Abstract
Natural language exhibits patterns of hierarchically governed dependencies, in which relations between words are sensitive to syntactic structure rather than linear ordering. While recurrent network models often fail to generalize in a hierarchically sensitive way (McCoy et al., 2020) when trained on ambiguous data, the improvement in performance of newer Transformer language models (Vaswani et al., 2017) on a range of syntactic benchmarks trained on large data sets (Goldberg, 2019; Warstadt et al., 2019) opens the question of whether these models might exhibit hierarchical generalization in the face of impoverished data. In this paper we examine patterns of structural generalization for Transformer sequence-to-sequence models and find that not only do Transformers fail to generalize hierarchically across a wide variety of grammatical mapping tasks, but they exhibit an even stronger preference for linear generalization than comparable recurrent networks.

1 Introduction
One of the fundamental properties of human languages is their sensitivity to relations among elements that are not easily characterized in linear terms. In phenomena like subject-verb agreement or reflexive anaphora, the relationship between the agreeing verb and its agreement target or the reflexive pronoun and its antecedent is not governed by linear properties like adjacency or recency, but instead by the hierarchical organization of the sentence. Similarly, the relationship between related sentences, which are represented in some grammatical theories as transformational operations or as lexical rules in others, is also governed by hierarchical organization. English polar questions, for instance, involve the fronting of an auxiliary verb in the corresponding declarative to a sentence-initial position. Questions with complex subjects like (1a) demonstrate that the verb that is fronted in such cases is the determined by hierarchical prominence (i.e., MOVE-MAIN yielding (1b)) and not linear considerations (MOVE-FIRST yielding (1c) or MOVE-LAST yielding (1d)).

(1) a. [The president who can smile] will lead those who would sing.
    b. Will the president who can smile __ lead those who would sing?
    c. * Can the president who __ smile will lead those who would sing?
    d. * Would the president who can smile will lead those who __ sing?

Chomsky (1971) argues that, in spite of receiving little input of the form in (1b), which would unambiguously demonstrate the necessity for a hierarchically governed dependency, children uniformly generalize the process of question formation in a hierarchical fashion. Such consistent behavior suggests that humans possess an inherent bias of some sort towards hierarchical generalization (though see Ambridge et al. (2008) and Perfors et al. (2011) for arguments against this view). Replicating such a bias in generalization would indicate the ability to mimic patterns of human cognition and learning.

Previous investigations of recurrent neural architectures have yielded some evidence for hierarchically-governed linguistic knowledge (Gulordava et al., 2018; Marvin and Linzen, 2018; Hu et al., 2020). Even greater success has been achieved with neural networks the incorporate explicit representation of syntactic structure (Kuncoro et al., 2018). Architecturally-constrained models when trained without explicit information about syntactic structure show only modest benefits (Shen et al., 2018; Kim et al., 2019; Merrill et al., 2019). However, all of these studies involve models that are trained on large quantities of text which may not be impoverished in domains that these bench-
marks assess. As a result, it is unclear whether any apparent hierarchical behavior reported in these works is the effect of a bias for hierarchical generalization or the accumulation of patterns explicitly guided by the training data. McCoy et al. (2020) take a different tack: the training data is carefully controlled so that hierarchical behavior can emerge only if a model itself is biased to extract hierarchical generalizations. Their experiments demonstrate that recurrent neural network seq2seq models show a clear preference for linear generalization.

The recently developed Transformer architecture has led to revolutionary advances across many areas of natural language processing, including machine translation and question answering (Vaswani et al., 2017; Devlin et al., 2019). Transformer-based models have also shown considerable success on benchmarks that appear to require the representation of hierarchical abstractions (Rogers et al., 2021; Goldberg, 2019; Warstadt et al., 2019). Further, investigations of Transformers’ representations of sentences (Hewitt and Manning, 2019; Lin et al., 2019) point to encodings of hierarchical syntactic structure. Yet, for the reasons noted above, it is difficult to conclude much about the inductive bias in the Transformer: they are trained on vast datasets, leaving open the question of the impact of inductive bias as opposed to training data (Warstadt and Bowman, 2020), but see Van Schijndel et al. (2019) for arguments that even massive data may not be sufficient). This paper contributes to our understanding by examining the degree to which the Transformer architecture is biased toward hierarchical generalization when the data underdetermine such generalization. Specifically, we study whether Transformers learning sequence-to-sequence mappings generalize in a structure sensitive way, and compare their performance with recurrent models.

