

# Do Language Models discriminate between relatives and pseudorelatives?

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## Abstract

Large Language Models (LLMs) are often evaluated against massive benchmarks based on general-purpose tasks, which, despite being useful for concrete applications, tell us very little about the capacity of LLMs to learn *specific* and *challenging* aspects of the grammar. Here, we evaluate whether LLMs learn to identify a particular structure attested in Romance (and French in particular), called the pseudorelative. This structure, which is often surface-similar to a relative clause, is linked to robust syntactic and semantic restrictions. We present a series of experiments to test if LLMs pretrained on massive yet general corpora, manage to learn those various restrictions. Our results suggest that LLMs learn some but not all of these properties, but crucially fail at recognizing the most specific of them: cliticization.

## 1 Background on pseudorelatives

Pseudorelatives (**PRs**) (Schwarze (1974); Radford (1975); Kayne (1975); Guasti (1988) a.o.) resemble relative clauses (**RCs**) but exhibit a specific cluster of properties: (1) their head noun can be cliticized; (2) they only feature subject gaps; (3) they only appear below perception verbs; (4) they require the matrix and embedded tenses to match; (5) they imply the existence/truth of the embedded event even under matrix negation (Moulton and Grillo, 2015). Those various properties are illustrated below.

- (1) Head noun cliticization  
Jean **la** voit qui sourit.  
Jean **3.SG.CL** sees that smiles.  
'Jean sees her smiling.'
- (2) Object gap (+cliticization)  
\* Jean la voit que Marc salue \_\_\_\_.  
Jean **3.SG.CL** sees that Marc greets.  
Intended: 'Jean sees Marc greeting her.'
- (3) Non-perception verb (+cliticization)  
\* Jean la **pense** qui sourit.  
Jean **3.SG.CL** **thinks** that smiles.

Intended: 'Jean thinks she is smiling.'

- (4) Tense mismatch (+cliticization)  
\* Jean la voit qui **souriait**.  
Jean **3.SG.CL** sees.PRS that smiled.**PST**.  
Intended: 'Jean sees her while she smiled.'
- (5) Event presupposition  
Jean ne la voit pas qui sourit.  
Jean **NEG 3.SG.CL** sees **NEG** that smiles.  
'Jean doesn't see her smiling (she **does**).'

Cliticization is perhaps the most robust diagnostic used to disambiguate PRs from RCs; without a cliticized head, and assuming conditions (2)-(5) are met, a PR will usually remain ambiguous with a (string-identical) RC. This is shown in (6).

- (6) No cliticization: ambiguous parse  
Jean voit Marie qui sourit.  
Jean sees Marie that smiles.  
'Jean sees Marie, who smiles.' (**relative**).  
'Jean sees Marie smiling.' (**pseudorelative**)

Because of its rareness in corpora, its ambiguity with relative clauses, and the inability of LLMs to access external disambiguating cues (comma, intonation), the pseudorelative remains relatively opaque to current NLP benchmarks (Wang et al., 2018, 2019; Bowman et al., 2015; Williams et al., 2018; Rajpurkar et al., 2016, 2018; Zellers et al., 2018) which are used to assess LLMs' performances. Do LLMs pretrained on massive (but also very general, non-targeted, and therefore impoverished) corpora learn something about pseudorelatives anyway?

## 2 Preliminary corpus study

We run a corpus study to verify the claim that LLMs are mostly exposed to structurally ambiguous sentences such as (6). We start with simple exact Google queries following the patterns in (7), where V denotes one of the verbs listed in Table 1, and CL is a clitic pronoun (*le* or *la* if V starts with a consonant, *l'* if V starts with a vowel).

