The Elephant in the Coreference Room: Resolving Coreference in Full-Length French Fiction Works

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Abstract

While coreference resolution is attracting more interest than ever from computational literature researchers, representative datasets of fully annotated long documents remain surprisingly scarce. In this paper, we introduce a new annotated corpus of three full-length French novels, totaling over 285,000 tokens. Unlike previous datasets focused on shorter texts, our corpus addresses the challenges posed by long, complex literary works, enabling evaluation of coreference models in the context of long reference chains. We present a modular coreference resolution pipeline that allows for fine-grained error analysis. We show that our approach is competitive and scales effectively to long documents. Finally, we demonstrate its usefulness to infer the gender of fictional characters, showcasing its relevance for both literary analysis and downstream NLP tasks.

1 Introduction

Coreference Resolution (CR)—the task of identifying and grouping textual mentions that refer to the same entity (e.g., a person, an organization, a place)—is a fundamental component of natural language processing (NLP). It underpins downstream applications such as information extraction (Yao et al., 2019), text summarization (Liu et al., 2021), and machine translation (Vu et al., 2024). Over the past decades, significant progress has been made in CR, evolving from rule-based multi-sieve systems to end-to-end neural models, encoder-decoder architectures, and large language models based approaches, all contributing to improvements on benchmark datasets (Porada et al., 2024).

These models have long been trained and evaluated solely on generic datasets such as OntoNotes (Hovy et al., 2006). As CR drew attention in other fields, it became evident that models trained on general datasets underperformed when applied to domain-specific tasks. To address this flaw, dedicated datasets have been developed, covering areas such as biomedical (Lu and Poesio, 2021) and encyclopedic data (Ghaddar and Langlais, 2016).

Driven by the availability of extensive digitized collections, literary texts have emerged as a key subject of digital humanities (Moretti, 2013). A large part of such research focuses on characters, considered a fundamental aspect of fiction works. The study of characters is essential for analyzing narrative structures, plot development or conducting diachronic studies. CR is crucial for applications such as quote attribution (Vishnubhotla et al., 2023), character archetypes inference (Bamman et al., 2014), and social networks extraction (Elson et al., 2010). Additionally, it has been employed to study the representation and behavior of characters according to their gender (van Zundert et al., 2023).

As outlined by Roesiger et al. (2018), literary texts present unique challenges for CR, including character evolution throughout the narrative and the prevalence of dialogues involving multiple participants. They also contain a high proportion of pronouns and nested mentions. Complex narrative structures—such as letters, flashbacks, and sudden narrator interventions—further complicate the task. Additionally, authors often rely on readers' contextual understanding rather than explicit statements, creating ambiguities when linking mentions.

To address these challenges, annotated datasets have been developed, covering multiple languages and genres, from classical novels and fantasy tales to contemporary literature. These resources enable training and evaluating in-domain coreference resolution models, leading to steady performance improvements (Martinelli et al., 2024). Despite visible progress on benchmarks, current state-of-the-art CR models still struggle with full-scale literary texts, limiting usefulness for downstream applications (Vishnubhotla et al., 2023).

A key factor contributing to this limitation lies in the scarcity of fully annotated long documents. Most existing datasets consist of short excerpts or

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relatively brief texts. Since coreference annotation is labor-intensive and costly, there exists a trade-off between annotating a larger number of short documents or a smaller number of long ones.

We argue that the lack of representative datasets for long literary texts is a major obstacle to effectively scaling CR models. This work aims to bridge this gap, and our contributions are as follows:

- an annotated dataset of character coreference for three full-length French novels spanning three centuries, showcasing the feasibility of combining automatic mention detection with manual coreference annotation.
- A modular CR pipeline scalable to long documents, enabling fine-grained error analysis and achieving competitive performance on benchmark dataset.
- A comprehensive study of the impact of document length on CR performance.
- A case study on character gender inference using CR models.[1].

2 Related Work

2.1 Coreference Models

Coreference resolution has undergone several paradigm shifts (Poesio et al., 2023), evolving from rule-based, linguistically informed models tested on limited examples to data-driven statistical approaches enabled by the creation of large annotated datasets such as those from the Message Understanding Conference (MUC) and the Automatic Content Extraction (ACE) shared tasks (Grishman and Sundheim, 1995; Doddington et al., 2004).

The adoption of neural network-based models, beginning with Wiseman et al. (2015), marked significant progress. The introduction of end-to-end models by Lee et al. (2017, 2018), further advanced CR by jointly detecting mention spans and resolving coreference, eliminating the need for external parsers and handcrafted mention detection models. Building on this foundation, higher-order inference (HOI) strategies and entity-level models were developed to refine entity representations during inference and leverage cluster-level information.

However, as highlighted by Xu and Choi (2020), the performance gains from these strategies have been marginal compared to the substantial improvements achieved by the use of more powerful encoders like ELMo, BERT and DeBERTaV3.

Alternative approaches using encoder-decoder architectures and large language models have been proposed, framing CR as sequence-to-sequence (Hicke and Mimno, 2024) or question-answering (Wu et al., 2020; Gan et al., 2024) tasks. While showing promising results, these methods are computationally intensive and do not scale efficiently to long documents or resource-constrained scenarios.