2 Experiments

Our experiments involve a variety of English-language transduction tasks that highlight hierarchically-governed patterns. For each task, the training data is ambiguous between a linear and hierarchical generalization. This allows us to evaluate performance on both a test set, drawn from the same distribution as the training set, and a gen set of data, that contains out-of-distribution data consistent only with hierarchical patterns of generalization.

We compare transformer models with a number of recurrent architectures (LSTMs and GRUs with no attention, with additive attention (Bahdanau et al., 2016), and with multiplicative attention (Luong et al., 2015)). Transformer models follow their usual implementation with self- and multi-headed attention. For each model type, we perform 10 runs, initialized with different random initial seeds, and report median accuracy metrics. Recurrent units are single-layer models, with hidden and embedding dimensions of 256. Transformers are 4-headed, 3-layer models with hidden and embedding dimensions of 128. All models are trained at a learning rate of 0.01 using SGD optimization for 100 epochs with early stopping.

2.1 Polar Question Formation

Our first task involves the process of question formation discussed earlier. We borrow the formulation of this task from McCoy et al. (2020): the training dataset consists of an input sentence (a simple declarative with relative clauses optionally modifying the subject and object), a transformation token, decl or quest, and an output sentence. The transformation token specifies what the form of the target output should be. Following the logic surrounding example (1), examples with subject-modifying relative clauses are never paired in the training data with the quest transformation token. As a result, the network is not trained on sentences in which an auxiliary verb must be fronted past an intervening relative clause, and the target generalization is therefore ambiguous between something akin to move-main and move-first. While a network that acquires the move-first generalization will succeed on the in-distribution test set consisting of examples of the same structure as in the training data, it will fail on the gen set consisting of input sentences with subject-relative clauses and the quest transformation.

All trained network types performed well on the in-distribution test set, attaining mean full-sentence accuracies of at least 95%. In contrast, none of the models succeeded on the gen set in full sentence accuracy. Following McCoy et al. (2020), we instead assess gen set performance using the more lenient metric of first-word accuracy. Since the gen set includes only sentences with distinct auxiliary verbs in the main and relative clauses, the identity of the first output word reveals whether the network has acquired a linear (move-first) or hierarchical (move-main) generalization. Results
are shown in Figure 1. As noted in McCoy et al. (2020), there is variation in performance among the different types of recurrent networks: GRUs with multiplicative attention achieved median accuracy of 32.9%. Transformers exhibit the worst median performance among all architectures surveyed, with a median first-word accuracy of just 0.03% and virtually no variability across different random initializations. Instead, Transformer models overwhelmingly predicted sequences consistent with a linear MOVE-FIRST rule on the GEN set. These results are robust across changes in learning rate.

2.2 Tense Reinflection

Our second mapping task, again borrowed from McCoy et al. (2020) involves the reinflection of a sentence with a past tense verb into one with either a past or present tense verb. Significantly, the English present tense involves structurally-conditioned agreement with the verb’s subject. In complex expressions like (2a), distractor nouns with different number within the subject linearly separate the verb from the subject, but the grammatical agreement is nonetheless governed by a hierarchical AGREE-SUBJECT relation (predicting (2b)), as opposed to an AGREE-RECENT relation (predicting (2c)).

(2) a. My newt near the elephants ran.
   b. My newt near the elephants runs.
   c. * My newt near the elephants run.

Our datasets consist of past-tense English sentences as inputs, optionally with prepositional phrases or relative clauses modifying the subject or object, along with PRES and PAST transformation tokens that indicate the form of the target output. For training and in-distribution test data, examples with the PRES token do not have modified subjects, so that the reinflection mapping is ambiguous between AGREE-SUBJECT and AGREE-RECENT. In contrast, the GEN set includes sentences where the two rules make different predictions (modified subjects with distractor having distinct number). Results are shown in Figure 2. Like the recurrent architectures, Transformers systematically fail to exhibit hierarchical in favor of linear generalization.

2.3 Negation

Our third task involves the conversion of an affirmative sentence into a negative one. Negation requires the insertion of the negative marker “not” immediately prior to the main verb.

