

# Probing for Dutch Relative Pronoun Choice

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## Abstract

We propose a linguistically motivated version of the relative pronoun probing task for Dutch (where a model has to predict whether a masked token is either *die* or *dat*), collect realistic data for it using a parsed corpus, and probe the performance of four context-sensitive BERT-based neural language models. Whereas the original task, which simply masked all occurrences of the words *die* and *dat*, was relatively easy, the linguistically motivated task turns out to be much harder. Models differ considerably in their performance, but a monolingual model trained on a heterogeneous corpus appears to be most robust.

## 1. Introduction

Large neural language models such as BERT (Devlin et al. 2019) are trained among others on a masked language prediction task, where the input consists of sentences where one word has been masked, and the model has to predict which of several candidate words is the most likely to appear in the masked position. Statistical, ngram-based, language models as well as early neural models such as word2vec (Mikolov et al. 2013) only take a very limited context into account when making predictions about a following or masked token. Transformer-based neural language models such as BERT in theory are sensitive to the full (left and right) context of a masked position when making predictions. One question that arises is whether this allows these neural models to make accurate predictions in cases where the correct answer depends on making grammatical distinctions that depend on a larger context (Linzen and Baroni 2021). For instance, in a subject-verb agreement task, one might probe the model for its ability to distinguish between singular and plural agreement in cases such as (1), where the model has to be sensitive to the fact that it is the number of the head noun of the subject phrase, and not that of the immediate preceding noun, that determines the form of the verb.

- (1) The length of the forewings (is/\*are) ...

The overview of probing research in Linzen and Baroni (2021) shows that results from such experiments are mixed. On the one hand, models display an accuracy that suggests that they are sensitive to part of speech and syntactic structure, while on the other hand there are also results that show that performance quickly decreases in syntactically complex cases. For instance, in sentences where the subject is modified by a relative clause (2), or where the first noun in the sentence is not heading the subject (3), models are less good at predicting the correct form of the verb. Apart from subject-verb agreement, case and gender distinctions, negative polarity, co-reference, and sensitivity to long-distance dependencies involving ‘gaps’ have also been used to probe models. Sahin et al. (2019) provide a multilingual suite of probing tasks.

- (2) The movie that the author likes, (is/\*are) good  
(3) The scientist thinks that parts of the river valley have/\*has

Delobelle et al. (2020) test RobBERT, a BERT-based neural language model for Dutch, and a number of competing language models, on a masked language prediction task where the model has to predict

for a given sentence whether the masked token is either *die* or *dat*. These two words can be used, among others, as relative pronouns, where *dat* can only occur with an antecedent that is a singular neuter (*het*) noun (4-a), and *die* can be used with either a singular non-neuter antecedent (*de*) (4-b) or a plural antecedent.

- (4) a. het portret van een vrouw dat bij hem op de ezel stond  
 the portrait of a woman that with him at the easel stood  
*the portrait of a woman that stood at his easel*
- b. de directeur van een bedrijf die in een Duitse auto rijdt  
 the director of a company that in a German car drives  
*the director of a company that drives a German car*

The task is inspired by a similar experiment from Allein et al. (2020). Allein et al. use data from the Europarl corpus<sup>1</sup> and Sonar<sup>2</sup> to train a neural classifier for *die/dat*-prediction, using an LSTM that is initialized with word embeddings obtained from a word2vec model. The trained classifier obtains accuracies of 83.2% (Europarl) and 84.5% (Sonar). Delobelle et al. collect data from the Dutch section of the Europarl corpus, where they use all sentences containing *die* or *dat* as test cases (288K sentences). They report accuracies of 90.2 (mBERT, a multilingual BERT model), 94.9 (Bertje, an alternative Dutch language model, (de Vries et al. 2019)) and 98.7% (RobBERT). It should be noted, though, that in many cases, there is no real ambiguity or need to pay attention to longer contexts. In (5-a), for instance, *dat* is used as subordinating conjunction in a position where *die* could never occur. In (5-b) *die* is used as relative pronoun with *gegevens* as antecedent, but there are no preceding nouns that could function as distractor. In (5-c), *die* is used as deictic pronoun introducing an NP where the noun with which the pronoun agrees is adjacent to the pronoun. Even if there is intervening material in such cases, it usually is not a noun that could act as distractor. This task is therefore not optimal for ‘probing’, as it is unclear to what extent information from the full context of the masked position is required to make the correct prediction.

