Can RNNs trained on harder subject-verb agreement instances still perform well on easier ones?

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Abstract

Subject-verb agreement is a phenomenon where the main subject agrees in grammatical number with its associated verb, oblivious to the presence of any other noun phrase in the sentence. This is exemplified as:

1. *The keys to the cabinet is on the table. \textsuperscript{1}

2. The keys to the cabinet are on the table.

In the above example, the number of the main verb are (plural) has to agree with the number of main subject keys (plural). Here, the intervening noun cabinet has the opposite number (singular) to that of the main subject. These intervening nouns are referred to as agreement-attractors (Bock and Miller, 1991). In natural language sentences, there can be any number of intervening nouns behaving as agreement-attractors and non-agreement attractors (nouns with the number the same as that of the main noun).

Previous work (Linzen et al., 2016; Marvin and Linzen, 2018; McCoy et al., 2018; Kuncoro et al., 2019; Noji and Takamura, 2020; Hao, 2020) assessed the ability of Language Models (LMs) based on RNN architectures to capture syntax-sensitive dependencies. McCoy et al. (2020, 2018) showed that hierarchical bias in the models, as well as the inputs, helps to generalize on unseen sentences. Arehalli and Linzen (2020) empirically claim that LSTM LM captures some aspects of agreement attraction effects. However, it is still not clear if good performance on SVA tasks is a result of the RNN’s ability to capture underlying syntax. On the other hand, prior work 24 (Chaves, 2020; Sennhauser and Berwick, 2018) provides evidence that LSTM models are more likely to learn surface level heuristics than the underlying grammar. Our work points towards the latter hypothesis.

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1\textsuperscript{The main noun, and the associated verb are bold. Intervening nouns are underlined, and * denote grammatically incorrect sentence.}

1 Introduction

Humans have shown great ability to generalize on sentences that they have never been exposed to, with their limited linguistic experience. Evidence of this behavior is their ability to perform Subject-Verb Agreement (SVA), which is explained by the presence of syntactic structure in language.
It is observed that the majority of sentences occurring in nature are simplistic, having no to few attractor nouns. However, having a skew of very few attractor nouns could lead to simpler prediction rules such as deduction based on the most recent noun without much training error. McCoy et al. (2018) have shown that training on hierarchically rich sentences increased the probability of learning the syntactic generalization. Thus to impart additional hierarchical cues, we train our models sentences with at least one attractor (Figure 1).

We test the hypothesis that if the models in consideration were to capture correct grammatical structure from the syntactically rich input, then they would be able to generalize out-of-distribution (OOD), i.e., testing on sentences without attractors when trained solely on sentences with at least one attractor. In our experiments, we further report the results for the models trained on a dataset without any aforementioned restriction on the count of attractors.

The kind of generalization learned by a model is guided by inductive biases. To account for the difference in the inductive biases that different RNN models might encode, we test on multiple schemes – LSTM, GRU, Decay RNN, and Ordered Neurons (ONLSTM). Details of these architectures are present in §3.

In addition to the accuracies of these models on our testing dataset, we perform a representation-level similarity analysis (§5.2) to assess the impact of our biased selection and compare the inductive biases of different recurrent schemes. We also perform a targeted syntactic evaluation Marvin and Linzen (2018) to assess if the models can associate the verbs with their subjects across different syntactic constructions (§5.3). The models capturing surface level regularities of the data would not be able to perform well on these constructed examples.

Our major contributions are the following:

- We show that despite providing stronger hierarchical cues through selectively sampled dataset (Figure 1), RNNs do not generalize well. This suggests that they are efficient at picking up shallow heuristics in a nuanced manner, rather than learning the underlying syntactical rules governing the subject-verb agreement.
- We further show that a soft hierarchical inductive bias imparted by ONLSTM in addition to a syntactically rich training set is also insufficient to capture the underlying grammar of the natural language.
- Our findings are consistent across the learning paradigms: self-supervised language modeling, and supervised grammaticality judgment, and testing examples: natural and a constructed dataset (Tables 2, 4).

2 Related Work

McCoy et al. (2018) conclude that some RNNs generalize hierarchically despite the absence of hierarchical inductive bias on question formation task, and pick up useful cues from the syntactically rich dataset. However, they could not conclude what do these RNNs capture which gives rise to non-trivial performance. In their subsequent work, McCoy et al. (2020) conclude that hierarchical generalization is only plausible by providing explicit hierarchical inputs to the model having an explicit hierarchical inductive bias in question formation. In this regard, our work considers testing a slacked version of their paradigm from a different set of experiments based on grammaticality judgment. We do not consider RNNs or the inputs which encode hierarchy explicitly, rather provide the models with hierarchical inductive bias with additional hierarchical cues through the agreement attraction effect.

van Schijndel et al. (2019) showed that the neural LMs lag far behind humans on the targeted Syntactic Evaluation (TSE) even when trained with the large corpus and increased model capacity. However, by the virtue of high variance in the performance of LMs on TSE across different random seeds, and hyperparameter tuning, Kuncoro et al. (2019) achieved much better numbers on the same settings. Noji and Takamura (2020) and Kuncoro et al. (2019) came up with different methodologies to improve performance on TSE via contrastive learning and knowledge distillation from models.
with explicit grammar induction (Dyer et al., 2016) respectively. In our work, we show that strategically choosing syntactically rich sentences can also improve this performance substantially (Table 3, 9).

It is a consensus among all these works that performing well on sentences having center embedding, especially agreement across Object relative clauses (RCs), is difficult (Noji and Takamura, 2020; Mueller et al., 2020). Although many of these previous work test their model’s capabilities on a set of syntactically challenging sentences, we also test the robustness of the models against the OOD samples in addition to TSE. We show that not only the low bias recurrent networks but also the one with inductive tree bias, fail to perform on straightforward OOD sentences, and thus failing the minimum functionality test suggested by Ribeiro et al. (2020).