2.2 Existing Datasets

While MUC and ACE laid the foundation for coreference datasets, OntoNotes has since become the primary benchmark for CR. Published in 2006 (Hovy et al.) and regularly updated, OntoNotes has been used in the CoNLL shared tasks (Pradhan et al., 2011, 2012). Its latest version (Weischedel et al., 2013) spans multiple languages (English, Chinese and Arabic), and genres, including conversations, news, web, and religious texts. The English part contains 1.6M tokens across 3,943 documents, averaging 467 tokens per document. OntoNotes does not contains singleton mentions—those that do not corefer with any other mention.

The growing interest for large literature corpora has driven the development of dedicated annotated datasets. The late 2010s saw the emergence of the first literary CR datasets, beginning with DROC (Krug et al., 2018), including samples from 90 German novels annotated with character coreference chains. With over 393,000 tokens (averaging 4,368 tokens per document), DROC remains the largest literary CR dataset to date. The RiddleCoref dataset (van Cranenburgh, 2019) followed, covering excerpts from 21 contemporary Dutch novels, though it is not publicly available due to copyright restrictions. Bamman et al. (2020) released LitBank, consisting of the first 2,000 tokens from 100 English novels. This dataset covers six entity categories (persons, faculties, locations, geopolitical, organizations and vehicles). Other datasets include FantasyCoref (Han et al., 2021), KoConovel covering 50 full-length Korean short stories (Kim et al., 2024), and LitBank-fr (Mélanie et al., 2024). This last dataset is noteworthy in that it covers longer excerpts of text—averaging 9,834 tokens and up to 30,987 for the longest document.

Despite these resources, extrinsic evaluations re-

[1]All code and data are publicly available at github.com/lattice-8094/propp. The trained coreference resolution pipeline is readily usable through the open-source `propp_fr` Python library.

[2]standardebooks.org

	Lang.	Domain	Doc.	Tokens	Tokens / Doc.	
					Avg.	Max.
Annotated Datasets						
OntoNotes^{en} (Weischedel et al., 2013)	English	Non-literary	3,493	1,600,000	467	4,009
DROC (Krug et al., 2018)	German	Fiction	90	393,164	4,368	15,718
RiddleCoref (van Cranenburgh, 2019)	Dutch	Fiction	21	107,143	5,102	-
LitBank (Bamman et al., 2020)	English	Fiction	100	210,532	2,105	3,419
FantasyCoref (Han et al., 2021)	English	Fantasy	214	367,891	1,719	13,471
KoCoNovel (Kim et al., 2024)	Korean	Fiction	50	178,000	3,578	19,875
LitBank-fr (Mélanie et al., 2024)	French	Fiction	28	275,360	9,834	30,987
Target Datasets						
Standard Ebooks[2]	English	Fiction	770	82,855,210	107,604	1,105,964
Chapitres (Leblond, 2022)	French	Fiction	2,960	240,971,614	81,409	878,645
Contribution						
Ours	French	Fiction	3	285,176	95,058	115,415

Table 1: Comparison of coreference annotation datasets: OntoNotes (English section), fiction datasets, and target datasets across languages.

veal that CR models perform poorly on full-length documents (van Zundert et al., 2023). Studies consistently show that performance degrades with increasing document length (Joshi et al., 2019; Toshniwal et al., 2020; Shridhar et al., 2023). This represents a major challenge given that practical applications involve digitized collections such as Project Gutenberg or Wikisource, where documents frequently exceed 90,000 tokens and can reach up to a million as illustrated in Table 1.

While some initiatives annotate entire books, they often diverge from standard guidelines. He et al. (2013) annotated *Pride and Prejudice* but focused solely on proper mentions. Similarly, van Zundert et al. (2023) labeled character aliases across 170 novels, omitting pronouns and noun phrases. Other datasets, such as QuoteLi3 (Muzny et al., 2017) and PNDC (Vishnubhotla et al., 2022), include coreference annotations for speakers and direct speech but lack broader character coverage.

Until recently, the only coreference resolution results reported on a document of substantial length (37k tokens) came from Guo et al. (2023), though their work omits singletons, plural mentions, and nested entities. Since then, Martinelli et al. (2025) released an extended dataset, BOOKCOREF$_{gold}$, comprising two fully annotated English-language novels averaging 97,140 tokens per document, along with benchmark results, further illustrating the growing interest in long-document CR.

These observations underscore the need for an annotated corpus of full-length literary documents. Such a resource will enable more robust evaluation and improvement of CR models, addressing the gap between current datasets and intended applications.

3 New Dataset

We selected three average-length French novels spanning three centuries, resulting in a total of 285,176 tokens. We chose to annotate coreference for character mentions only for several reasons. First, most downstream tasks in literary NLP focus on characters. Second, previous work shows that characters account for the majority of annotated mentions—83.1% in LitBank. Restricting annotations to character mentions allows us to leverage the 31,570 mentions already annotated in LitBank-fr to train an accurate mention detection model.

For consistency and interoperability, we adhere to the annotation guidelines from Mélanie et al. (2024). We annotate all mentions referring to a character, including pronouns, nominal phrases, proper nouns, singletons and nested entities. Coreference links capture strict identity relations.

On [their]$_1$ way to visit [John]$_2$, [[my]$_3$ parents]$_1$ met [[Mrs. Smith]$_4$ and [[her]$_4$ husband]$_5$]$_6$.

