Are Larger Language Models Better at Disambiguation?

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Abstract

Humans deal with temporary syntactic ambiguity all the time in incremental sentence processing. Sentences with temporary ambiguity that causes processing difficulties, often reflected by increase in reading time, are referred to as garden-path sentences. Garden-path theories of sentence processing attribute the increases in reading time to the reanalysis of the previously ambiguous syntactic structure to make it consistent with the new disambiguating text. It is unknown whether transformer-based language models successfully resolve the temporary ambiguity after encountering the disambiguating text. We investigated this question by analyzing completions generated from language models for a type of garden-path sentence with ambiguity between a complement clause interpretation and a relative clause interpretation. We found that larger language models are worse at resolving such ambiguity.

1 Introduction

Linguistic analysis of neural language models suggests that pre-trained language models capture the syntax of natural languages (Hewitt and Manning, 2019) and represent the incremental syntactic processing states similar to those of humans (Marvin and Linzen, 2018; Futrell et al., 2019). People experience processing difficulties while they encounter a continuation of a sentence that conforms to the less likely interpretation of the previously ambiguous syntactic structure. Such processing difficulties, called garden path effects, can be observed in eye-tracking and self-paced reading experiments as increases in reading time for the disambiguating continuation (Frazier and Rayner, 1982; Christianson et al., 2001). Through the surprisal theory (Hale, 2001; Levy, 2008), prior studies observed garden path effects in autoregressive language models (van Schijndel and Linzen, 2018; Futrell et al., 2019). However, it is unclear whether autoregressive language models finally resolve the temporary syntactic ambiguity after being exposed to the disambiguating text.

We probed the incremental syntactic representations of language models by analyzing their completions of garden-path prefixes. We used a set of garden-path sentences that were originally curated to study the garden-path effect in humans (Altmann et al., 1992). We chose this set of garden-path sentences since completions of this set of sentences generated by language models seem to be indicative of their incremental syntactic representations. In other words, the completions generated by a language model can be used to probe whether the language model successfully resolves the temporary syntactic ambiguity after they have seen the disambiguating text.

We gathered 30 garden-path sentences from Altmann et al. (1992) and modified some of them to make each of them have a similar form. We evaluated autoregressive language models of five families on whether each of them successfully resolve the temporary ambiguity in each of the 30 garden-path sentences. For each model, we sampled 50 completions and used a dependency parser to judge whether each completion is grammatically correct. Aggregating those judgments, we found that larger language models are worse at resolving temporary ambiguities. A follow-up experiment based on models' preference between two possible continuations of garden path prefixes showed the same trend with weaker significance. Overall, this paper provides evidence that larger language models are worse at recovering from syntactic ambiguity, suggesting that they are not maintaining explicit syntactic structures.

2 Related Work

Multiple studies have found that larger language models are not always better. From a behavioral perspective, a recent inverse scaling challenge col-

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lected and reported a diverse set of tasks which the larger language models show worse performance (McKenzie et al., 2023). Most tasks reported are not about fundamental linguistic capabilities. For example, one of the tasks involves redefining particular symbols and evaluating whether language models recognize the redefinition. Another study looked at how BERT-style models understand garden path sentences via auxiliary question answering tasks and found that BERT-style models do not perform better than humans on question answering accuracy despite being bidirectional (Irwin et al., 2023).

From a cognitive modeling perspective, it was shown that surprisals from larger and more capable (measured by perplexity) language models are worse at predicting human reading time of naturally occurring texts due to their superhuman capabilities of predicting rare words. (Oh and Schuler, 2023; Oh et al., 2024). It was also shown that surprisals from neural language models cannot entirely explain human syntactic processing difficulties (van Schijndel and Linzen, 2020; Arehalli et al., 2022; Huang et al., 2024). The lack of explanatory power, however, is not compared among models of different sizes.

Several works have looked at how language models handle ambiguity. Aina and Linzen (2021) studied whether language models recognize structural ambiguities by analyzing completions from the models. However, it did not focus on comparing models of varying sizes. Hanna and Mueller (2024) investigated how language models process garden-path sentences with mechanistic interpretation. Irwin et al. (2023); Li et al. (2024); Amouyal et al. (2025) investigated how language models process garden-path sentences with question answering. However, those work only looked at how language models process garden-path sentences indirectly through comprehension questions.