- (7) a. “Il V \* qui”  
He V wildcard that  
b. “Il {le, la, l’} V qui”  
He CL V that

The number of hits for these queries are gathered in Table 1. If some perception verbs are clearly more frequent than others (compare *voir*, ‘see’ vs. *épier*, ‘spy on’), the tendency regarding cliticized constructions is clear: they are between 10,000 and 100,000 times less frequent than the string-ambiguous structures similar to (6).

exact query → V↓	(7a)	(7b)	$\frac{\#(7b)}{\#(7a)+\#(7b)}$
voit (see)	262,000,000	22,440	8.5e-5
aperçoit (spot)	11,700,000	1,230	1.1e-4
regarde (look at)	192,000,000	6,370	3.3e-5
observe (watch)	51,100,000	759	1.5e-5
épie (spy on)	237,000	1	4.2e-6
surprend (catch)	21,900,000	247	1.1e-5
entend (hear)	70,200,000	7,820	1.1e-4
écoute (listen to)	121,000,000	18,200	1.5e-4

Table 1: Number of results for non-cliticized (ambiguous) and cliticized (unambiguous) PR structures returned by Google Search for different perception verbs.

To confirm this intuition, we matched a series of regular expressions<sup>1</sup> against a subset of the French OSCAR corpus (Ortiz Suárez et al., 2019; Caswell et al., 2021; Abadji et al., 2021), used to train models such as CamemBERT (Martin et al., 2020). The results shown in Table 2 confirm that a typical French LLM is mostly trained on ambiguous PR structures. Learning properties (1)-(5) would therefore require the models to exploit weak signals in the data to draw syntactic and semantic generalizations. The experiments that follow test whether LLMs achieve this goal – or not.

### 3 Experiment 1

Adapting a recent psycholinguistic experiment (Pozniak et al., 2019), we test if 8 LLMs trained on general French corpora (see Tab. 3 rows 1-8), learned the association between properties (3)-(4), pertaining to the type of the embedding verb and tense anaphoricity. The expected effects are: a

<sup>1</sup>The regular expressions were refined from the templates in (7) to include all possible subject pronouns and allowed up to 3 unspecified words in the wildcard (\*). This restricts the search space for ambiguous relative constructions of the form of (6) but ensures that other constructions (such as an unambiguous relative clause located “far away” from the perception verb) are not matched by accident. It also allows to speed-up the search. Consequently, the matches and the proportions gathered respectively in the second and last columns of Table 2 should be respectively read as lower- and upper-bounds.

regular expression → V↓	(7a)	(7b)	$\frac{\#(7b)}{\#(7a)+\#(7b)}$
voir	15157	168	1.1e-2
apercevoir	725	1	1.4e-3
regarder	2442	28	1.1e-2
observer	813	0	0.0
épier	13	0	0.0
surprendre	99	0	0.0
entendre	1975	27	1.3e-2
écouter	632	1	1.6e-3

Table 2: Number of matches for non-cliticized (ambiguous) and cliticized (unambiguous) regular expressions on 10,160,000 documents from the OSCAR corpus (containing a total of 52,037,098 documents).

preference for embedding of (pseudo)relatives under perception verbs (as opposed to e.g. stative verbs); a preference for matching tenses between the matrix clause and the embedded clause; an interaction between those two factors, favoring tense matching specifically under perception verbs. We take the interaction to be the most critical effect. These predictions were assessed reusing the  $2 \times 2$  design (verb\_type  $\times$  tense\_match) introduced by the original study. Example stimuli illustrating this design are given in (8) and their parameters are summarized in Table 4.

ID	Model	Lang.	Reference
1	flaubert_base_uncased	fr	Le et al. (2020)
2	camembert-base	fr	Martin et al. (2020)
3	gpt2-base-french	fr	(Cla)
4	gpt2-wechsel-french	fr	Minixhofer et al. (2022)
5	bert-base-multi-lingual-cased	multi	Devlin et al. (2018)
6	xlm-roberta-base	multi	Conneau et al. (2019)
7	xlm-roberta-large	multi	Conneau et al. (2019)
8	xlm-mlm-17-1280	multi	Lample and Conneau (2019)
9	bert-large-cased	en	Devlin et al. (2018)
10	gpt2-large	en	Radford et al. (2019)
11	xlnet-large-cased	en	Yang et al. (2019)

Table 3: Models used in Exp. 1 and 2

- (8) Example stimuli reused from (Pozniak et al., 2019).
- Marie a écouté le ministre qui critiquait le président.
  - ?Marie écoute le ministre qui critiquait le président.
  - Marie a été mariée au ministre qui critiquait le président.
  - Marie est mariée au ministre qui critiquait le président.