This sentence illustrates some annotation principles:

- Mention types: pronoun (*my*), nominal phrase (*her husband*), and proper noun (*John*);
- Nested entities, including third-level nesting (e.g., *her* within *Mrs. Smith and her husband*);
- Plural mentions (*their*, *my parents*, *Mrs. Smith and her husband*) are treated as distinct coreference chains separate from their individual components;
- Singletons, such as *John*, are annotated even if they are not referenced again.

3.1 Mentions Detection Model

While Mélanie et al. (2024) report strong results for mention detection, we opted to retrain our own model. Our approach builds on a stacked BiLSTM-CRF architecture inspired by Ju et al. (2018), leveraging contextual token embeddings from CamemBERT$_{\text{LARGE}}$ (Martin et al., 2020). When evaluating for exact match with gold annotations, We achieved an improvement of 4.99 in F1-score on the test set from LitBank-fr (Table 2). To assess generalization performance and due to the small number of documents in the dataset, we also conducted a leave-one-out cross-validation (LOOCV). Details of the model architecture and hyperparameters are available in the Appendix A.

Model	P	R	F1	Support
Mélanie et al. (test set)	85.0	92.1	88.4	4,061
Ours (test set)	**91.29**	**95.59**	**93.39**	4,061
Ours (LOOCV)	90.72	93.52	92.05	31,570

Table 2: Mention detection performances.

Coreference annotation is usually carried out in two stages: annotating the mention spans, then linking mentions referring to the same entity together. Given our model's 92.05 F1-score, we consider its performance sufficient to automate the first operation, significantly reducing annotation time.

3.2 Coreference Annotation

Coreference annotation is performed manually, building on the automatically detected mentions. A single annotator reviews the text, assigns entity identifiers to each mention, corrects errors from the mention detection step, deleting spurious mentions, adding missed ones, and adjusting incorrect boundaries. This process yield gold-standard annotations for both mentions and coreference chains.

To assess annotation consistency, we double-annotated a sample from each of the three novels (5,000 tokens per text, 5% of the corpus). Inter-annotator agreement (IAA) was measured for mention spans (F1-score) and coreference chains (MUC, B^3, and $CEAF_e$). Results show high consistency: mention span F1-score of 97.47 (vs. 86.0 in Bamman et al. (2019)), benefiting from our focus on a single, well-defined entity type. Coreference agreement is also high: MUC 96.40, B^3 91.02, and $CEAF_e$ 71.65 (86.36 CoNLL F1). The lower $CEAF_e$ reflects differences in annotator decisions regarding long coreference chains and ambiguous cases such as plural entities leaving room for multiple valid interpretations. These results overall demonstrate the reliability and robustness of our annotations.

To perform annotation we use SACR, an open-source, browser-based interface (Oberle, 2018). This tool meets our requirements, allowing efficient processing of long texts, tracking a large number of entities and handling nested mentions.

Mention detection errors mainly involve difficult cases, such as nested and ambiguous mentions (animals with agentivity, appositions, reflexive pronouns) or other edge cases. It shows the feasibility of leveraging automatic mention detection to accelerate coreference annotation. The manual annotation of a 100k-token text takes around 40 hours.

3.3 Dataset Statistics

Table 3 summarizes statistics from our dataset. The entity spread refers to the distance between the first and the last mention of an entity (Toshniwal et al., 2020). This highlights a key specificity of literary texts, characters can be referred to thousands times over several hundred pages, comprising thousands of tokens.

Average Mentions / Doc.	13,178
Singletons Ratio	1.15%
Coreference Chains / Doc.	159
Average Mentions / Chain	82
Maximum Mentions / Chain	4,932
Average Entity Spread (tokens)	17,529
Maximum Entity Spread (tokens)	115,369
Second-Level Nested Mentions	5.74%
Third-Level Nested Mentions	0.30%
Plural Mentions Ratio	8.13%
Proper Mentions	12.79%
Nominal Mentions	12.26%
Pronominal Mentions	74.95%

Table 3: Dataset statistics summary.

Another important metric for characterizing coreference is the distance to the nearest antecedent (Han et al., 2021). For each mention, we locate the previous mention belonging to the same coreference chain and measure the difference in terms of mention positions. Bamman et al. (2020) analyzed the distribution of distance to nearest antecedent for proper nouns, noun phrases and pronouns. We replicate their experiment and report similar results. While 95% of pronouns appear within 7 mentions of their last antecedent, this distance reach up to 270 mentions for proper nouns and noun phrases.

This observation calls for distinct handling of pronouns, common, and proper nouns during CR. The the last 1% of proper and common noun mentions exhibit a distance of over 1,700 mentions, presenting a significant challenge for CR. See Appendix B for the full distribution of antecedent distances.

3.4 Corpus Merging

Since we followed the guidelines from Mélanie et al. (2024), the newly annotated dataset is fully compatible with the character annotations from the LitBank-fr dataset. It allows us to merge the two datasets, resulting in a combined dataset containing 31 documents and 71,105 character mentions. This decision is motivated by the goal of evaluating generalization across a broader range of texts.

This merged dataset becomes the largest annotated literary coreference dataset in terms of tokens (560,536), average document length (18,081 tokens), and maximum document length (115,415 tokens). Unless otherwise specified, all results presented in this paper pertain to this merged corpus, which we refer to as `Long-LitBank-fr`.

