrase separating the main subject-verb dependency. Its activity is positive during the processing of the entire embbeded phrase and transitions to a negative value at the time when the main verb is presented, but not before, even if other verbs preceded it (as in the examples with relative clauses). This suggests that unit 1150 encodes the existence of an embedded phrase separating the main subject-verb dependency in the sentence. Interestingly, cell activity of this unit consistenly increased during the procesding of the embedded phrase, similarly to what was observed in several electrodes in the language network in intracranial studies on sentence processing cite nelson 2017 - refer to figure. TODO: for this, also add to our figures cell activity of unit 1150. In the next section, we show how these dynamics of unit 1150 are important in controlling the timing of gate activity in the LR number units - 776 and 988.

?Do we also want to note that unit 1150 had an effect also on the NA-task when ablated alone...?

5.3 Processing of relative clauses

[1]

[1]

6 Discussion

[1] Bock + asymmetry plural/singular (non-phonological explanation)

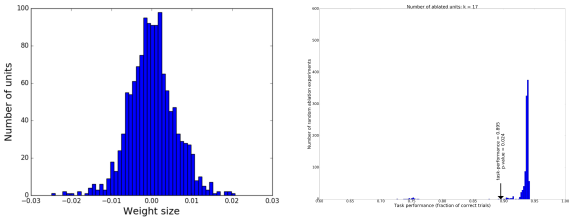

Figure 5: (A) Distribution of the resulting weight values from the tree-depth regression model. Outlier weights were defined as having a value that is distant from the mean by more than three standard deviations (17 outlier weights in total - marked in red). (B) Task performance of 1000 models after ablating 17 random units (in blue) and based on the 17 outlier weights from the tree-depth regression model (black arrow). The reduction in performance due to outlier-weights ablation is statistically significant ($p - value < 0.05$) when compared to the null distribution generated by the random ablations.

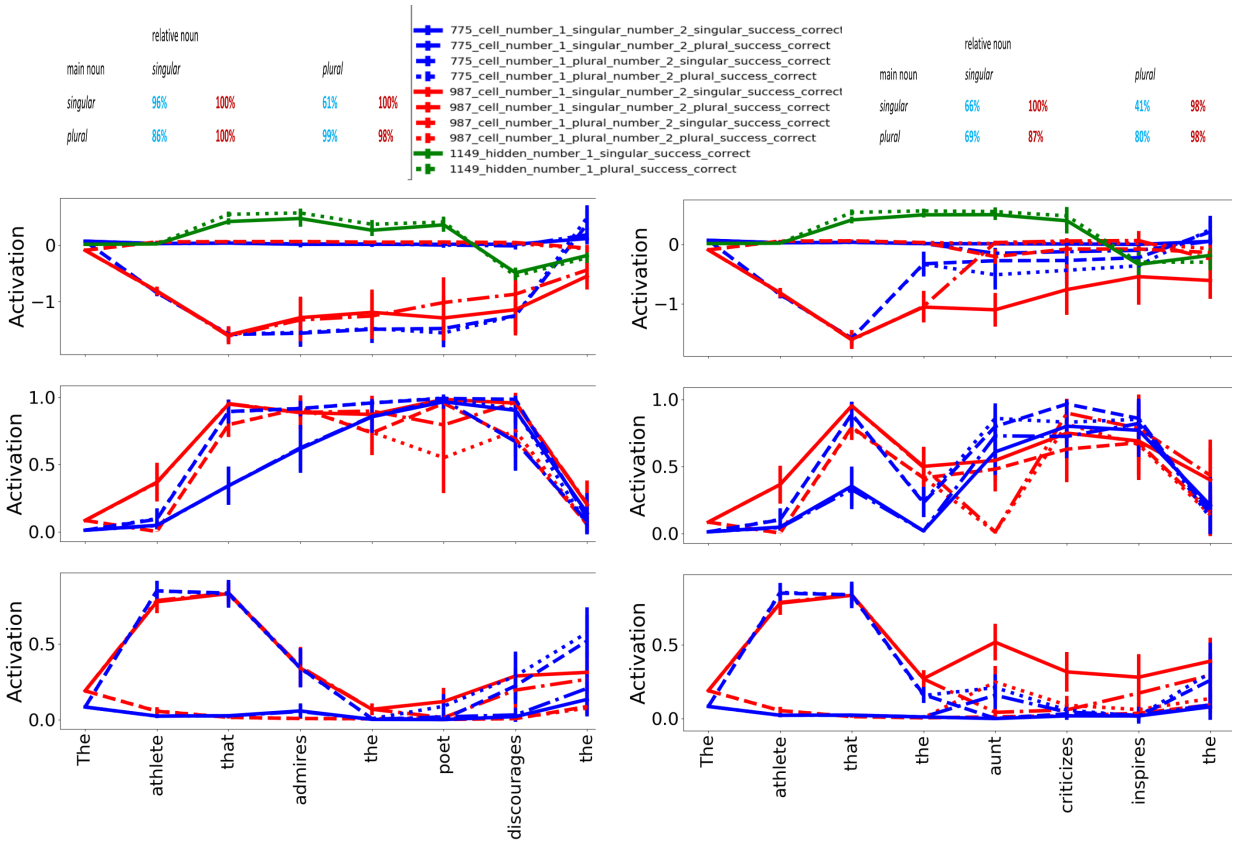

Figure 6: Subject-verb agreement in relative clauses: agreement-task accuracy for (A) subject relatives and (B) object relatives. (C & D) The corresponding cell activations for the number units (775 and 987) and the syntax unit 1149. (E & F) The corresponding forget-gate activity and (G & H) input-gate activity of the number units.

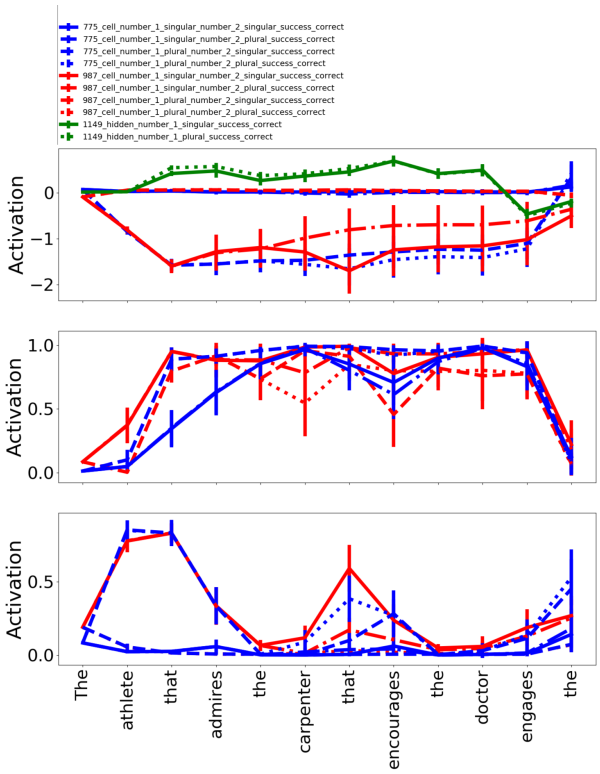

Figure 7: Processing of subject relatives with double embeddings. (A) Cell activity of the number and syntax units (775, 987 and 1149) (B) The corresponding forget-gate and (C) input-gate activity.