3 Experiment 1: Probing for Syntactic Representation by Completions

The purpose of this experiment is to compare how language models of different sizes resolve temporary syntactic ambiguity. We chose garden path sentences where the completions generated by a language model are indicative of its incremental syntactic representation. The original material was collected by Altmann et al. (1992) to investigate the effect of referential context on sentence processing.

An example garden path sentence of our evaluation set is

(1) The householder told the builder that he had arranged to pay that the bill was fair.

Until one encounters *that the bill*, the sentence is ambiguous. The segment of text, *that he had arranged to pay*, can be interpreted as either a relative clause or a (partial) sentential complement clause. After one encounters *that the bill*, this ambiguity can be resolved. At this point, the relative clause interpretation is the only consistent interpretation. Increase in reading time was observed for the disambiguating region, *that the bill*, in the garden path sentence compared to that of a non-ambiguous control (Altmann et al., 1992). Garden path theories predict that one will adopt the sentential complement interpretation at first (Frazier and Rayner, 1982). It attributes the increase in reading time to the reanalysis of structure after one encounters the disambiguating texts. However, it is possible that language models are led down the garden path and don't resolve the ambiguity even after encountering the disambiguating region.

To find out whether a language model resolves the temporary ambiguity, consider the disambiguated prefix,

(2) The householder told the builder that he had arranged to pay that the bill ...

If a language model successfully resolves the temporary ambiguity, it should recognize that *the bill* is the subject of a clause that serves as the complement of the predicate *told*. On the other hand, if a language model fails to resolve the ambiguity, the model often incorrectly treats *the bill* as the complement of *pay* and it may generate ungrammatical completions without a complete sentential complement. An example ungrammatical completions generated by a language model is

(3) * The householder told the builder that he had arranged to pay that the bill in two weeks.

Therefore the completions generated by language models can serve as a probe for the incremental syntactic representation of the language models.

Materials We gathered 30 sentences from Altmann et al. (1992) and transformed them into a similar form such that each sentence contains a temporary syntactic ambiguity between a relative

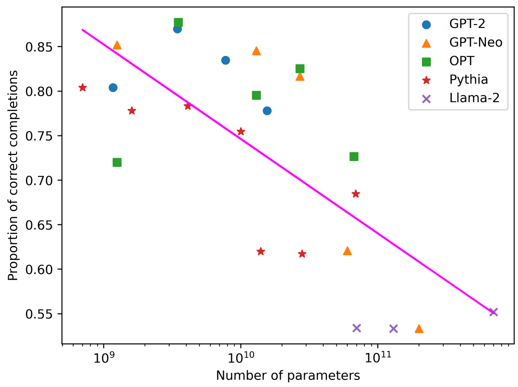

Figure 1: The proportion of grammatical completions for models of different sizes. It shows a log-linear relationship between the model's size and proportion of grammatical completions. A permutation test (10,000 samples) shows that the negative slope is significant ($p < 0.005$).

clause interpretation and a complement clause interpretation and the disambiguating region starts with a noun phrase (e.g., *the bill*) which is the subject for another clause. We provided the disambiguated prefixes of a similar form as that of Example 2 to the language model. The full prefixes can be found the in appendix A.

Evaluation For each prefix, we sampled 50 completions (with temperature = 1) from language models with different sizes in five model families, including GPT-2 (Radford et al., 2019), GPT-Neo (Black et al., 2021, 2022), OPT (Zhang et al., 2022), Pythia (Biderman et al., 2023), and Llama-2 (Touvron et al., 2023). We measured how well each model resolves the ambiguity by the proportion of grammatical completions that it generated. To judge whether a completion is grammatical, we can look at whether the model's completion treats the noun phrase at the end of the prefix as the subject of a complete clause. We automatically analyzed the structure of the part of the sentence after the second complementizer *that* using the spaCy dependency parser (Honnibal and Johnson, 2015). If the noun phrase in the disambiguating region is annotated as the subject of a clause, we know that the completion is grammatical. On the other hand, if it is annotated as the root of the tree, we know that the completion is ungrammatical. We observed that the dependency parser correctly discriminates between the two cases for 98 out of 100 sampled model completions. Note that this automatic labeling scheme may produce false positives since a completion may still be ungrammatical even if the noun phrase in the disambiguating region is treated as the subject of the complement clause. However, we observed that this rarely happens on our test sentences and it can only underestimate the proportion of ungrammatical completions.