4 Coreference Resolution

Several coreference resolution pipelines are available off-the-shelf, such as the *CoreferenceResolver* module from Spacy[3], Fastcoref (Otmazgin et al., 2022) and AllenNLP (Gardner et al., 2018). BookNLP (Bamman et al., 2020), is a pipeline performing, among other, mentions detection and coreference resolution for English. A French adaptation, BookNLP-fr, was developed by Mélanie et al. (2024) and trained on the LitBank-fr dataset. The BookNLP pipelines implement an end-to-end coreference resolution model (Ju et al., 2018).

Diverging from recent trends of end-to-end architectures, we propose to implement coreference resolution as a modular pipeline, facilitating the study of each component's role and enabling fine-grained error analysis.

Additionally, the use of compact, specialised models (∼15M and ∼11M parameters for mention detection and mention scoring models) is motivated by practical end-use considerations: the need to process large literary corpora under limited computational resources. This is further supported by recent critiques of the "bigger-is-better" trend in AI, arguing that simply increasing scale doesn't always lead to better results. Instead, smaller, task-specific models have been shown to offer more sustainable, transparent, and often competitive solutions for domain-specific applications (Varoquaux et al., 2025).

4.1 Pipeline Description

Our mention-pair-based coreference resolution pipeline is composed of the following modules:

Mention Detection: We employ the mention detection module described in section 3.1, which consists of a stacked BiLSTM-CRF architecture using token-level embeddings from pretrained $\text{CamemBERT}_{\text{LARGE}}$ model as input. We retrained it on the merged corpus, achieving an increase of 2.82 points in F1-score (94.87). As mention detection can impact overall CR performance, we make it possible to bypass the errors introduced by this module by using gold mentions as input to the mention-pair encoder.

Considered Antecedents: To address the quadratic complexity of considering all antecedents, recent approaches introduce hyperparameters to uniformly limit the number of considered antecedents (Thirukovalluru et al., 2021; Wu et al., 2020). Inspired by Bamman et al. (2020) and supported by our observations regarding antecedent distance, we adopt a mention-type-specific approach. We limit the number of antecedents to 30 for pronouns and 300 for proper and common nouns.

Mention Pair Encoder: Mention-pairs are encoded by concatenating the representations of the two mentions with a feature vector that includes attributes such as gender, grammatical person, and the distance between the mentions. For multi-token mentions, the representation is calculated as the average of the first and last tokens embeddings.

Mention Pair Scorer: Encoded mention-pairs are passed into a feedforward neural network trained to predict if two mentions refer to the same entity. Details about the features, model architecture and parameters are provided in the Appendix C.

Antecedent Ranker: Following Wiseman et al. (2015), candidate antecedents are ranked according to their predicted scores. During inference, the highest-scoring antecedent is selected unless all scores fall below 0.5, in which case the null antecedent is assigned.

Entity Clustering: Default strategy for linking mentions into clusters is to scan the document from

[3]https://spacy.io/api/coref

left to right, each new mention is either merged into the cluster of its best-ranked antecedent or left as a standalone entity. Coreference chains are defined as the set of mentions in a cluster.

We explore additional strategies to address specific challenges and improve overall performance.

Handling Limited Antecedents: Limiting the number of antecedents can lead to split coreference chains. A common strategy in literary texts is to link all matching proper nouns at the document level, along with their derivatives. While previous works have been using hand-crafted sets of aliases to link proper mentions (Bamman et al., 2020), we leverage local mention-pairs scoring to perform coreference resolution at the document scale. Let's say that all local predictions involving mentions of "Sir Ralph Brown" and "Raphael" are coreferent, we propagate this decision to all mention-pairs at the global scale, bridging the gap between a mention and an antecedent that would otherwise be out of the range of locally considered antecedents.

Leveraging Non-Coreference Predictions: While most mention-pair models focus on coreference links, the cross-entropy loss used during training involves that they are equally trained to predict non-coreference. We propose leveraging high-confidence non-coreference predictions to prevent later incorrect cluster merging. Mention-pairs containing a coordinating conjunction, such as "[Ralph] and [Mr. Delmare]", are a strong indication of non-coreference between these mentions, which can be used to prevent the merging of these entities at document level. This approach is combined with an "easy-first" clustering strategy (Clark and Manning, 2016), which processes mentions in order of confidence rather than left-to-right, thus delaying harder decisions.

The addition of these two strategies is refered to as the *easy-first, global proper mentions coreference approach*. This approach follows a hierarchical iterative process, where high-confidence local mention-pair predictions are resolved first, constraining subsequent decisions at the document level. This post-processing module is not trained.

4.2 Evaluation Metrics

We evaluate CR performance using MUC (Vilain et al., 1995), B^3 (Bagga and Baldwin, 1998), and $CEAF_e$ (Luo, 2005) scores. For overall performance assessment we report the average F1-score of the three metrics which we refer to as the CoNLL F1-score (Pradhan et al., 2012). We use the scorer implementation by Grobol.[4]

4.3 Document Length

While Poot and van Cranenburgh (2020) investigated the impact of document length on CR by truncating documents to different sizes, we adopt a splitting approach. This allows us to evaluate CR performance on more text excerpts.

Given a target sample size of L tokens, we first select all documents from our corpus that exceed this length. Each document is split into non-overlapping samples, each containing L tokens. CR is performed independently on each sample, and the results are averaged across samples of a given document. The overall CR scores are calculated as the macro-average across all retained documents.