Chaves (2020); Sennhauser and Berwick (2018) show that the LSTMs capture surface statistical regularities in the dataset rather than acquiring linguistic rules. In this regard, our work extends their findings by showing even implicit hierarchical inductive bias, shown to be present in ONLSTM learns shallower heuristics, rather than the grammatical rules. We show in §5.2 that ONLSTM is closely related to vanilla LSTM from the learned internal representations point of view, and conclude that there is no discernible difference between the two in our set of experiments.

3 Architectures

In this work, we conduct our experiments on four recurrent schemes – LSTM (Hochreiter and Schmidhuber, 1997), GRU (Cho et al., 2014), Decay RNN (DRNN) (Bhatt et al., 2020), and ONLSTM (Shen et al., 2019). The governing equations of these architectures are mentioned in §A.1. ONLSTM, unlike other models in consideration, is a recurrent network with soft hierarchical inductive bias. DRNN is a recurrent network without any gating mechanism which imposes biological constraints on the neurons. Amongst all the mentioned RNNs, DRNN is the one with the least capacity, and has been shown to outperform standard RNN, and has been on par with other gated networks on grammaticality judgment tasks.

| Property                              | Natural | Selective |
|---------------------------------------|---------|-----------|
| Training size                         | 97842   | 97842     |
| Ratio of Singular to Plural main nouns| 0.67    | 0.45      |
| Ratio of Singular to Plural nouns (total) | 0.79    | 0.71      |
| Fraction of 0 attractors              | 0.93    | -         |
| Fraction of 1 attractors              | 0.056   | 0.79      |
| Fraction of 2 attractors              | 0.011   | 0.15      |
| Fraction of 3 attractors              | 0.003   | 0.037     |

Table 1: Training data statistics.

4 Dataset

Throughout the work, for training our models, we use sentences from the Wikipedia corpus made available by Linzen et al. (2016). We train our models for two objectives: language modeling and binary classification for grammaticality judgment (§5). For training, we further choose two subsets from the main dataset, based on the number of attractors in each sentence (Figure 1). Table 1 contains the quantitative description of the training data.

The first subset contains the sentences that are bound to have at least one attractor. They are generated by selective sampling from the corpus, and we will refer them by the “Selective Sampling” dataset. For a more naturalistic choice of data, we have another subset having the sentences that may or may not have any attractor. This subset is generated by randomly picking up the sentences from the corpus, and we will refer them by “Natural Sampling” dataset.

To perform well on the selectively sampled dataset, models cannot resort to learn simple heuristics such as learning to associate the main verb with the preceding noun rather than the main noun. However, these heuristics are encouraged by a naturally sampled dataset due to heavy skew towards sentences without attractors (Table 1).

The other benefit of training on a selectively sampled dataset is the fact that it provides us with the capability to conduct minimum functionality test (Ribeiro et al., 2020), and assess if the models are using shortcuts to handle complex inputs. The sentences without any attractor are grammatically simple and allow for out-of-distribution testing as they are not seen while training on the selectively sampled dataset. Thus, there is no lower bound on the number of attractors in the test set. For uniform comparison, we keep the testing set identical across

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2 We also use “syntactically rich dataset” to denote this subset.
the subsets of the training data. The testing set contains 157k sentences for both the binary classifier and the LM.

For the binary classifier, we augment each sentence with its corresponding counterfactual example. Training settings for our experiments are mentioned in §A.2. Apart from testing on the sentences from the corpus, we also test our models on the synthetically generated sentences for the targeted syntactic evaluation (§5.3).

5 Experiments

Our experiments are motivated by Linzen et al. (2016), where they examined the ability of recurrent networks to capture syntax-sensitive dependencies. They propose three tasks, namely verb number prediction, grammaticality judgment through classification, and language modeling. Bhatt et al. (2020) showed that even vanilla RNN could perform well on the verb number prediction task, which then fails miserably on the grammaticality judgment task because of the inability to capture the locus of grammaticality. Therefore, in this work, we focus on evaluating the models’ ability to make grammatical judgment decisions through classification, a supervised algorithm, and LM, which is self-supervised. For each task, we will train models (furthermore on five different random seeds) on both the subsets from the corpus. Consider the following sentences.

1. *The keys to the cabinet is on the table.

2. The keys to the cabinet are on the table.

A classifier is supposed to label sentence 1 as a grammatically incorrect sentence, while sentence 2 as a grammatically correct sentence. Considering the same example, for the grammaticality judgment through the LM, we first train on a standard LM objective, however, during inference, we check if $P(\text{are} — \{\text{The},...,\ \text{cabinet}\}) > P(\text{is} — \{\text{The},...,\ \text{cabinet}\})$. In the following sections, we will present the results on the test sentences taken from the Wikipedia corpus (§5.1) for both the LM and the binary classifier, followed by an analysis of their learned internal representations (§5.2). We then perform a TSE followed by its fine-grained analysis (§5.3) to understand the common failures made by the models and discuss its prediction confidence (§5.4).

5.1 Performance on Natural Sentences

Table 2 shows the testing results of the models trained on both configurations for different learning algorithms. For the models trained on a naturally sampled dataset, the performance of the model degrades with increasing count of attractors between the subject and the corresponding verb. Bold marks the maximum accuracy for each subset across the attractor, for each model; standard deviations are mentioned in A.4. Note that the models trained on the selectively sampled dataset are not able to generalize OOD (sentences without attractors.)