Sentence	verb_type	tense_match
(a.)	perception	y
(b.)	perception	n
(c.)	stative	y
(d.)	stative	n

Table 4: Summary of the  $2 \times 2$  design of (Pozniak et al., 2019) reused in Exp. 1

Building on (Hale, 2001; Levy, 2008), our proxy for grammaticality was taken to be the log-probability assigned to a given sentence by the

LLM (see equations below). It was computed using the minicons library (Misra, 2022).

$$\begin{aligned} \text{GRAMMATICALITY}(w_t) &\simeq -\text{SURPRISAL}(w_t) \\ &= \log P(w_t | w_1 \dots w_{t-1})^2 \end{aligned}$$

$$\text{GRAMMATICALITY}(w_1 \dots w_t) \simeq -\sum_{i=1}^t \text{SURPRISAL}(w_i)$$

Linear mixed-effect modeling (performed with statsmodels, (Seabold and Perktold, 2010)) reveals that 9/8 LMs favor matching tenses, and 4/8 more so under perception verbs (verb\*tense interaction) – supporting the expected interaction between (3) and (4) in French. Among the best performing models are a French-only (autoregressive) GPT-2 model (model 3) and a (bidirectional) multilingual RoBERTa model (model 7).

ID	best AIC?	verb_type	tense	interaction
1	n	.X	n.s.	.✓
2	n	.✓	**✓	n.s.
3	y	n.s.	**✓	*✓
4	y	n.s.	**✓	.✓
5	n	n.s.	**✓	n.s.
6	y	n.s.	**✓	.✓
7	y	n.s.	**✓	*✓
8	n	**✓	n.s.	n.s.

Table 5: Significance results of LME modeling for grammaticality  $\sim$  verb\_type+tense+verb\_type\*tense + (1|frame), where frame refers to the lexical skeleton shared by all stimuli in e.g. (8).<sup>3</sup>

English models (cf Tab. 3, rows 9-11) tested on English equivalents of the stimuli exemplified in (8), did not exhibit similar effects – consistent with English not allowing pseudorelatives. Plots of the distributions of grammaticality scores obtained with xlm-roberta-large (model 7) in both languages are given in Figure 1.

## 4 Experiment 2

We test the same LLMs on 4800 semi-automatically generated sentences following the template in (9) and differing in (1) head noun cliticization; (2) the gap’s position (subject/object) and (3) the matrix verb’s type (perception vs. attitude/action).

<sup>2</sup>In the case of BERT-like bidirectional models, this formula is adapted to masked language modeling: the probability of a word is computed given its left *and* right context.

<sup>3</sup>The ‘best AIC?’ column specifies if the formula yielded the lowest Akaike Information Criterion, as opposed to other simpler formulas without interactions or main effects. Other notations: ‘.’ =  $p \in [.05; .1]$ ; ‘\*’ =  $p \in [.01; .05]$ ; ‘\*\*\*’ =  $p \in [0; .01]$ ; ✓=coefficient validates the hypothesis; X=coefficient disproves the hypothesis.

<sup>4</sup>The scores are overall negative because they correspond to negative log probabilities (cf. equations above).

ID	best AIC?	verb type	tense	interaction
5	y	**✓	*X	*X
6	n	.✓	.X	.X
7	n	n.s.	*X	n.s.
8	n	**✓	n.s.	n.s.
9	n	n.s.	n.s.	.✓
10	n	**✓	*✓	n.s.
11	n	n.s.	n.s.	n.s.

Table 6: Significance results of LME modeling with English data. Same notations and parameters as Table 5. Strikingly, all but 1 model did not yield the best AIC for the formula involving an interaction term.