4.4 Coreference Resolution Results

4.4.1 Mention-Pairs Scorer Results

The mention-pairs scorer, evaluated using leave-one-out cross-validation with gold mention spans, achieved an overall accuracy of 88.10%. As shown in Table 4, performance disparities between classes reflect the underlying class imbalance, with significantly higher precision and recall for non-coreferent pairs (class 0). Most errors occurred for mention pairs where the scorer's confidence is low ($\sim$0.5) (Appendix D). As we use the highest ranked antecedent strategy, not all scorer decisions are used during entity clustering, mitigating the number of wrong decisions considered.

Coref.	P	R	F1	Support
0	92.31	93.18	92.74	5.52M (82%)
1	68.49	65.62	67.02	1.25M (18%)

Table 4: Mention-pairs scorer performance on Long-LitBank-fr corpus. Precision (P), Recall (R).

4.4.2 Highest Ranked Antecedent

After sorting, the correct antecedent was predicted in 88.05% of cases, highlighting the effectiveness of this approach. Errors occurred for 8,496 mentions (11.95%). In 1,478 cases (2.08%), the range of considered antecedents is too narrow, leaving true antecedents out of reach. For these mentions, the null antecedent is assigned approximately half the time, while an unrelated antecedent is assigned in the other half. In 7,018 cases (9.87%), the true

[4] https://github.com/LoicGrobol/scorch

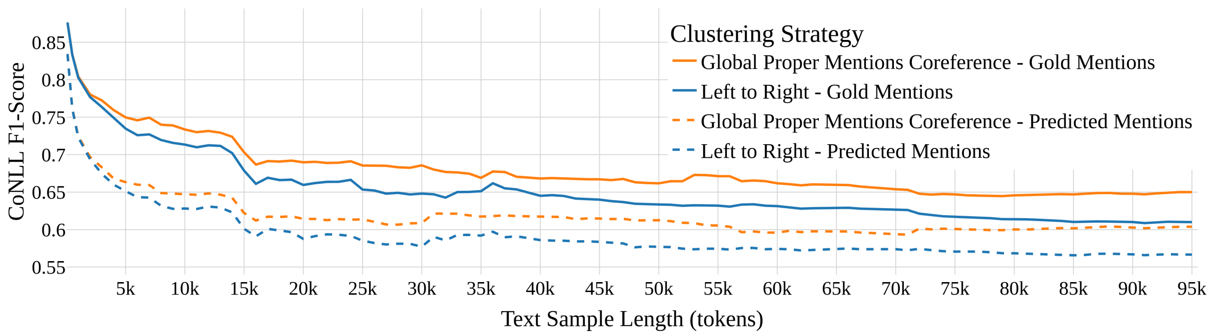

Figure 1: Impact of document length on CR performance for different strategy. Gold and predicted mentions.

antecedent is within reach, but the model incorrectly assigned a different antecedent in nearly 90% of instances. In the remaining 10%, the null antecedent is wrongly predicted.

The additional global proper mentions coreference strategy aims at reducing both types of errors, by bridging the gap between proper mentions and their long distance antecedent, and by limiting clustering of mentions that are believed to be distinct from local mention-pair scores.

4.4.3 Entity Clustering Strategies

The global proper mentions strategy leads to an overall gain in performance measured by CoNLL F1-score of 1.68 points. We observe a slight drop for MUC, but a significant improvement on both B^3 and $CEAF_e$.

Strategy	MUC	B^3	$CEAF_e$	CoNLL
Left to Right	**94.61**	62.95	60.36	72.64
Global Proper CR	94.45	**67.32**	**61.18**	**74.32**

Table 6: Coreference resolution for Long-LitBank-fr corpus. Average F1-scores. Gold mentions.

These scores reflect the overall performance gain of this strategy on the full `Long-LitBank-fr` corpus (averaging 18,081 tokens per document). However, it is best suited to long texts that present both the risk of out-of-reach antecedent, and sufficient local evidence on proper mentions-pairs to propagate document-wide decisions.

4.4.4 Influence of Document Length

When analyzing performance gains as a function of document length, we observe that the MUC score remains relatively stable. For $CEAF_e$ we see a consistent improvement of around 1 point, regardless of document length. The most striking trend is observed on the B^3 score: for documents exceeding 20,000 tokens, the gain from the global proper mentions strategy increases significantly, ranging from 5 to 10 points. See Appendix E.

From Figure 1, we observe that the overall CR performance decreases with document length. Much of the performance loss is observed in the lower range. This might well explain why CR models trained and evaluated on documents of limited length (<10k), have been deceiving when used for downstream tasks on full length documents.

The proper mentions global coreference strategy consistently outperform the vanilla left-to-right method. Performance gains is mostly negligible for short documents (< 2k tokens), but becomes significant and stable beyond, reaching +3 points on the CoNLL F1-score. This shows the effectiveness of our approach for handling CR in longer documents.

Additionally, Figure 1 shows the impact of using predicted mentions as input to the mention-pair encoder, leading to a performance drop of ∼7%, this result is consistent with previous publications.

4.4.5 Comparison to Baseline

For French, our new pipeline consistently outperforms the model proposed by Mélanie et al. (2024) on their test set, setting a new baseline on this specific dataset. We also report average performances on the 3 newly annotated novels for future comparison ; both with gold and predicted mentions.