| Architecture | Natural Sampling | Selective Sampling |
|--------------|-----------------|-------------------|
|              | 0               | 1                 | 2                 | 3               | 0                     | 1                | 2           | 3               |
| LANGUAGE MODEL |                 |                   |                   |                 |                     |                   |             |                  |
| LSTM         | 0.98            | 0.91              | 0.84              | 0.78            | 0.89               | 0.98              | 0.98        | 0.95            |
| ONLSTM       | 0.98            | 0.92              | 0.86              | 0.82            | 0.90               | 0.98              | 0.98        | 0.95            |
| GRU          | 0.97            | 0.88              | 0.78              | 0.73            | 0.87               | 0.98              | 0.97        | 0.94            |
| DRNN         | 0.96            | 0.69              | 0.47              | 0.36            | 0.83               | 0.97              | 0.94        | 0.91            |
| BINARY CLASSIFIER |           |                   |                   |                 |                     |                   |             |                  |
| LSTM         | 0.97            | 0.93              | 0.87              | 0.82            | 0.80               | 0.98              | 0.96        | 0.97            |
| ONLSTM       | 0.97            | 0.91              | 0.84              | 0.81            | 0.64               | 0.98              | 0.97        | 0.98            |
| GRU          | 0.97            | 0.88              | 0.76              | 0.69            | 0.62               | 0.95              | 0.94        | 0.96            |
| DRNN         | 0.97            | 0.90              | 0.81              | 0.77            | 0.70               | 0.97              | 0.96        | 0.96            |

Table 2: Performance of LM and classifier with an increasing number of attractors between the main subject and verb. Bold marks the maximum accuracy for each subset across the attractor, for each model; standard deviations are mentioned in A.4. Note that the models trained on the selectively sampled dataset are not able to generalize OOD (sentences without attractors.)
Decay RNN.

This behavior of models on OOD samples is counter-intuitive, even though those sentences are grammatically simpler. We note that the increment in error rates is much more in the case of a classifier than the LM. This shows that, even when the models are trained via supervised learning objective on syntactically rich and counterfactually augmented data, they are still using shallower heuristics by manipulating the data variables in a nuanced way. Thus, the models are unable to capture the actual syntactic rules.

While our selectively sampled subset contains sentences with at least one attractor, it should be noted that these sentences also contain intervening nouns (over 30%) which are non-attractors. Hence, there are sentences in which a non-attractor noun (same number as the main subject) immediately precedes the verb rather than an attractor noun. Therefore, the agreement performance of the models trained on this dataset cannot arise from an overly simple heuristic like disagreeing with the most recent noun, and the observed decline in the OOD performance implies that less trivial heuristics are being learnt which nevertheless fail to capture the actual syntax.

5.2 Analysis of representations

From Table 2, one cannot infer the representation-level changes caused by the model’s inductive bias, and the choice of dataset. Therefore, to analyze the differences in the learned internal representations among the models trained on the two subsets of the data, we perform a representation similarity analysis (RSA) (Abnar et al., 2020; Laakso and Cottrell, 2000). RSA is a standard tool of multivariate statistical analysis used to quantify the relation between the representations. Furthermore, it will also give us some insights about the nature of representations learned via different training objectives aka supervised and self-supervised. For the comparison, we take 2000 sentences selected randomly from the test set. We trained each model on five different random seeds, comparing 40 models (20 for each subset) for both the LM and the binary classifier. The procedure for RSA is described in §A.5. We make the following observations from Figure 2.

First, we observe that a plane can separate the models trained on the two subsets of the data, for both the LM and the classifier. This implies that the choice of input sentences plays an important role, which is evident from the fact that the clusters are not formed based on the model’s inductive bias.

Second, we observe that the representations of ONLSTM and LSTM are not well separable, neither for the LM nor for the classifier across configurations. This shows that even after having complex gates and activation to induce hierarchical bias, the model is still similar to LSTM on the representational level. Moreover, we observe that projected representations for GRU and LSTM are well separable for both the LM and the classifier on both the subsets of the data. This differentiates the two architectures, which are often used interchangeably on the representation level, and such differences may be arising due to the squashing phenomena in GRUs pointed out by McCoy et al. (2020).

Third, we compare the RSA plots for the LM and the classifier. For the binary classifier (Figure 2a), albeit we observe a little variance in the accuracy on the test set across the different seeds, the variance (spread of the points) in the projected space is substantial when compared to that of the LM. More analysis of this variance is available in §A.5. This points to the existence of multiple valleys in the loss landscape for the binary classification objective, and we posit that an LM objective is much more reliable when comparing the ability to capture the syntax sensitive dependencies.

5.3 Targeted Syntactic Evaluation (TSE)

We now aim to test the impact of training the language models on the strategically chosen inputs across different syntactic constructions. We would also like to verify if the inability of the models (trained on the selectively sampled dataset) to adapt OOD as shown in §5.1 is also consistent on artificially constructed sentences. The models capturing surface level regularities of the data would not be able to perform well on these constructed examples as described in Marvin and Linzen (2018).

Table 3 mentions the results of TSE on the LM for both the subsets of the data. For each model, we observe that as the difficulty of the sentences increases, models trained on the selectively sampled dataset starts surpassing their counterparts, trained on the other subset. They perform better on sentences involving agreement across the prepositional phrase, or subject/object relative clauses. However,

6In the previous sections, we showed that the binary classifier is neither stable to the random initialization nor performed well on the OOD sentences. Therefore, we will only consider LMs for TSE.
Table 3: Accuracy of models on targeted syntactic evaluation. Quantities in bold marks the maximum accuracy for each model across the configuration. ORC: Objective Relative Clause, SRC: Subject Relative Clause, Prep Phrase: Prepositional Phrase, VP: Verb Phrase. *A*/IA in the parenthesis represents an animate/inanimate main subject. Models trained on selectively sampled subset perform well on the difficult sentences, but not on the simpler ones.