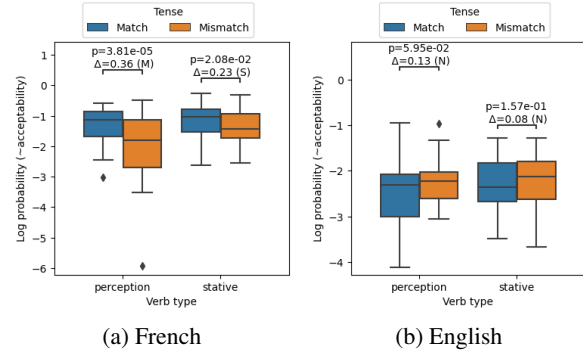
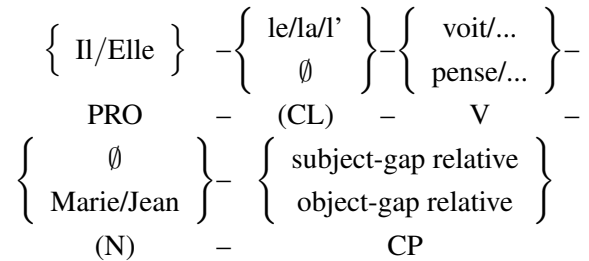


Figure 1: Distributions of the grammaticality scores<sup>4</sup> for Exp. 1 with xlm-roberta-large.  $\Delta$  refers to Cliff’s Delta (non-parametric measure of effect size). N, S, M resp. mean ‘negligible’, ‘small’, ‘medium’.

### (9) Template for the stimuli of Exp. 2



### (10) Example stimuli for Exp. 2

- Il voit Marie qui embrasse Jean.
- Il voit Jean que Marie embrasse.
- Il la voit qui embrasse Jean.
- \* Il le voit que Marie embrasse.
- \* Il pense Marie qui embrasse Jean.
- \* Il pense Jean que Marie embrasse.
- \* Il la pense qui embrasse Jean.
- \* Il le pense que Marie embrasse.

Given this design, we expect an overall preference for matrix perception verbs, subject gaps and non-cliticized constructions, but also a positive interaction between perception verbs and clitics, perception verbs and subject gaps, clitics and subject gaps, and all three variables together. As Tab.

Sentence	clitic?	gap	verb_type
(10a)	n	S	perception
(10b)	n	O	perception
(10c)	y	S	perception
(10d)	y	O	perception
(10e)	n	S	attitude
(10f)	n	O	attitude
(10g)	y	S	attitude
(10h)	y	O	attitude

Table 7: Summary of the  $2 \times 2 \times 2$  design of Exp. 2

8 shows, linear mixed-effect modeling reveals a robust preference for subject-gaps (8% models, cf. col. 3) and more so under perception verbs (5% models, cf. col. 6), supporting (2)+(3). The desired clitic\*gap\*verb\_type interaction however, was only captured by 1/8 models (cf. col. 8). Strikingly also, the interaction between cliticization and subject gaps is predicted by most models to have a negative effect on grammaticality, *contra* (1)+(2).

ID	v	g	c	v*c	v*g	c*g	v*c*g
1	. ✓	** ✓	** ✓	** ✗	. ✗	** ✓	n.s.
2	. ✓	** ✓	** ✓	** ✗	** ✓	** ✗	n.s.
3	n.s.	** ✓	** ✗	** ✓	** ✓	** ✗	. ✓
4	n.s.	** ✓	** ✗	** ✗	** ✗	** ✗	** ✓
5	n.s.	** ✓	** ✗	** ✓	n.s.	** ✗	n.s.
6	n.s.	** ✓	** ✗	** ✓	** ✓	** ✗	. ✗
7	n.s.	** ✓	** ✗	** ✓	** ✓	** ✗	** ✗
8	n.s.	** ✓	** ✗	** ✗	** ✓	**	n.s.

Table 8: Significance results of LME modeling for grammaticality  $\sim$  verb\_type + gap + clitic + verb\_type \* clitic \* gap. Same notations as before.