See Appendix G for cross-dataset and cross-language coreference performance comparison.

While this experiment reveals performance limitations exacerbated by document length, commonly

Corpus (test set)	Model	Mentions	Tokens / Doc	MUC	B^3	CEAFe	CoNLL
LitBank-fr (test-set)	Mélanie et al. 2024	Gold	2,000	88.0	69.2	71.8	76.4
LitBank-fr (test-set)	Ours	Gold	2,000	**92.43**	**70.67**	**75.59**	**79.56**
Long-LitBank-fr (3 docs)	Ours	Gold	93,019	96.64	52.36	46.45	65.15
Long-LitBank-fr (3 docs)	Ours	Predicted	93,019	95.59	45.4	35.95	58.98

Table 5: CR performance on LitBank-fr test-set and on the three fully annotated novels. Gold and predicted mentions.

used CR metrics (MUC, B^3, $CEAF_e$) have been criticised for presenting systematic flaws. Alternative metrics such as LEA (Moosavi and Strube, 2016) and BLANC (Recasens and Hovy, 2011) have been proposed as better aligned with linguistic intuitions. Others argue for extrinsic evaluation (O'Keefe et al., 2013; Vishnubhotla et al., 2023), where CR is assessed based on its contribution to easier to evaluate, downstream tasks.

5 Gender Prediction Case study

As mentioned, studies gravitating around character gender have attracted substantial attention from computational humanities researchers (Underwood et al., 2018). A key challenge is accurately predicting the gender of as many character mentions as possible to ensure representative results.

Early works relied on heuristics to infer gender from explicit clues (he, Mrs, the man), achieving high precision (90%) but lower recall (30-50%), due to the high proportion of ambiguous mentions in literary texts. Recent works leverages CR for broader gender prediction (Vianne et al., 2023).

5.1 Data Preparation

We use the *Long-Litbank-fr* corpus. Starting with all character mentions, we discard singletons (2.74%) and plural mentions (9.84%). We manually annotate the gender of the remaining 62,162 mentions at the entity level. We adopt a binary approach to gender. Works of fiction are subject to play on characters' gender, such as gender revelation or asymmetry of knowledge between characters. To assign character gender we adopt the omniscient perspective (Kim et al., 2024), refering to the knowledge one have at the end of the entire book. We discard chains whose gender cannot be annotated with certainty, leaving us with 804 entities and 61,852 mentions (86.99% of all mentions).

5.2 Prediction Pipeline

To predict the gender of character mentions we implement a multi-stage solution:

Heuristic rules: assign gender based on heuristics from explicit gender clues (pronouns, noun phrases, articles and adjectives).

First-name database: determine the gender of proper mentions using a statistical database of first names given in France since 1900.[5]

Coreference propagation: resolve coreference, compute the male/female ratio of processed mentions, and assign the majority gender to all mentions within the coreference chain.

We compare our results with those of Naguib et al. (2022) who used a similar combination of heuristic rules and CR to infer character gender.

5.3 Case Study Results

CR significantly improves recall compared to rule-based methods. While heuristics achieve high precision (>98%), they suffer from low recall (37-47%), reflecting the significant number of mentions whose gender cannot be inferred without additional context. Our approach outperforms the baseline by leveraging sophisticated heuristic rules, a first-names database, and a more effective CR pipeline. Although CR slightly reduces precision—a consequence of clustering errors—the substantial recall gain makes it a robust method overall.

	Male			Female		
	P	**R**	**F1**	**P**	**R**	**F1**
Baseline Naguib et al. 2022	95.0	45.0	60.6	97.0	58.0	72.7
Heuristic Rules	**99.8**	37.0	54.0	**98.9**	46.7	63.4
+ First-name data	99.8	38.4	55.4	98.8	47.4	64.1
+ Coreference	95.4	**91.6**	**93.4**	90.4	**93.4**	**91.9**

Table 7: Mentions gender prediction performance (Precision, Recall, F1).

6 Conclusion

We highlight critical limitations in coreference resolution (CR) for literary texts, particularly the scarcity of representative datasets, limiting the possibility to train and evaluate models tailored for literary computational studies. To bridge this gap, we release an annotated corpus of character coreference chains for three full-length French novels spanning three centuries (285,000+ tokens). We introduce a modular CR pipeline tailored for long documents, integrating global coreference propagation for proper nouns and an easy-first clustering approach. After carrying out a detailed error analysis of each component, we study the impact of document length on overall coreference performance. Our approach is competitive with existing state-of-the-art models, demonstrating good performance on longer texts. To demonstrate practical value, we apply it to character gender inference, significantly improving recall over rule-based baselines while maintaining high precision, and outperforming other CR-based approach. This study

[5] French National Institute of Statistics and Economic Studies (*INSEE*).

underscores the need for robust datasets and well-evaluated models to advance literary CR research.

Limitations

While our dataset is among the largest annotated literary datasets in terms of tokens (285,000), it is limited by the fact that it only contains three documents. This implies that it does not encompass the full diversity of time periods, literary movements, and genres within French literature. This limitation may impact the generalizability of the coreference resolution (CR) models trained on this dataset. The proposed *Long-LitBank-fr* corpus resulting from the concatenation with the *LitBank-fr* dataset mitigates this issue by increasing diversity and improving the potential for model generalization.