Result We calculated the accuracy of each model as the proportion of completions that are grammatical. The accuracy of each language model is shown in Figure 1. The line fit shows a trend that larger models are worse at generating grammatical completions. A permutation test was conducted to determine the significance of the slope. Each simulation was constructed by randomly permuting the sample completions among all different models. A permutation test of 10,000 simulation shows that the negative slope is highly significant ($p < 0.005$).

Discussion The result that larger language models are worse at resolving temporary syntactic ambiguities is at first surprising. It contradicts the perceived general trend that larger language models have better linguistic capabilities (though see Oh and Schuler (2023); Oh et al. (2024)).

This result, however, does not imply that smaller language models are better at resolving temporary ambiguities. It is possible that smaller language models focus on the more recent information while completing a prefix. In contrast, larger language models may rely on the broader context and treat the disambiguating texts as a text error. The next experiment investigates this hypothesis using a modified set of sentences used in experiment 1.

4 Experiment 2

A follow-up experiment was conducted to test whether larger language models are more likely to treat the local contradicting information as a text error compared to smaller language models. To test this, we present the model a set of prefixes with text errors near the end. The following is one example of such prefixes,

(4) * The householder had arranged to pay that the bill ...

This prefix is constructed by removing the main predicate with the ambiguous relative clause from the same stimulus used in experiment 1. Note that there is no obvious grammatical completion of Example 4. If it is the case that smaller language

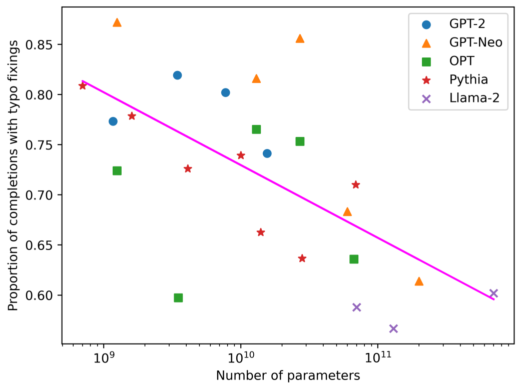

Figure 2: This figure shows the tendency of different models on recognizing text errors. Larger language models tend to treat the local contradicting information as text errors while smaller language models tend to ignore the broader context.

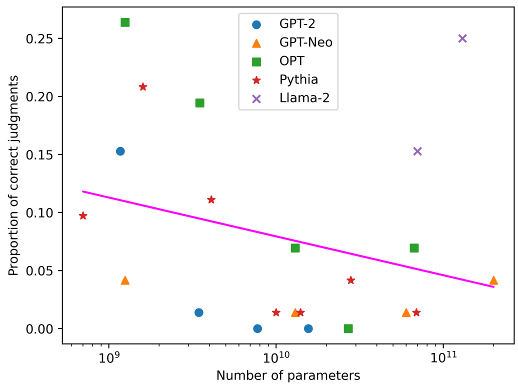

Figure 3: Proportion of correct judgments for models of different sizes.

models are more likely to focus on the more recent information but larger language models tend to focus on the broader context, the smaller models will complete the prefix as if *the bill* is a subject that starts a clause and the larger models will complete the prefix as if *that the bill* is a text error. Here's one example completion which indicates that the language model treats the end of the prefix as a text error as if the word "that" was not in the sentence,

(5) * The householder had arranged to pay that the bill to the landlord.

Similar to experiment 1, we used the completions generated by a language model to probe for the model's representation of the prefix.

Materials We modified the 30 sentences used in experiment 1 to make each of them have a similar form as example 4. Each sentence contains a text error with a duplicate determiner.

Evaluation Similar to experiment 1, for each model and each prefix, we sampled 50 completions. To distinguish whether the model treats the duplicate determiners as a text error, we used the spaCy dependency parser to recognize whether the noun phrase at the end of the prefix is the root of the dependency tree. We aggregated all the completions generated by the language model to calculate the proportion of the completions where the duplicate determiners are recognized as a typo.

Result As shown in Figure 2, larger models are more likely to recognize the duplicate determiners as a text error and complete as if only one determiner exists while smaller models are more likely to ignore the earlier part of the prefix and complete it as if the noun phrase at the end is the start of a clause.