(3) a. The bird will sing.
   b. The bird will not sing.

When an adverbial clause is placed before or after the main clause (4), the main verb is no longer consistently the linearly first or last verb in the sentence.

(4) a. The bird will sing because the cat will swim.
   b. The bird will not sing because the cat will swim.
   c. Because the cat will swim the bird will not sing.

Our dataset consists of affirmative sentences, with adverbial clauses optionally preceding or following the main clause. These are transformed either into (identical) affirmatives or corresponding negatives. The training and in-distribution test set excludes sentences with initial adverbial clauses that must be mapped to negatives. As a result, this data set is ambiguous between a linear NEG-FIRST generalization and a hierarchical NEG-MAIN. This ambiguity is resolved in the GEN set, which contains sentences with preceding adverbials that must be converted into negative sentences, following the NEG-MAIN generalization.
All models, including the Transformer, perform exceedingly well on in-distribution data, attaining near-ceiling full-sentence accuracy on the TEST set. By contrast, all models, again including the Transformer, fail uniformly on the GEN set, attaining near-zero performance even using a more forgiving metric looking only at correct placement of the negative marker. Closer examination of the model outputs on the GEN set reveals that networks of all sorts overwhelmingly produce predictions consistent with the linear generalization (NEG-FIRST).

2.4 Reflexive Anaphoric Interpretation

Our final task, similar to that of Kim and Linzen (2020) and Frank and Petty (2020), involves the semantic parsing of a sequence into a predicate calculus representation, as in (5).

(5) Alice sees Bob → SEE(ALICE, BOB)

For entities whose meaning is context-independent, like nouns or verbs, this task involves learning a combination of token correspondence and form composition. As Frank and Petty (2020) note, reflexive anaphora like “herself” present a challenge since their meaning is not context-independent but rather conditioned on a linguistically-determined antecedent. In sentences with complex subjects, like that in (6) with a prepositional phrase modifier, the identification of the correct antecedent for the anaphor is conditioned not by the linear distance between a potential antecedent and the reflexive but rather by the hierarchical relation between the antecedent and reflexive.

(6) The boy by the king sees himself → SEE(BOY, BOY) ∧ BY(BOY, KING)

Our in-distribution data consists of sentences, transitive and intransitive, paired with predicate calculus representations of their meanings. Input sentences in this set may have complex subjects or the reflexive objects (“herself” or “herself”), but not both. As a result, the training and TEST data does not disambiguate whether the reflexive is coreferent with the grammatical subject or the noun phrase immediately preceding the verb. The GEN set contains only sentences reflexive objects and complex subjects containing prepositional phrases, and therefore serves to distinguish between the linear and hierarchical generalizations.

All models examined perform well on the TEST set, attaining median full sequence accuracy of 100%. Results on the GEN set, as shown in Figure 3, are more varied. We categorize the predictions made by the network into three distinct classes: subject-verb linear, where the model interprets the subject of the verb as being the linearly most recent noun (incompatible with the training data); reflexive linear, where the model interprets the antecedent of the reflexive as being the linearly most recent noun (compatible with the training set); and hierarchical, where the model correctly interprets both the subject and antecedent in a manner consistent with the hierarchical structure of the sentence (also compatible with training). Transformers and GRU models overwhelmingly make predictions consistent with reflexive linearity. LSTMs are more varied, with inattentive LSTMs attaining the highest hierarchical scores of all network types with a median performance of 65.8%.

3 Conclusion

Transformers have shown great success on syntactic benchmarks. Is this because the architecture has useful syntactic biases, or is it because cues to hierarchical structure are present in their training data? Our results find no evidence for the former, suggesting that their syntactic successes can mainly be attributed to their ability to leverage massive training sets rather than linguistically-relevant architectural biases. Though the Transformer models studied here were the best performers on in-distribution data across all tasks, their strong preference for linear over hierarchical generalization suggests an explanation for their poor performance on tasks requiring structural generalization (Kim and Linzen, 2020) despite their promise in other syntactically sensitive tasks. Finally, we note that the preference we have observed for linear generalization is consistent with previous theoretical work on the (limited) expressive power of Transformers (Hahn, 2020; Merrill, 2019).
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