The best performing model for this experiment appears to be a French-only GPT-2 model (model 3) – which was also among the best models for Exp. 1. Grammaticality scores corresponding to this model are plotted in Fig. 4.

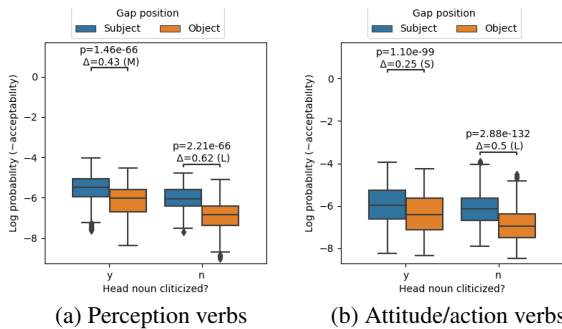


Figure 2: Distributions of the grammaticality scores for Exp. 2 with gpt2-base-french. Same notations as before.

## 5 Experiment 3

We finally test property (5) on 4 BERT-like LMs fine-tuned to perform natural language inference

(see Table 9).

ID	Model	Lang.	Reference
12	camembert-base-xnli	fr	(Doy)
13	xlm-roberta-large-xnli-finetuned-mnli	multi	(Ozs)
14	mDeBERTa-v3-base-mnli-xnli	multi	(Laurer et al., 2022)
15	mDeBERTa-v3-base-xnli-multilingual-nli-2mil7	multi	(Laurer et al., 2022)

Table 9: Models used in Exp. 3

Given a negated matrix perception verb embedding a clause  $\mathcal{C}$  either as an infinitive or as a (pseudo)relative, with or without cliticization of its subject ( $2 \times 2$  design, see (11)), we measure how likely LLMs are to infer the truth of  $\mathcal{C}$  (“target inference”, **TI**).

(11) Template for the stimuli of Exp. 3

$\left\{ \begin{array}{l} \text{Il/Elle} \\ \text{Marie/Jean} \end{array} \right\}$	ne	$\left\{ \begin{array}{l} \text{le/la/l'} \\ \emptyset \end{array} \right\}$	$\left\{ \begin{array}{l} \text{voit/...} \\ \text{subject-gap relative} \\ \text{subject-gap infinitive} \end{array} \right\}$	pas –
PRO	NEG	(CL)	V	NEG–
$\left\{ \begin{array}{l} \emptyset \\ \text{Marie/Jean} \end{array} \right\}$	–	$\left\{ \begin{array}{l} \text{subject-gap relative} \\ \text{subject-gap infinitive} \end{array} \right\}$		
(N)	–		CP	

(12) Example stimuli for Exp. 2

- a. Il ne voit pas Marie qui danse.  
He NEG sees NEG Marie that dances.  
 $\Rightarrow$  Marie is dancing. **TI ✓**
- b. Il ne la voit pas qui danse.  
He NEG CL sees NEG that dances.  
 $\Rightarrow$  She is dancing. **TI ✓**
- c. Il ne voit pas Marie danser.  
He NEG sees NEG Marie dancing.  
 $\not\Rightarrow$  Marie is dancing. **TI ✗**
- d. Il ne la voit pas danser.  
He NEG CL sees NEG dancing.  
 $\not\Rightarrow$  She is dancing. **TI ✗**

Sentence	clitic?	emb_clause
(12a)	n	relative
(12b)	y	relative
(12c)	n	infinitive
(12d)	y	infinitive

Table 10: Summary of the  $2 \times 2$  design of Exp. 3

We expect the TI to be overall stronger when the embedded clause is a relative as opposed to an infinitive, whether or not the head noun is cliticized. The effect of cliticization in the case of a structure embedding a relative is a little bit

less clear: in the absence of cliticization the clause is ambiguous between a PR and a RC, and it is reasonable to think that both parses encourage a TI. Assuming that the RC parse imposes a somewhat stronger TI than a PR parse, then we might expect sentences like (12b), which are unambiguously PRs due to cliticization, to lead to a slightly weaker TI than sentences like (12a) which allow a RC parse. In other words, we expect non-cliticized sentences embedding an RC to yield the strongest TI.