- (5) a. U begrijpt die/**dat** we te maken hebben met een bijzondere prestatie  
 You understand that we to do have with a special achievement  
*You understand that we are dealing with a special achievement*
- b. De gegevens **die**/dat u invult  
 The data that you enter
- c. De toestand van **die**/dat wegen is slecht  
 The condition of these roads is bad

We propose to turn the *die/dat* prediction task into a proper probing task by focussing on cases where a relative pronoun occurs in the masked position (thus ignoring prediction of the relatively easy subordinate conjunction and deictic pronoun cases) and where there is at least one distractor. We explain how we collected relevant examples from a parsed corpus, and test two monolingual and two multilingual neural language models for their ability to make the right predictions and thus establish to what extent such models are sensitive to longer contexts.

## 2. Relative Clause Attachment

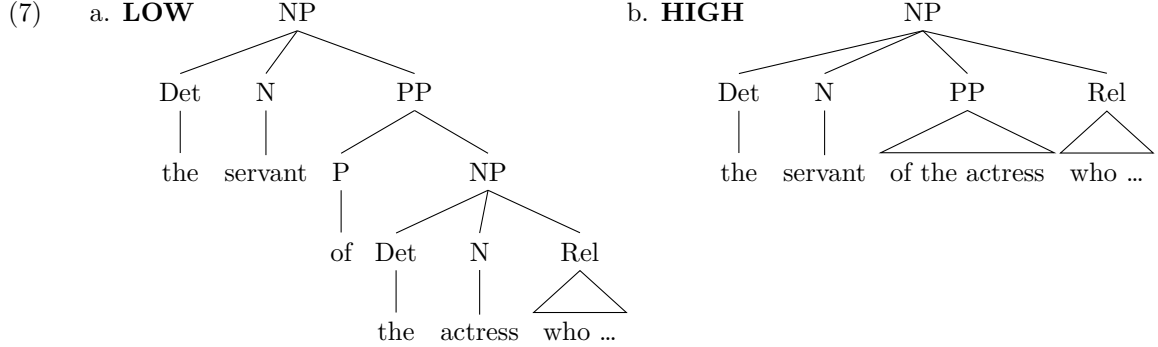
Relative clause attachment has been studied extensively from a psycholinguistic perspective (starting with Cuetos and Mitchell (1988)), also for Dutch (Desmet et al. 2006). The canonical example is:

- (6) Someone shot the servant of the actress who was on the balcony

1. <https://www.statmt.org/europarl/>

2. <https://taalmaterialen.ivdnt.org/download/tstc-sonar-corpus/>

Here, the relative clause could be attached either to the lower noun *actress* as in (7-a) or the higher noun *servant* as in (7-b). It has been claimed that preference for high or low attachment is not universal, with speakers of some languages having a preference for low attachment, where other languages, such as Dutch, prefer high attachment (Brysbaert and Mitchell 1996). Desmet et al. point out that corpus data shows that in Dutch, low attachment is the most frequent configuration as well, and high attachment only is more frequent in cases where the highest noun is animate. The preference of test subjects is in line with this observation if one takes these factors into account during construction of the test items.



Whereas psycholinguistic studies have used a sentence completion task to probe the preference for test subjects for either high or low attachment of the relative clause, we change the task into a masked word prediction task suitable for testing a language model by only masking the relative pronoun. As the language model is trained on raw text and never sees any syntactic structures, we exclusively concentrate on those cases where the two preceding nouns in the complex noun phrase have opposite gender (*neuter* or *non-neuter*, respectively), thus triggering either *die* or *dat*, which we take as signs of high or low attachment in this particular context.

- (8) a. Het is het proza<sub>neu</sub> van een vrouw<sub>nonn</sub> [MASK] een hoge prijs betaalde  
 It is the prose of a woman [MASK] a high price paid  
*It is the prose of a woman that paid a high price*
- b. Melk is het enige product<sub>neu</sub> van de koe<sub>nonn</sub> [MASK] aan de paniek is ontsnapt  
 Milk is the only product of the cow [MASK] from the panic is escaped  
*Milk is the only product of the cow that has escaped from the panic*

Example (8-a) illustrates low attachment, where the relative clause is modifying the lower noun *vrouw*, and the correct pronoun is *die<sub>nonn</sub>*. (8-b) illustrates high attachment, where the relative clause modifies *product*, and the masked pronoun therefore is *dat<sub>neu</sub>*.