| Subject Verb Agreement | #sentences | LSTM | ONLSTM | GRU | DRNN |
|------------------------|------------|------|--------|-----|------|
|                        |            | Natural | Selective | Natural | Selective | Natural | Selective | Natural | Selective |
| Simple                 | 312        | 0.59 ±0.01 | 0.86 ±0.01 | 0.98 ±0.02 | 0.86 ±0.01 | 0.98 ±0.01 | 0.84 ±0.04 | 0.97 ±0.02 | 0.79 ±0.05 |
| Short VP               | 3432       | 0.85 ±0.02 | 0.73 ±0.06 | 0.88 ±0.02 | 0.73 ±0.08 | 0.81 ±0.03 | 0.69 ±0.04 | 0.70 ±0.05 | 0.66 ±0.04 |
| Within ORC (A)         | 9984       | 0.79 ±0.06 | 0.73 ±0.05 | 0.78 ±0.10 | 0.79 ±0.06 | 0.78 ±0.02 | 0.50 ±0.02 | 0.75 ±0.08 | 0.46 ±0.04 |
| Within ORC (IA)        | 4032       | 0.77 ±0.06 | 0.64 ±0.06 | 0.75 ±0.08 | 0.59 ±0.04 | 0.73 ±0.02 | 0.50 ±0.03 | 0.69 ±0.06 | 0.46 ±0.05 |
| Within no that ORC (A) | 9984       | 0.73 ±0.06 | 0.61 ±0.05 | 0.72 ±0.08 | 0.57 ±0.07 | 0.72 ±0.03 | 0.47 ±0.04 | 0.63 ±0.04 | 0.45 ±0.06 |
| Within no that ORC (IA) | 4032      | 0.66 ±0.04 | 0.61 ±0.05 | 0.56 ±0.06 | 0.87 ±0.02 | 0.62 ±0.04 | 0.47 ±0.04 | 0.68 ±0.06 | 0.45 ±0.06 |
| Long VP                | 250        | 0.65 ±0.03 | 0.69 ±0.07 | 0.67 ±0.04 | 0.67 ±0.06 | 0.63 ±0.04 | 0.65 ±0.04 | 0.56 ±0.05 | 0.65 ±0.03 |
| Across Prep Phrase (A) | 29952      | 0.86 ±0.04 | 0.89 ±0.03 | 0.88 ±0.03 | 0.88 ±0.01 | 0.81 ±0.02 | 0.88 ±0.02 | 0.68 ±0.04 | 0.83 ±0.01 |
| Across Prep Phrase (IA)| 4032       | 0.87 ±0.03 | 0.94 ±0.02 | 0.88 ±0.02 | 0.95 ±0.01 | 0.86 ±0.02 | 0.94 ±0.01 | 0.69 ±0.06 | 0.91 ±0.02 |
| Across SRC             | 9984       | 0.81 ±0.03 | 0.89 ±0.05 | 0.81 ±0.05 | 0.87 ±0.02 | 0.77 ±0.05 | 0.86 ±0.05 | 0.58 ±0.04 | 0.80 ±0.05 |
| Across ORC (A)         | 9984       | 0.73 ±0.10 | 0.82 ±0.07 | 0.78 ±0.07 | 0.84 ±0.02 | 0.72 ±0.06 | 0.79 ±0.05 | 0.63 ±0.04 | 0.78 ±0.05 |
| Across ORC (IA)        | 4032       | 0.74 ±0.09 | 0.84 ±0.10 | 0.81 ±0.07 | 0.87 ±0.02 | 0.74 ±0.08 | 0.85 ±0.05 | 0.65 ±0.07 | 0.86 ±0.02 |
| Across no that ORC (A) | 9984       | 0.61 ±0.04 | 0.72 ±0.08 | 0.62 ±0.05 | 0.78 ±0.02 | 0.60 ±0.02 | 0.68 ±0.06 | 0.64 ±0.03 | 0.73 ±0.02 |
| Across no that ORC (IA)| 4032       | 0.66 ±0.04 | 0.77 ±0.11 | 0.66 ±0.06 | 0.84 ±0.03 | 0.62 ±0.04 | 0.72 ±0.07 | 0.68 ±0.06 | 0.83 ±0.02 |
| Average Performance    | 104296     | 0.78 ±0.03 | 0.78 ±0.02 | 0.79 ±0.03 | 0.78 ±0.01 | 0.75 ±0.01 | 0.73 ±0.02 | 0.66 ±0.02 | 0.71 ±0.02 |

Figure 2: RSA of hidden units of recurrent networks (5 different seeds for each model). We observe that for both the learning objectives, one can divide the 2D space using a plane separating models trained on two subsets of the data.

this improvement in the performance came at a cost where their performance on simple sentences, having agreement across short verb phrases, and agreement within object relative clauses decreases.

Sentences involving simple agreement, short verb phrase coordination, and agreement within clauses do not have an attractor between the subject and the main verb. Table 4 further classifies

the performance of the LM on the synthetic data with the count of attractors. Our findings from Table 4 corroborates our results from §5.1 (Table 10), where the model trained on selectively sampled dataset performed worse on sentences without attractor.

| Architecture | Natural | Selective |
|--------------|---------|-----------|
| LSTM         | 0.77 ±0.05 | 0.66 ±0.04 | 0.63 ±0.04 | 0.83 ±0.06 |
| ONLSTM       | 0.76 ±0.07 | 0.70 ±0.06 | 0.60 ±0.05 | 0.85 ±0.01 |
| GRU          | 0.74 ±0.02 | 0.64 ±0.02 | 0.51 ±0.02 | 0.81 ±0.04 |
| DRNN         | 0.67 ±0.04 | 0.44 ±0.04 | 0.48 ±0.04 | 0.79 ±0.03 |

Table 4: Performance of Language Models across attractors on the artificial corpus. Models trained on selectively sampled subset do not generalize well on OOD sentences without attractor.

Fine-Grained Analysis

In this section, we perform fine-grained analysis of the LSTM LM. TSE results reported in Table 3. This will help us understand the failure cases of the LM, which can help devise techniques to mend those cases. We present a detailed breakdown in terms of singular and plural main/embedded subjects in A.9. However, we analyze some of the notable aspects here.

Figure 3 depicts the performance of LSTM LM on three agreement conditions - across Object RC, Preposition Phrase, and Subject RC, each with animate main nouns with both configurations. The performance of models trained with the naturally sampled data, across all the agreement conditions, is worse on sentences with an attractor than sen-

\[\text{We had similar findings for other language models which are mentioned in the §A.9, Table 11, 12 and 13.}\]
sentences with no attractor, i.e., SS\textsuperscript{8} performs better than SP case, and PP performs better than PS case. However, the performance improved on attractors when these models are trained on the selectively sampled dataset.