5 Experiment 3: Probing for Syntactic Representation by Targeted Evaluation

The method used in experiment 1 can reveal whether language models resolve the ambiguity between the relative clause interpretation and the sentential clause interpretation. However, it is not clear how it can be applied to investigate language models' representation of other types of ambiguities. In this experiment, we used syntactic judgment of language models to probe how they represent garden path prefixes. Consider a pair of prefixes that only differ in the last token, such as,

(6) David's father told the builder that David's mother had arranged to pay that the bills were fair and was proud of himself/*herself.

If the language model successfully discards the sentential clause interpretation, it should prefer *himself* over *herself*. Therefore language models preference on such pairs of prefixes can shed light on whether they disambiguate garden path prefixes.

Materials We gathered 36 sentences with ambiguity between a relative clause interpretation and a sentential clause interpretation from Altmann et al. (1992). We manipulated the gender of the subject of the matrix clause and that of the subject of the relative clause and append *and was proud of* *himself/herself* at the end of each sentence. This resulted in 72 pairs of sentences. One of the sentence in each pair indicates successful disambiguation and the other sentence indicates incorrect representation. The complete set of test sentences is in Appendix B.

Result As shown in Figure 3, we observed a trend that larger language models produce fewer correct judgments. A permutation test shows a weak significance of this trend ($p < 0.1$).

6 Conclusion

By analyzing completions of garden-path sentences generated by language models and examining the preference of language models on a set of pairs of garden path sentences, we showed that larger language models are worse at resolving temporary syntactic ambiguities. This challenges the view that neural language models maintain explicit syntactic structure during their incremental processing of language.

7 Limitations

We only investigated models' behavior on limited types of garden-path sentences since it is not obvious how completions of other types of garden-path sentences can tell us whether the model successfully resolves the ambiguity. Also, we only investigated language models' behavior in English. In experiment 3, we noticed that the two Llama-2 variants have comparable performance as the smaller GPT2 variants and OPT variants. It is possible that the trend is reversed for models that are larger than the ones we tested with. We leave it for future work.

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A Stimuli for experiment 1

1 The householder told the builder that he had arranged to pay that the bill

2 The woman told the policeman that she had been trying to avoid that the arrestment

3 The student told the tutor that she had consulted that the professor

4 The doctor told the patient that she had been ready to examine that the X ray

5 The captain told the colonel that he had contacted that the commander

6 The manager told the woman that he was confident about that the project

7 The minister told the councilor that he had agreed to see that the proposal

8 The bank manager told the woman that he had misunderstood that the situation

9 The driving instructor told the woman that he had been impressed by that her skill

10 The solicitor told the woman that he had doubts about that the validity

11 The headmistres told the boy that she was worried about that his behavior

12 The sales assistant told the man that she had dealt with that the faults

13 The journalist told the woman that he had been working with that the next issue

14 The doctor told the woman that he was worried about that the health condition

15 The electrician told the man that he was impressed by that his explanation

16 The teacher told the father that she was shocked by that his attitude

17 The musician told the guitarist that he was impressed by that the play

18 The auctioneer told the woman that he had just sold a painting for that the price

19 The politician told the journalist that he agreed with that the deal

20 The Queen Mother told the comedian that she was amused by that the show

21 The film director told the actress that he had heard of that her accomplishments

22 The baker told the old lady that he had been baked a cake for that the party

23 The couple told the boy that they had brought a gift for that their child

24 The photographer told the model that he had taken bad photos of that the pose

25 The social worker told the father that she was horrified by that his attitude

26 The ski instructor told the girl that he was happy with that her performance

27 The patient told the nurse that he was complaining about that the chest pain

28 The young boy told the girl that he was frightened of that his classmate

29 The man told the policewoman that he had been talking to that the young girl

30 The antique dealer told the woman that he was talking to that another dealer

B Stimuli for experiment 3

1 John's mother told the builder that John's father had arranged to pay that the bills were very fair and was proud of **herself**/himself

2 John's mother told the tutor that John's father had consulted that the projects had been boring and was proud of **herself**/himself

3 John's mother told the policewomen that John's father had been talking to that the incidents were terrifying and was proud of **herself**/himself

4 John's mother told the patient that John's father had some good news about that the X ray images were clear and was proud of **herself**/himself