It should be noted that our probing experiment serves a very different purpose than the reading comprehension experiments. The psycholinguistic research has concentrated on answering the question whether there is an inherent preference for low or high attachment by speakers of a given language, and has used specifically constructed test items, in which context ideally does not make either one of the attachment options much more plausible than the other. Properly controlling for confounding factors remains an issue, however (Hemforth et al. 2015). We use models trained on a corpus of naturally occurring data and also test on corpus data. In such data, most relevant cases, even when there are two potential antecedents, will be such that one antecedent is clearly more plausible than the other. Statistics indicate that low attachment in general is much more frequent than high attachment in actual corpus data, and that, for Dutch, the relative pronoun *die* occurs more often than *dat*. Thus, a language model trained on such data is likely to develop a preference for low attachment, and for predicting *die* over *dat*, but a model that is sensitive to context should

still be able to predict high attachment or *dat* as pronoun in cases where the alternative would lead to semantic incoherence.

### 3. Data Collection

To collect realistic examples, we searched a newspaper corpus, containing articles from *Algemeen Dagblad* and *NRC Handelsblad* 1994-1995. This corpus has not been used during training of any of the language models we use in the experiment, and thus there cannot be memorization effects (Carlini et al. 2020). The corpus was automatically parsed with Alpino (van Noord 2006). Our corpus query searched for sentences containing a complex NP with the structure of either (7-a) or (7-b) and with the additional constraints that the two relevant nouns had to be singular and of opposite gender and that the embedded PP had to be headed by *van* (*of*). The latter constraint was added to reduce the number of false hits due to parsing errors, as *van*-PPs almost always modify a noun and occur rarely as modifiers of verbs. We did not impose any other constraints. In particular, any number of other modifying elements (adjectives, other PPs) can be present, and the relative clause may be extraposed.

The Alpino parser uses a statistical model obtained from a corpus to disambiguate sentences, and, as low attachment is more frequent than high attachment, tends to do better on low attachment cases than on high attachment cases. This is reflected in the extracted sentences for the high attachment case, as these contain a substantial number of false hits. Therefore, we manually selected 1951 true positives from the 2534 hits returned by the query. A brief inspection of the low-attachment cases showed that these hardly contain false hits. We therefore did not filter these. As low attachment is also much more frequent than high attachment and we wanted to use balanced data, we included 2000 instances of low attachment. Note that while false hits (and duplicate sentences) were removed, sentences that actually are ambiguous after masking the pronoun, such as (9), were kept.

- (9) ... een dagboek van de nieuwe topman [MASK] een tip oplicht van de geheimen van de  
a diary of the new head [MASK] a tip reveals of the secrets of the  
onderhandeling .  
negotiation  
*a diary of the new head that reveals the secrets of the negotiation*

Here, the choice for *dat* amounts to choosing *dagboek* as antecedent (in line with the source) whereas *die* amounts to choosing *topman* as antecedent, which is a semantically plausible interpretation as well. The datasets and code used in this paper are available at github.<sup>3</sup>

### 4. Language Models

We tested on two multilingual and two monolingual context-sensitive language models (Table 1). Whereas statistical (ngram) language models are typically trained to make a prediction about the next token in a sentence, neural language models are trained using a masked-language model (MLM) objective, where some words in the text are masked and the model has access to both left and right context to make a prediction. All models of the BERT-variety (Devlin et al. 2019) use a complex neural architecture that includes an attention mechanism that allows the model to learn which words in the input are most important for making a prediction about the masked position. The question thus arises whether this enables the model to learn that, say, the head noun inside a complex subject NP is the relevant word for predicting the correctly inflected form of the finite verb, or whether the model instead learns a simpler but structure insensitive rule (such as attending to the closest preceding noun) that would allow it to make the right prediction in most cases without paying attention to structure. Similarly, for the *die/dat* probing task as we have designed it, the model must decide

3. [https://github.com/gossebouma/die\\_vs\\_dat](https://github.com/gossebouma/die_vs_dat)

| Model   | Corpus                                  | Training objective | Reference               |
|---------|---|--------------------|-------------------------|
| RobBERT | Dutch section of OSCAR (web, 39GB)      | MLM                | (Delobelle et al. 2020) |
| Bertje  | Dutch Wikipedia, Sonar, Novels (12GB)   | MLM                | (de Vries et al. 2019)  |
| mBERT   | Wikipedia for 104 languages             | MLM and NSP        | Github <sup>a</sup>     |
| XLm-R   | Common Crawl (web, multilingual, 2.5TB) | MLM                | (Conneau et al. 2020)   |