For all the cases under consideration presented in Figure 3a, the performance of the LSTM LM is worst when the main noun is singular with the plural embedded subject (SP case). This observation is consistent with the observations of Arehalli and Linzen (2020), where the plural attractors have shown to have a stronger attraction effect than the singular attractors, which is indeed the case for humans as well (Bock and Cutting, 1992). Note that, the naturally sampled dataset has more plural attractors while the selectively sampled one has an almost balance of plural and singular attractors (Table 1). Thus, our findings are not due to a lack of plural attractors in training.

For agreement across the prepositional phrase and subject RC, when the models are trained on a selectively sampled dataset, the accuracy on the SP case increases at the expense of decreased accuracy on the SS case. We also observe that the attraction effect from attractors in Subject RCs is more than those in the Prepositional phrase for the models trained on the naturally sampled dataset. Our observation is in opposition to what Arehalli and Linzen (2020) had presented. This contradiction can be due to the difference in the metric used by Arehalli and Linzen (2020) in their work to evaluate agreement attraction effects.

In §9 we also present comparison of models trained on selectively sampled subset with Kun-coro et al. (2019).

In 5 out of 6 cases (3 for each data-subset), the performance on sentences with the PP case is much better than the performance on sentences with the SS case. However, Marvin and Linzen (2018) suggested the opposite trend in their fine-grained analysis for agreement across Object RC cases. This might be attributed to the differences in the corpus and the training size; they trained their LM on Gulordava et al. (2018) dataset with 30 times more data points than used in our work. For prepositional phrase case, Hupkes (2020) showed that the prediction for the plural verb is causally linked to the main subject, whereas the prediction for the singular verb is stored outside the subject using information ablation. However, such conclusions cannot be drawn from the results presented in this paper.

\textsuperscript{8}SS implies that the sentence has a singular main noun with a singular embedded subject, and likewise for other cases.

In §9 we also present comparison of models trained on selectively sampled subset with Kun-coro et al. (2019).

![Graph representing accuracy comparison](image)

(a) Accuracy: LSTM trained on naturally sampled subset

![Graph representing accuracy comparison](image)

(b) Accuracy: LSTM trained on selectively sampled subset

Figure 3: A fine-grained analysis of LSTM LM on Obj/Subj Relative Clauses and Preposition Phrases, demarcated by the inflection of the main subject (MS) and the embedded subject (ES) respectively. P: Plural, S: Singular

| Model     | Natural Average Confidence | Selective Average Confidence | Natural Average Confidence | Selective Average Confidence | PLMS-Analysis |
|-----------|----------------------------|------------------------------|----------------------------|-------------------------------|----------------|
| LSTM      | 5.72                       | 2.56                         | 303.91                     | 12.90                         |                |
| ONLSTM    | 5.80                       | 2.64                         | 331.83                     | 14.08                         |                |
| GRU       | 5.13                       | 2.40                         | 169.28                     | 11.02                         |                |
| DRNN      | 5.15                       | 2.38                         | 172.78                     | 10.77                         |                |

Table 5: Average prediction confidence; Models trained on selectively sampled dataset have low prediction confidences on the OOD sentences, compared to the one trained on the other subset.

### 5.4 How confident are language models?

Surprisal scales the cognitive effort required to process the information. It is defined as $-\log(p(x_n|x_{1...n-1}))$, where $x_n$ represents the upcoming token, while $x_{1...n-1}$ represents the previous tokens. We define prediction confidence as the difference in the surprisal for the incorrect verb, and the correct verb: the more, the better. The accuracy of a model does not indicate how confident the model is while making predictions. Therefore, in this section, we compare the performance of models trained on the two subsets by looking at their average confidence at verb position, evaluated on 16k simple sentences from the
natural corpus (testing set) with the following sub-structure:

The <Subject> <Verb>

Note that this sub-structure points to sentences where we consider agreement without attractors (i.e., OOD). Table 5 mentions the average prediction confidence and the average\(^9\) ratio of probabilities\(^10\) of a grammatical verb and ungrammatical verb. We can see that the average probability of choosing a grammatically correct verb over an incorrect verb is significantly less for the models trained on the selectively sampled subset than the naturally sampled subset. Thus, even the difference between the accuracies of LM trained on the two subsets, as mentioned in the Table 10 is close to 10% on the sentences with no attractors, models trained with selectively sampled dataset are less confident with their predictions. Moreover, we can also see that ON-LSTM LM is equally less confident as LM-LSTM when trained this selectively sampled dataset, despite having a hierarchical inductive bias.

We also conduct an experiment that has been proposed in a previous study (Lepori et al., 2020) to impart hierarchical bias to the models, and found out that it did not help in our scenario (§A.7).

6 Discussion and Conclusion

In this work, we analyzed the response of neural language models and binary classifiers for grammaticality judgment to a strategically chosen training set. We observed that the models’ inability to perform well on out of distribution (OOD) sentences is consistent, irrespective of learning mechanism (supervised or self-supervised), innate architectural bias, and testing set – natural or artificial sentences.

Our analysis showed that the error rates of models trained on sentences with at least one agreement attractor are higher on sentences with no attractors (OOD) than on sentences with attractors, for both corpus sentences (Table 2) and artificial sentences (Table 4). This observation is counter-intuitive because the models were trained on syntactically rich sentences and yet failed to perform well on simpler sentences. Had our RNN models picked up the correct grammatical rules, we would not have observed this behavior.

We observed another counter-intuitive result in Table 3 for targeted syntactic evaluation. The models trained on the selectively sampled dataset performed much better on difficult constructed sentences involving agreement across nested dependencies (lower half of Table 3). Whereas they performed poorly on the simpler sentences involving agreement within nested dependencies (upper half of Table 3).

Our analysis of representations showed that the training set bias dominated over the model’s inductive bias in the formation of clusters. This gives rise to an interesting direction for further exploration of what causes such patterns. Further, there was no discernible difference between the learned representations of ONLSTM and LSTM models.