Linear mixed-effect modeling reveals that embedded relative constructions systematically lead to a stronger target inference as opposed to infinitives (cf. Table 11 col. 3), which is *consistent* with property (5), might be driven by the RC-parse only. Non-cliticized subjects also lead to a stronger target inference across the board (col. 4). This is made particularly clear in Figure 3. This pattern cannot be fully explained by the theory but makes sense if we consider that non-cliticized constructions are way more frequent in the data (so that LLMs may be more confident about the inferences related to such constructions, as opposed to cliticized ones). Finally,  $\frac{2}{4}$  models associate non-cliticized RC-embedding constructions to a stronger TI, which corresponds to the stipulation discussed in the previous paragraph. This all suggests that LLMs associate the target inference with the occurrence of RCs, but not really PRs: otherwise, *cliticized* relative constructions (unambiguously PRs) would have lead to stronger target inferences. Figure 3 in particular, shows that cliticized constructions featuring an embedded relative (unambiguously PRs), do not lead at all to a strong TI, suggesting the RC-parse (and not the PR-parse), is driving this inference.

ID	best AIC?	embedded clause (RC)	clitic	RC/clitic interaction
12	y	** (+)	** (-)	** (-)
13	y	** (+)	** (-)	** (+)
14	y	** (+)	** (-)	** (+)
15	y	** (+)	** (-)	** (-)

Table 11: Significance results of LME modeling for  $\text{target\_inference\_strength} \sim \text{emb\_clause} + \text{clitic} + \text{emb\_clause} * \text{clitic}$ .

## 6 Discussion and outlook

In this work, we investigated a structure (the pseudorelative) with two interesting distributional properties: (1) it can be ambiguous with a relative

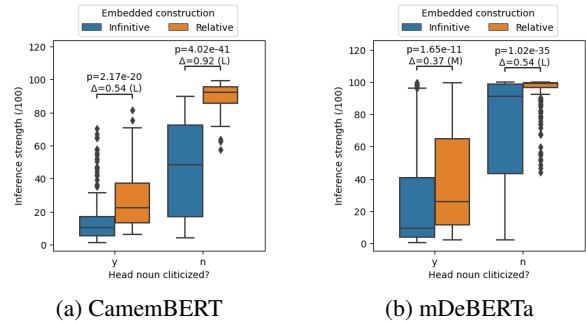


Figure 3: Distributions of the TI strength scores (/100) for Exp. 3 and models 12 and 15.

clause when the head noun is *not* cliticized; (2) the disambiguating (cliticized) structure is less frequent in corpora by several orders of magnitude. We think that the conjunction of these two properties makes learning the specific syntactic and semantic properties of PRs particularly challenging, even for models trained on large amount of data.

The experiments we run show that LLMs capture certain properties of PRs, pertaining to acceptable filler-gap dependencies, matrix verbs, and tense combinations. Interestingly,  $\frac{3}{4}$  multilingual models exposed to both French (a PR-language) and English (devoid of PRs) in Exp. 1 managed to contrast the two languages. Yet, the property that is perhaps the most specific to pseudorelatives, cliticization, does not seem to influence sentence probability scores in Exp. 2, and inference patterns in Exp. 3. This raises the question whether LLMs really get the specificity of the pseudorelative as a *syntactic construction* (Exp. 2) with a specific *semantics* (Exp. 3); or whether they simply recycle general processing heuristics applicable to other structures (e.g. standard RCs). Such heuristics may involve a preference for shorter dependencies (subject-gaps) across the board; or learning a statistical correlation between the use of perception verbs and the *agentive* structure of the perceived event.

Future work may involve investigating other languages allowing the pseudorelative, but also refining the current design by looking at the influence of the different perception verbs. We think this might be particularly relevant given the rather large frequency differences between these verbs in actual corpora (cf. Tables 1 and 2), and the potential imbalance between ambiguous vs. unambiguous PR-structures for each of those verbs.

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