Table 1: Neural-language models used in the probe.

a. <https://github.com/google-research/bert/blob/master/multilingual.md>

|       | High attachment |              |         |       |              | Low attachment |              |         |       |              |
|-------|-----------------|--------------|---------|-------|--------------|----------------|--------------|---------|-------|--------------|
|       | N               | Bertje       | RobBERT | mBERT | XLm-R        | N              | Bertje       | RobBERT | mBERT | XLm-R        |
| dat   | 788             | <b>0.789</b> | 0.537   | 0.510 | 0.590        | 1000           | <b>0.931</b> | 0.782   | 0.769 | 0.852        |
| die   | 1163            | 0.740        | 0.650   | 0.711 | <b>0.783</b> | 1000           | 0.937        | 0.836   | 0.885 | <b>0.957</b> |
| total | 1951            | <b>0.761</b> | 0.601   | 0.624 | 0.700        | 2000           | <b>0.934</b> | 0.809   | 0.827 | 0.905        |

Table 2: Probing results for high and low attachment

which of two preceding nouns is more likely as antecedent, where the following context (containing the relative clause) may contain crucial information for making the correct decision. Some models also use a next-sentence prediction (NSP) task for training, where the model is trained to predict whether two concatenated sentences occurred in the given order in the corpus or not. While this can be relevant for downstream tasks such as question answering, it is probably less relevant for learning to attend to linguistic structure. A language model can be trained on a monolingual corpus, but recently it has been shown that multilingual models, trained on a concatenation of monolingual corpora (with upsampling of the data for low-resource languages), can outperform monolingual models, especially for low-resource languages (Pires et al. 2019). We used the pretrained models present on [huggingface.co](https://huggingface.co).<sup>4</sup>

## 5. Experiments and Discussion

The results of the probing experiment are in Table 2. Note that in order to do well on this task, a model must take both left and right context into account. The left context provides two nouns, while the right context contains the relative clause. In order to decide on the correct pronoun, the model must work out whether the relative clause is more likely to be attached to the higher or lower noun in the left context. The high attachment cases are much harder than low attachment for all models. This is not unexpected, as low attachment is more frequent in the corpus from which the test sentences are extracted and probably in the training corpora as well, and high attachment requires the model to attend to a noun that is relatively far from the masked position with an intervening noun that has the opposite gender. Bertje is the only model that does equally well on the *die* and *dat* cases, where the other models all have a tendency to prefer *die* over *dat*. Apart from Bertje, the multilingual model XLm-R suffers least from the difference between *die* and *dat* and therefore does better than the other two models.

### 5.1 Error Analysis

We manually inspected the sentences where Bertje made a wrong prediction. We assume that the distribution of errors for the other models will be similar. We distinguished between cases where

4. <https://huggingface.co/GroNLP/bert-base-dutch-cased>, <https://huggingface.co/pdelobelle/robbert-v2-dutch-base>, <https://huggingface.co/xlm-roberta-base>, <https://huggingface.co/bert-base-multilingual-cased>

|             |     | N   | Error | Ambig | Other |
|-------------|-----|-----|-------|-------|-------|
| <b>LOW</b>  | die | 61  | 25    | 25    | 11    |
|             | dat | 72  | 29    | 26    | 17    |
| <b>HIGH</b> | die | 100 | 76    | 22    | 2     |
|             | dat | 100 | 55    | 38    | 7     |

Table 3: Error analysis for Bertje of low attachment errors and two 100 sentence samples of high attachment errors

the system made a wrong prediction that leads to an incoherent sentence (*Error*), cases where the alternative pronoun and antecedent is not excluded by the context (*Ambiguous*), and cases where something else may lead to the wrong pronoun being predicted (*Other*). The latter includes cases where a neuter noun denotes a human being (where both *dat* and *die* are acceptable) and cases where there is an additional distractor.

Ambiguous cases are examples such as (10), where both the first round or the tournament can be held according to modified rules (*dat* appears in the test sentence, but the model predicts *die*).

- (10) de eerste ronde van het bekertoernooi, dat/die in gewijzigde opzet zal worden  
the first round of the cup-tournament that in modified modus will be  
afgewerkt  
held  
*the first round of the tournament, that will be held in a modified form*

Other cases are among other examples with a human antecedent, as in (11). Neuter nouns with a human antecedent are an exception to grammatical pronoun agreement, in that they can be referred to by both *die* and *dat*. In this case the test sentence has *dat* where the model predicts *die*.