We also observed that the language models trained on the syntactically rich dataset are substantially less confident in predicting the agreement for these sentences when compared to their counterparts trained on the original raw dataset (§5.4). This indicates that the models are using nuanced but shallow heuristics to solve the task, rather than capturing the intended hierarchical structure.

We observed that the hierarchical inductive bias in the ONLSTM is not sufficient to perform well on OOD sentences. McCoy et al. (2020) argued that architecture with explicit tree bias with syntactically annotated inputs is needed to capture syntax for sequence-to-sequence tasks. In our work, we show that the ONLSTM (soft tree bias) with the syntactically rich dataset (soft structural information) is insufficient to generalize well to OOD sentences and capture the underlying rules of the grammar. Our targeted syntactic evaluation analysis pinpoints the cases which our models fail to capture, and improving the performance on such cases is a key future direction.

Our observations suggest that RNNs being fundamentally statistical models can efficiently capture the correlation of the output variable with the input without actually learning the underlying hierarchical structure, which is consistent with the conclusions of Sennhauser and Berwick (2018) and Chaves (2020). Thus, we need to be cautious in inferring the ability of such models to capture syntax-sensitive dependencies. Performance on any particular kind of construction might always reflect some overfitting to it, even if it is syntactically rich or complex. Hence, broad-based testing on instances of various types and complexity levels is essential.
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A Appendix

A.1 Model Architectures
Following are the equations of the models used in this paper. ‘$\circ$’ denotes the hadamard product.

A.1.1 Long Short Term Memory (LSTM)
Following are the equations governing the standard LSTM (Hochreiter and Schmidhuber, 1997) with the standard notations.

$$
i_t = \sigma (W_i [h_{t-1}, x_t] + b_i)
$$

$$
f_t = \sigma (W_f [h_{t-1}, x_t] + b_f)
$$

$$
g_t = \tanh (W_g [h_{t-1}, x_t] + b_g)
$$

$$
o_t = \sigma (W_o [h_{t-1}, x_t] + b_o)
$$

$$
c_t = f_t \circ c_{t-1} + i_t \circ g_t
$$

$$
h_t = o_t \circ \tanh (c_t)
$$

A.1.2 Gated Recurrent Unit (GRU)
Following are the equations governing the standard GRU (Cho et al., 2014) with the standard notations.

$$
r_t = \sigma (W_r [h_{t-1}, x_t] + b_r)
$$

$$
z_t = \sigma (W_z [h_{t-1}, x_t] + b_z)
$$

$$
\tilde{h}_t = \tanh (W_x [r_t \circ h_{t-1}, x_t] + b_x)
$$

$$
h_t = z_t \circ h_{t-1} + (1 - z_t) \circ \tilde{h}_t
$$

A.1.3 Ordered Neurons (ONLSTM)
Ordered Neuron or Ordered Neuron LSTMs (Shen et al., 2019) are recurrent schemes that have been claimed to represent hierarchical information in their representations by their $\text{cumax}$ or cumulative softmax activation. The following are the equations of Ordered Neurons with the standard notations.

$$
f_t = \sigma (W_f [h_{t-1}, x_t] + b_f)
$$

$$
i_t = \sigma (W_i [h_{t-1}, x_t] + b_i)
$$

$$
o_t = \sigma (W_o [h_{t-1}, x_t] + b_o)
$$

$$
c_t = f_t \circ c_{t-1} + i_t \circ g_t
$$

$$
h_t = o_t \circ \tanh (c_t)
$$

A.1.4 Decay RNN (DRNN)
Decay RNN (DRNN) (Bhatt et al., 2020) is a bio-inspired recurrent baseline without any gating mechanism. Authors also show that DRNN surpasses vanilla RNNs on linguistic tasks.

$$
c^{(t)} = \left(\text{ReLU}(W)W_{\text{dale}}\right)h^{(t-1)} + U x^{(t)} + b
$$

$$
h^{(t)} = \tanh \left(\alpha h^{(t-1)} + (1 - \alpha)c^{(t)}\right)
$$

Here $\alpha \in (0,1)$ as a learnable parameter and $W_{\text{dale}}$ is a diagonal matrix which provides biological constraints.

A.2 Training Settings
In our experiments, we train a two-layered LM where we keep the hidden size at 650 units and the input size as 200 units. We perform standard dropout with a rate of 0.2 and the batch size 128. Optimization starts with a 0.001 learning rate for all architecture and clips the gradient if necessary.

For Binary classifiers, we use a single-layered recurrent unit, batch size of 64, hidden, and input size of 50 units. For LSTM and ONLSTM, the initial learning rate is 0.005, while for the GRU and DRNN, it is 0.01. No gradient clipping is performed to train the classifier.

All models are optimized with Adam (Kingma and Ba, 2015), and the codes are written in Pytorch (Paszke et al., 2019).

A.3 Binary Classifier and Counterfactual Augmentation
For the binary classifier, we augment each sentence with its corresponding counterfactual example. Augmenting with counterfactual examples is effective in reducing the spurious correlation in sentiment analysis (Kaushik et al., 2020). In our case, the counterfactual example will be constructed by flipping the number of the main verb of a grammatically correct sentence. Thus, we use correct as well as the incorrect version of the same sentence in training. This results in the training size of 195k sentences for the binary classifier. Table 6 shows the performance with/without counterfactual augmentation. Note that, the accuracy improved substantially for ONLSTM trained on the selectively sampled dataset.
A.4 Performance on Natural Sentences

In Table 10 we give a full version of Table 2 (§5.1) including the standard deviations on 5 different runs.

A.5 Representation Similarity Analysis

Representation similarity analysis or RSA (Abnar et al., 2020; Laakso and Cottrell, 2000) is a technique to analyze the representation level differences among the models. RSA is a standard tool of multivariate statistical analysis used to quantify the relation between the representations. In RSA, we evaluate the second-order similarity to avoid comparing the learned representations from different spaces. For the comparison, we take 2000 natural sentences selected randomly from the test set. A general procedure to perform RSA in 2 dimensions for any number of models is given below:

1. For every model, if the hidden states are a matrix of dimension (2000, N), where N is the hidden dimension, then evaluate the similarity matrix as $XX^T$. We then row-wise standard normalize this similarity matrix to get ($S$).