Another limitation is that we focused solely on annotating coreference chains for characters. Some downstream applications may require resolving coreference for other entity types (e.g., geographical entities, events). Since our annotations are restricted to characters, a model trained exclusively on this data may not easily transfer to tasks involving other entity types. In such cases, enriching the annotations would be necessary for broader applicability.

Furthermore, our study is limited to French-language texts, and we did not explore cross-lingual generalization of our pipeline. Expanding the dataset to include full documents in other languages could improve its applicability. This could be achieved through annotation transfer or by leveraging multilingual models, which would help reduce the cost of manual annotation.

Finally, while extrinsic evaluation is not the primary focus of this work, we have only begun to assess our pipeline through its application to character gender inference. A more comprehensive evaluation of the models' suitability for full-document literary analysis would require additional extrinsic assessments, such as network extraction or quote attribution.

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A Mention Detection Model

The mention detection module consists of two stacked BiLSTM-CRF models, each trained on a different nesting level of mentions. During inference, predicted spans from both models are combined. If two mention spans overlap, the span with the lower prediction confidence is discarded.

BERT embeddings: The raw text is split into overlapping segments of length L (the maximum embedding model context window) with an overlap of $L/2$ to maximize the context available for each token. Each segment is passed through the CamemBERT$_{\text{LARGE}}$ model, and we retrieve the last hidden layer as the token representations (1024 dimensions). The final token embedding is computed as the average from overlapping segments. We do not fine-tune CamemBERT for this task.

BIOES tag prediction: For each sentence, token representations are passed through the BiLSTM-CRF model, which outputs a sequence of BIOES tags: B-PER (Beginning of mention), I-PER (Inside), E-PER (End), S-PER (Single-token mention), and O (Outside).

A.1 Model Architecture

- **Locked Dropout** (0.5) applied to embeddings for regularization.
- **Projection Layer**: Highway network mapping 1024 $\rightarrow$ 2048 dimensions.
- **BiLSTM Layer**: Single bidirectional LSTM (256 hidden units per direction).
- **Linear Layer**: Maps 512-dimensional BiLSTM outputs to BIOES label scores.
- **CRF Layer**: Enforces structured consistency in predictions.

A.2 Model Training

- **Data Splitting**: Leave-One-Out Cross-Validation (LOOCV) with an 85%/15% train-validation split.
- **Batch Size**: 16 sentences per batch.
- **Optimization**: Adam optimizer (lr = 1.4×10^{-4}, weight decay = 10^{-5}).
- **Learning Rate Scheduling**: ReduceLROnPlateau (factor = 0.5, patience = 2).
- **Average Training Epochs**: 20.
- **Hardware**: Trained on a single 6GB Nvidia RTX 1000 Ada Generation GPU.

B Nearest Antecedent Distribution

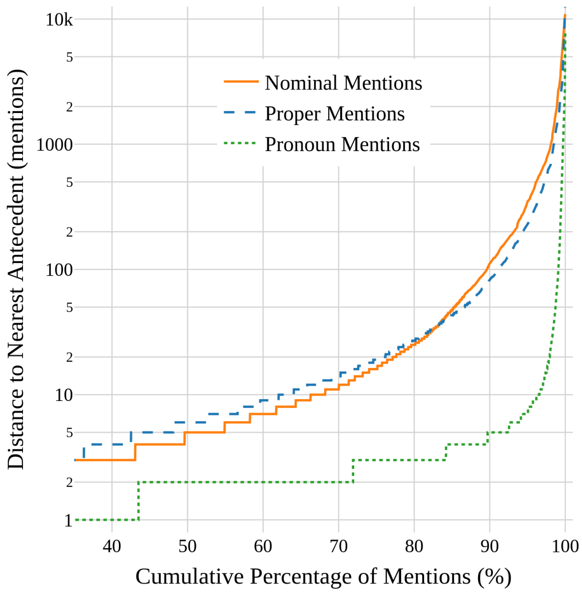

Figure 2: Distance to nearest antecedent for mentions of different type.

C Coreference Resolution Model

C.1 Model Architecture

- **Model Input**: 2,165-dimensional vector, composed of concatenated:
  - **CamemBERT embeddings**: Maximum context embeddings for both mentions (2 × 1,024 = 2,048 dimensions).
  - **Mention Features** (106 dimensions):
    - Mention length.
    - Position of the mention's start token in the sentence.
    - Grammatical category (pronoun, common noun, proper noun).
    - Dependency relation of the mention's head (one-hot encoded).
    - Gender (one-hot encoded).
    - Number (one-hot encoded).
    - Grammatical person (one-hot encoded).
  - **Mention Pair Features** (11 dimensions):
    - Distance between mention IDs.
    - Distance between start and end tokens of mentions.
    - Sentence and paragraph distance.
    - Difference in nesting levels.
    - Ratio of shared tokens between mentions.
    - Exact text match (binary).
    - Exact match of mention heads (binary).

    * Match of syntactic heads (binary).
    * Match of entity types (binary).

- **Hidden Layers**:
  - Three fully connected layers.
  - 1,900 hidden units per layer with ReLU activation.
  - Dropout rate of 0.6 for regularization.
- **Final Layer**:
  - Linear layer mapping from 1,900 dimensions to a single scalar score.
  - Output: Continuous value between 0 (not coreferent) and 1 (coreferent).