- (11) de dood van haar buurjongetje Esajas dat/die van het dak gevallen is  
the death of her boy-nextdoor Esajas that of the roof fallen is  
*the death of the boy nextdoor Esajas, who is fallen of the roof*

Intervening distractors can also cause mismatches, such as in (12), where the neuter noun *aeroshell* is an apposition to the first noun *hitteschild* (non-neuter), making the model prefer *die* over *dat*. In this case, both options lead to a grammatical and semantically equivalent sentence.

- (12) het hitteschild van 2 meter diameter, de aeroshell, dat/die de instrumenten moet  
the heat-shield of 2 meter diameter, the aeroshell, that the instruments must  
beschermen  
protect  
*a heat-sheald of 2 meters wide, the aeroshell, that must protect the instruments*

Table 3 shows that for the low attachment cases, the number of ambiguous cases is almost the same as the number of ‘real’ errors (i.e. errors leading to an unacceptable sentence). For the high-attachment cases, the number of real errors is higher, probably because performance on this configuration is also worse than on low-attachment cases. The number of errors due to some other reason in the low attachment cases is slightly higher than in the high attachment errors, probably a consequence of the fact that the low-attachment cases were not manually filtered.

As errors on the ambiguous cases, and some fraction of the other cases, do not lead to semantically or syntactically incoherent sentences, one might argue that the reported accuracies are actually a bit pessimistic, as some of the cases that are counted as an error are actually linguistically acceptable. Another indication for the fact that true ambiguity and presence of neuter nouns denoting a human influences results, is the fact that humans, when asked to do the same task as the model, also do not perform at 100% accuracy. In a small experiment, we asked three subjects to predict the masked pronoun for a balanced sample of 200 sentences. All annotators noticed that it was a hard task that required careful reading of the, often long and complex, sentences and feared that they might not have done well. Performances varied between 75% and 95%. While this result should be seen as very preliminary, it does suggest that it is a hard task for humans as well.

## 5.2 Regression Testing

One might wonder to what extent left or right context alone is a good predictor for the task. For instance, assuming that low attachment is the default, the model might use the observation that high attachment is much more likely for some  $N_1$  van  $N_2$  combinations. If the model learns what the most likely pronoun is for such combinations, it might do well on the task without taking right context into account. We suspect that this is true for instance for somewhat idiomatic expressions such as *een politiek symbool van de eerste orde* (a political sign of great significance), *de meest vraatzuchtige zeug van het westelijke halfmond* (the most hungry pig of the western hemisphere), and *een terrein van grote zorg* (an area of great concern) and cases where the second noun denotes an amount or temporal or monetary unit such as *de periode van mijn leven* (the period of my life), *een vrouw van een jaar of zeventig* (a woman approximately seventy year old), *het probleem van deze week* (the problem of this week), *een kind van deze eeuw* (child of this century). But although such cases do occur in the data, they do not seem to be especially frequent. It might also be that the relative clause contains indicators that either *die* or *dat* is far more likely. If that is the case, a model could make accurate predictions by only taking right context into account. In the majority of examples, the relative pronoun has the function of subject in the relative clauses (13-a). Object relatives (13-b) are far less frequent. In subject relatives, the pronoun (and its antecedent) have to be possible as subjects of the verb involved.

- (13) a. de basis van ieder team dat iets wil bereiken  
           the base of every team that something wants achieve  
           *the foundation of every team that wants to achieve something*  
       b. de taal van het land dat ik bezoek  
           the language of the country that I visit  
           *the language of the country that I visit*

Of the 2273 verb forms that occur as head of a relative clause in the newspaper corpus we used for obtaining the test sentences, only 66 occur with *dat* more often than *die*. They include forms such as *aangeboden* (offered), *gepresenteerd* (presented), *voorziet* (anticipates), *opgesteld* (written), *verschijnt* (appears), *gesloten* (closed). They are mostly passive participles for which the grammatical subject is usually inanimate and thus the probability of a neuter noun as antecedent of the relative pronoun goes up.