5 John's mother told the colonel that John's father had contacted that the enemies were now advancing and was proud of **herself**/himself

6 John's mother told the man that John's father had been insulted by to take a running jump and was proud of **herself**/himself

7 John's mother told the woman that John's father was confident about to return in a fortnight and was proud of **herself**/himself

8 John's mother told the councillor that John's father had agreed to see to submit further details and was proud of **herself**/himself

9 John's mother told the policeman that John's father had been trying to avoid to contact the lawyer and was proud of **herself**/himself

10 John's mother told the woman that John's father had misunderstood to repeat the last question and was proud of **herself**/himself

11 John's mother told the officer that John's father had been meeting that gradually things were changing and was proud of **herself**/himself

12 John's mother told the woman that John's father had been impressed by to ensure she drove with care and was proud of **herself**/himself

13 John's mother told the woman that John's father had doubts about to confirm the new statement and was proud of **herself**/himself

14 John's mother told the boy that John's father was worried about to concentrate on his homework and was proud of **herself**/himself

15 John's mother told the man that John's father had dealt with that the faults would be repaired and was proud of **herself**/himself

16 John's mother told the woman that John's father had been working with to outline the next case and was proud of **herself**/himself

17 John's mother told the woman that John's father was worried about to be positive about the illness and was proud of **herself**/himself

18 John's mother told the woman that John's father was impressed by to explain it all to her friend and was proud of **herself**/himself

19 John's mother told the father that John's father was shocked by that his attitude was appalling and was proud of **herself**/himself

20 John's mother told the guitarist that John's father was impressed by to audition again on Friday and was proud of **herself**/himself

21 John's mother told the wife that John's father was worried about to come and visit more often and was proud of **herself**/himself

22 John's mother told the woman that John's father had risked his life for to install a smoke detector and was proud of **herself**/himself

23 John's mother told the woman that John's father had just sold a painting for to give him the fee and was proud of **herself**/himself

24 John's mother told the man that John's father was pleased to see to order another coffee and was proud of **herself**/himself

25 John's mother told the journalist that John's father agreed with to write a report on the subject and was proud of **herself**/himself

26 John's mother told the comedian that John's father was amused by to impersonate the other guests and was proud of **herself**/himself

27 John's mother told the actress that John's father had heard of to audition for the next film and was proud of **herself**/himself

28 John's mother told the old lady that John's father had baked a cake for to pay the bill on Saturday and was proud of **herself**/himself

29 John's mother told the boy that John's father had brought a gift for to share it with his friend and was proud of **herself**/himself

30 John's mother told the woman that John's father wanted to go with to meet her outside the museum and was proud of **herself**/himself

31 John's mother told the woman that John's father was talking to that the chairs were exquisite and was proud of **herself**/himself

32 John's mother told the model that John's father had taken bad photos of to pose again the next day and was proud of **herself**/himself

33 John's mother told the father that John's father was horrified by to change his attitude and was proud of **herself**/himself

34 John's mother told the girl that John's father was happy with to try a more difficult slope and was proud of **herself**/himself

35 John's mother told the nurse that John's father was complaining about to treat her with more care and was proud of **herself**/himself

36 John's mother told the girl that John's father was frightened of to bully someone her own age and was proud of **herself**/himself

37 John's father told the builder that John's mother had arranged to pay that the bills were very fair and was proud of **himself**/herself

38 John's father told the tutor that John's mother had consulted that the projects had been boring and was proud of **himself**/herself

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65 John's father told the boy that John's mother had brought a gift for to share it with his friend and was proud of **himself**/herself

66 John's father told the woman that John's mother wanted to go with to meet him outside the museum and was proud of **himself**/herself

67 John's father told the woman that John's mother was talking to that the chairs were exquisite and was proud of **himself**/herself

68 John's father told the model that John's mother had taken bad photos of to pose again the next day and was proud of **himself**/herself

69 John's father told the father that John's mother was horrified by to change his attitude and was proud of **himself**/herself

70 John's father told the girl that John's mother was happy with to try a more difficult slope and was proud of **himself**/herself

71 John's father told the nurse that John's mother was complaining about to treat him with more care and was proud of **himself**/herself

72 John's father told the girl that John's mother was frightened of to bully someone her own age and was proud of **himself**/herself