2. For every model (i, j) pair of models, we then evaluate the row-wise inner product between $S_i$ and $S_j$ and then take an average of all the values to get $M_{ij}$.

$$M_{ij} = \frac{1}{2000} \sum_{k=1}^{2000} S_{ik} S_{jk}$$

3. We then perform Multidimensional scaling of the matrix $M$ to 2 dimensions. This is available in Scikit Learn (Pedregosa et al., 2011).

A.6 Analysis of Variance

In this section, we will analyze the spread of the projected representations across different random seeds. Note that, since the projection is in 2 dimensions, to measure the spread evaluate $\ell_2$ norm of a vector of standard deviations across individual components. Table 7 shows that BC is more susceptible to a local optimum across random initializations.

| Architecture | Natural Sampling | Selective Sampling |
|--------------|-----------------|--------------------|
|              | LM              | BC                 | LM              | BC                 |
| DRNN         | 44.85           | 168.81             | 3.76            | 40.80              | 458.80            | 11.24            |
| GRU          | 220.36          | 626.24             | 2.84            | 83.93              | 624.06            | 7.44             |
| LSTM         | 66.03           | 941.76             | 14.26           | 57.68              | 729.18            | 12.64            |
| ONLSTM       | 71.48           | 586.42             | 8.20            | 58.41              | 698.10            | 11.95            |

Table 7: L2 Norm of a vector of component-wise standard deviations for both the LM and Binary Classifier (BC). The third column represents the ratio of the two norms for BC and LM. This shows that across random initializations, BC is more susceptible to a local optimum.

A.7 Fine-Tuning

Lepori et al. (2020) showed that the syntactic robustness of RNNs could be improved by fine-tuning the trained models on a small amount of syntactically challenging data. We consider a similar exercise for our trained language models (Selective sampling), where we further fine-tuned the model with the challenging artificially generated sentences. To avoid a significant shift in the domain of training sentences for the LM, i.e., from the natural sentences to synthetically generated sentences, we avoid adding sentences with agreement across relative clauses. We fine-tune our LM only on prepositional phrases involving one attractor noun. In Table 8, we present the analysis when we fine-tune our trained LMs for 1 and 5 epochs on different fine-tuning set size.

We notice that the accuracy of sentences without attractor decreases with fine-tuning for all the models, including the one with tree inductive bias.

A.8 Comparison with other works based on TSE

We now compare the LSTM model trained on selectively sampled data with the existing results from Kuncoro et al. (2019) on LSTM network distilled with a RNNG (Dyer et al., 2016) as a teacher in the Table 9. Note, the models by Kuncoro et al. (2019) are trained on the Wikipedia dataset made available by Gulordava et al. (2018) not on the one made available by Linzen et al. (2016), which we
have used to train our models. However, both are extracted from Wikipedia. Only a small model (Small DSA LSTM) was taken to have a fair comparison in terms of dataset size. Small LSTM mentioned by Kuncoro et al. (2019) is trained on 600k sentences, while ours is trained on 98k sentences.

### A.9 Fine-Grained analysis of TSE

Table 11, 12 and 13 presents a fine-grained analysis of TSE (§5.3) with demarcations based on number of the main subject and the embedded subject. We report the mean and standard deviation of 5 models with different seeds.

| Architecture | $N=535$ | $N=1069$ | $N=1601$ |
|--------------|---------|----------|----------|
|              | No fine-tune | Epoch=1 | Epoch=5 | Epoch=1 | Epoch=5 | Epoch=1 | Epoch=5 |
| LSTM         | 0.90     | 0.86     | 0.64     | 0.83     | 0.72     | 0.78     | 0.75     |
| ONLSTM       | 0.91     | 0.87     | 0.48     | 0.84     | 0.44     | 0.78     | 0.60     |
| GRU          | 0.87     | 0.85     | 0.80     | 0.83     | 0.78     | 0.80     | 0.78     |
| DRNN         | 0.83     | 0.80     | 0.77     | 0.78     | 0.76     | 0.77     | 0.78     |

Table 8: Reduction in out of distribution performance with an increasing number of challenging fine-tuning examples and with epochs of re-training. Bolds mark the best performance across the columns for each model.
Selective Sampling & 0.62 & 0.89 & 0.87 & 0.82 & 0.73 & 0.78 & 0.96 & 0.54 & 0.89 & 0.61 & 0.88 & 0.94 & 0.85 & 0.69 & 0.88 & 0.54 & 0.89 & 0.61 & 0.88 & 0.94 & 0.85 & 0.69

Humans & 0.96 & 0.94 & 0.88 & 0.82 & 0.73 & 0.78 & 0.96 & 0.54 & 0.89 & 0.61 & 0.88 & 0.94 & 0.85 & 0.69 & 0.88 & 0.54 & 0.89 & 0.61 & 0.88 & 0.94 & 0.85 & 0.69

Table 9: Comparison of our LSTM models with the existing results on the LSTM network distilled with an RNN. Grammars as a teacher. Bolds mark the best model for each test in a row; humans are not taken into consideration while bolding. Kuncoro et al. (2019) compares the probability of the grammatically correct verb with its ungrammatical counterpart. Kuncoro et al. (2019) train their small LSTM LM on a subset of Gulordava et al. (2018) Wikipedia corpus.