While these observations suggest that there might be some cases where right or left context alone is a good predictor of the correct pronoun, it does not directly answer the question to what extent both right and left context are required to perform well on the task. As an alternative, we tested to what extent performance degrades if left and right context do not form a semantically coherent sentence. In particular, we created synthetic data in which the right context is (semantically) unrelated with the left context. Two sets of test data were created. In the ‘matching’ cases, a left context was combined with a random right context starting with the same relative pronoun as in the original data. I.e. in cases of low attachment with pronoun *dat*, we created a new example by taking

|      |            | Actual | Synthetic data |              |
|------|------------|--------|----------------|--------------|
|      |            |        | matching       | non-matching |
| LOW  | <i>dat</i> | 0.931  | 0.802          | 0.792        |
|      | <i>die</i> | 0.937  | 0.851          | 0.831        |
|      | overall    | 0.934  | 0.827          | 0.811        |
| HIGH | <i>dat</i> | 0.789  | 0.595          | 0.551        |
|      | <i>die</i> | 0.740  | 0.622          | 0.560        |
|      | overall    | 0.761  | 0.608          | 0.555        |

Table 4: Results for Bertje on actual and synthetic data.

the left context (containing the two nouns) and combining it with a random right context (containing the relative clause), but still starting with *dat*. The result is often semantically incoherent, as in (14). In the ‘non-matching’ cases, we combined a *dat* selecting left context with a right context starting with *die*, as in (15). The predictions for Bertje on these data-sets are shown in table 4.

- (14) Aan de voorgevel van het gebouw [MASK] zich van meet af aan sterk heeft  
 At the front of the building [MASK] itself from beginning of at strong has  
 gemaakt voor de Tiger  
 made for the Tiger  
*At the front of the building [which] argued for the Tiger from the beginning*
- (15) Het indexcijfer van de industriële produktie [MASK] vanmorgen tientallen Palestijnen  
 The index of the industrial production [MASK] morning tens Palestinians  
 in de moskee heeft vermoord  
 in the mosque has killed  
*The index of the industrial production [which] killed tens of Palestinians in the mosque this morning*

For synthetic data, the model is considerably less capable of predicting the correct pronoun (assuming that the left context provides the ‘correct’ answer) than for the original corpus material. This means that both left and right context are important for making the correct prediction, and that data in which left and right contexts do not form a semantically coherent input, are harder for the model than original data. Although ‘non-matching’ synthetic examples are a bit harder than ‘matching’ examples, the difference between the two is small compared to the difference with actual data. This suggests that the relative clauses alone do not provide a strong signal for predicting either *dat* or *die*, and that the model is confused as soon as a semantically incoherent sentence is encountered, independent of the original pronoun in the relative clauses.

## 6. Conclusion

Transformer-based neural language models are able to perform remarkably well on masked language prediction tasks. To see to what extent such models are sensitive to linguistic structure, we reformulated the *die/dat* prediction task for Dutch. Inspired by previous work in psycholinguistics, we collected a corpus of test sentences where a relative clause could in theory be attached to one of two preceding nouns, and the model has to be able to select the correct antecedent noun in order to make the correct prediction. There are significant differences in performance between the four BERT models that we probed. The Bertje model did best in the probe, but with a monolingual model doing best and worst on the task, it cannot be concluded that monolingual models are always to be preferred over multilingual models (or vice versa). A more important factor might be the corpus



used for training the language models. The sentences used in the probe are all relatively complex, due to the fact that we select sentences with a complex NP containing a PP and a relative clause. Such sentences might be more frequent in corpora that include newspaper text than in corpora consisting of text from Wikipedia or the web only.

In the newspaper corpus we used, we estimate that around 80% of the relevant cases are instances of low attachment. It might well be that in other corpora the distribution is even more skewed, making it increasingly hard for the model to learn to make the right predictions for high attachment cases. The non-neuter relative pronoun *die* is somewhat more frequent than *dat* (approx. 60% and 40%, respectively) in our data. It seems that this cannot explain the tendency for some models to prefer *die*, although this preference might be stronger in more recent corpora, especially if they also contain informal text (Audring 2013, Bouma 2017).

The fact that we can test for high or low attachment by simply masking the pronoun is due to the fact that Dutch relative pronouns agree with the antecedent. In light of the discussion from the psycholinguistics literature on (speakers of) languages having a preference for either high or low attachment, it would be interesting to repeat this probe for other languages. For languages that do not have relative pronoun agreement, one might use singular and plural nouns, and relative clauses where these have the subject role, so the verb can be masked to test whether the model can predict the correctly inflected form.

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