C.2 Model Training

- **Data Splitting**: Leave-One-Out Cross-Validation (LOOCV) with an 85%/15% train-validation split.
- **Batch Size**: 16,000 mention-pairs per batch.
- **Optimization**: Adam optimizer (lr = 1.4×10^{-4}, weight decay = 10^{-5}).
- **Antecedent Candidates**:
  - 30 for pronouns.
  - 300 for common and proper nouns.
- **Hardware**: Trained on a single 6GB Nvidia RTX 1000 Ada Generation GPU.

D Mention-Pairs Scorer Error Distribution

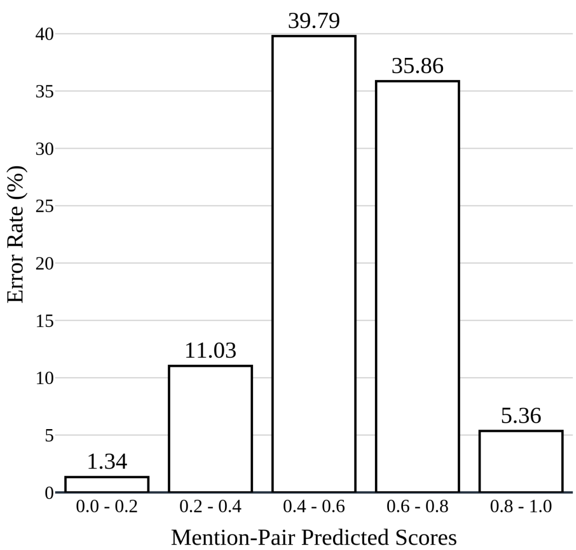

Figure 3: Error Rate by Mention-pair Predicted Score Range.

E Detailed performance gain from clustering strategy

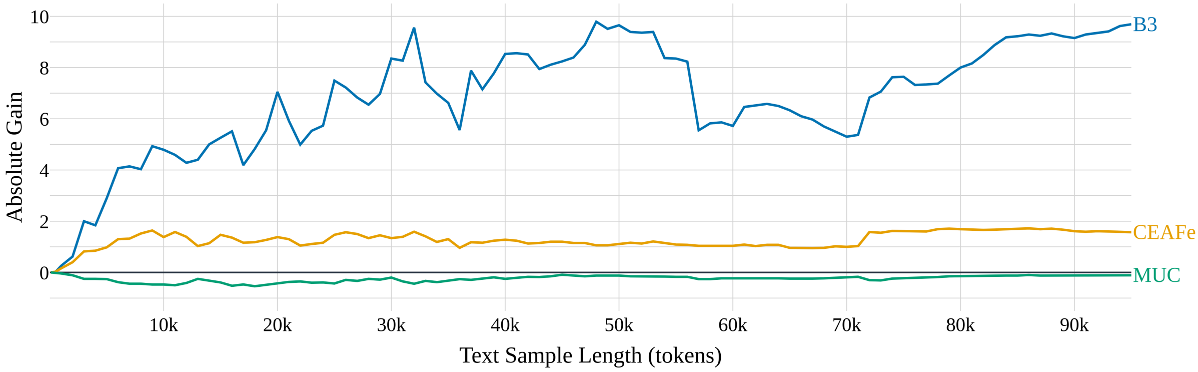

Table 8: Absolute CR performance gain from the global proper mentions clustering strategy over vanilla left-to-right, as a function of document length. Predicted mentions.

F Annotated Dataset Details

Year	Author	Text	Tokens
1731	Antoine-François Prévost	*Manon Lescaut*	71,219
1832	George Sand	*Indiana*	115,415
1923	Delly	*Dans les ruines*	98,542

Table 9: Annotated Dataset Details

G Comparison of CR performance with other datasets and languages

Corpus	Model	Mentions	Tokens / Doc	MUC	B^3	CEAFe	CoNLL
LitBank (*English*)	Bamman et al. 2020	Gold	2,105	88.5	72.6	76.7	79.3
LitBank-fr (LOOCV)	Ours	Gold	2,105	91.93	74.6	75.35	80.63
LitBank (*English*)	Bamman et al. 2020	Predicted	2,105	84.3	62.73	57.3	68.1
LitBank (*English*)	Thirukovalluru et al. 2021	Predicted	2,105	89.50	78.21	67.59	78.44
LitBank-fr (LOOCV)	Ours	Predicted	2,105	84.58	74.77	63.30	73.21
KoCoNovel (*Korean*)	Kim et al. 2024	Predicted	3,578	71.06	57.33	44.19	57.53
Long-LitBank-fr (LOOCV)	Ours	Predicted	3,578	88.31	68.79	47.17	68.09
G. Orwell, *Animal Farm*	Guo et al. 2023	Predicted	37,000	-	-	-	36.3
Long-LitBank-fr (LOOCV)	Ours	Predicted	37,000	92.79	52.35	32.89	59.34
$\text{BookCoref}_{\text{gold}}$	Longdoc	Predicted	76,419	93.5	62.4	45.3	67.0
$\text{BookCoref}_{\text{gold}}$	$\text{Maverick}_{\text{xl}}$	Predicted	76,419	94.3	55.3	33.4	61.0
Long-LitBank-fr (LOOCV)	Ours	Predicted	76,000	94.99	47.51	37.49	60.00

Table 10: Comparison of CR performance with other work on literary coreference with predicted and gold mentions.