| Architecture | Natural Sampling | Selective Sampling |
|--------------|------------------|--------------------|
|              | 0                | 1                  | 2                  | 3                  | 0                | 1                | 2                  | 3                  |
| **LANGUAGE MODEL** | | | | | |
| LSTM | 0.98 (±0.00) | 0.91 (±0.01) | 0.84 (±0.03) | 0.78 (±0.06) | 0.89 (±0.01) | 0.98 (±0.00) | 0.98 (±0.00) | 0.95 (±0.01) |
| ONLSTM | 0.98 (±0.00) | 0.92 (±0.01) | 0.86 (±0.01) | 0.82 (±0.03) | 0.90 (±0.01) | 0.98 (±0.00) | 0.98 (±0.00) | 0.95 (±0.01) |
| GRU | 0.97 (±0.00) | 0.88 (±0.01) | 0.78 (±0.02) | 0.73 (±0.03) | 0.87 (±0.01) | 0.98 (±0.00) | 0.97 (±0.00) | 0.94 (±0.01) |
| DRNN | 0.96 (±0.00) | 0.69 (±0.02) | 0.47 (±0.03) | 0.36 (±0.03) | 0.83 (±0.01) | 0.97 (±0.00) | 0.94 (±0.01) | 0.91 (±0.01) |
| **BINARY CLASSIFIER** | | | | | | |
| LSTM | 0.97 (±0.01) | 0.93 (±0.02) | 0.87 (±0.03) | 0.82 (±0.03) | 0.60 (±0.06) | 0.98 (±0.00) | 0.96 (±0.00) | 0.97 (±0.01) |
| ONLSTM | 0.97 (±0.01) | 0.91 (±0.05) | 0.84 (±0.07) | 0.81 (±0.07) | 0.64 (±0.08) | 0.98 (±0.00) | 0.97 (±0.00) | 0.98 (±0.01) |
| GRU | 0.97 (±0.00) | 0.88 (±0.01) | 0.76 (±0.02) | 0.69 (±0.04) | 0.62 (±0.05) | 0.95 (±0.01) | 0.94 (±0.02) | 0.96 (±0.01) |
| DRNN | 0.97 (±0.00) | 0.90 (±0.01) | 0.81 (±0.02) | 0.77 (±0.02) | 0.70 (±0.02) | 0.97 (±0.00) | 0.96 (±0.00) | 0.96 (±0.01) |

Table 10: Performance of LM and classifier with an increasing number of attractors between the main subject and verb. Bolds mark the maximum accuracy in each configuration across the attractor, for each model; the more the better.

| Condition | Case | LSTM Natural | LSTM Selective | ONLSTM Natural | ONLSTM Selective | GRU Natural | GRU Selective | DRNN Natural | DRNN Selective | # Sentences |
|-----------|------|--------------|---------------|----------------|-----------------|------------|--------------|--------------|----------------|-------------|
| **Simple Ag** | S | 0.98 (±0.01) | 0.74 (±0.04) | 0.89 (±0.05) | 0.73 (±0.02) | 0.97 (±0.02) | 0.96 (±0.01) | 0.98 (±0.00) | 0.95 (±0.04) | 156 |
| | P | 1.00 (±0.01) | 0.98 (±0.02) | 0.99 (±0.03) | 0.99 (±0.01) | 0.91 (±0.07) | 0.91 (±0.07) | 0.95 (±0.04) | 0.87 (±0.09) | 156 |
| **Short VP** | S | 0.96 (±0.05) | 0.86 (±0.13) | 0.96 (±0.04) | 0.63 (±0.04) | 0.81 (±0.17) | 0.83 (±0.08) | 0.83 (±0.06) | 0.67 (±0.08) | 1716 |
| | P | 0.90 (±0.06) | 0.86 (±0.08) | 0.89 (±0.09) | 0.81 (±0.17) | 0.83 (±0.08) | 0.83 (±0.06) | 0.80 (±0.06) | 0.67 (±0.08) | 1716 |
| **Long VP** | S | 0.40 (±0.04) | 0.52 (±0.10) | 0.42 (±0.08) | 0.39 (±0.17) | 0.40 (±0.05) | 0.32 (±0.10) | 0.30 (±0.09) | 0.34 (±0.06) | 280 |
| | P | 0.90 (±0.07) | 0.86 (±0.09) | 0.92 (±0.04) | 0.95 (±0.05) | 0.85 (±0.08) | 0.98 (±0.03) | 0.83 (±0.04) | 0.95 (±0.04) | 280 |

Table 11: Fine-grained experimental results on constructed sentences. Example sentences for each condition are reported in the supplementary material of Marvin and Linzen (2018). For models trained on selective sampled data configuration, we observe that the performance of the models is far worse for singular main nouns than plural nouns. Low average performance on sentences with Long Verb Phrase coordination in comparison to other conditions may be attributed to a long-term non-local agreement that needs to be captured by the models. Aggregated results for these conditions are reported in Table 3.
Table 12: Fine-grained experimental results on constructed sentences having one intervening noun (agreement conditions are reported in Table 3. These sentences have local dependency (parents and love in the example) where interference is caused by the first noun (farmer). In the second column, the former character (PS) indicates the grammatical number of the first noun, and the next character indicates the grammatical number of the main noun against which the agreement is being tested. Other example sentences for each condition are reported in the supplementary material of Marvin and Linzen (2018). We observe interference effects from the singular initial noun (SP/PS cases) to be more significant than the plural initial noun (PPP/SS cases). The results for animate noun case is consistent with inanimate case (First and second rows are consistent, and third and fourth rows are consistent). We also observed that for models trained on naturalistic data configuration, the performance of ‘Within Object RC’ is better than on ‘Within Object RC without that’, which corroborates the findings of Marvin and Linzen (2018). However, no such distinction can be concluded for models trained on selectively sampled data configuration. Aggregated results for these conditions are reported in Table 3.

Table 13: Fine-grained experimental results on constructed sentences having one intervening noun (agreement attractor - SP/PS or non-agreement attractor - PP/SS) between the main noun, and the associated verb. Example sentences for each condition are reported in the supplementary material of Marvin and Linzen (2018). The performance on sentences with SP/PS cases is better for models trained on naturalistic data configuration than selectively sampled configuration. The results on condition with animate main nouns are not consistent with the ones having an inanimate main noun. The reason behind this inconsistency is still unclear. Aggregated results for these conditions are reported in Table 3.