FRASIMED: a Clinical French Annotated Resource Produced through Crosslingual BERT-Based Annotation Projection

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Abstract

Natural language processing (NLP) applications such as named entity recognition (NER) for low-resource corpora do not benefit from recent advances in the development of large language models (LLMs) where there is still a need for larger annotated datasets. This research article introduces a methodology for generating translated versions of annotated datasets through crosslingual annotation projection and is freely available on GitHub (link: https://github.com/JamilProg/crosslingual_bert_annotation_projection). Leveraging a language agnostic BERT-based approach, it is an efficient solution to increase low-resource corpora with few human efforts and by only using already available open data resources. Quantitative and qualitative evaluations are often lacking when it comes to evaluating the quality and effectiveness of semi-automatic data generation strategies. The evaluation of our crosslingual annotation projection approach showed both effectiveness and high accuracy in the resulting dataset. As a practical application of this methodology, we present the creation of French Annotated Resource with Semantic Information for Medical Entities Detection (FRASIMED), an annotated corpus comprising 2'051 synthetic clinical cases in French. The corpus is now available for researchers and practitioners to develop and refine French natural language processing (NLP) applications in the clinical field (https://zenodo.org/record/8355629), making it the largest open annotated corpus with linked medical concepts in French.

Keywords: annotation projection, crosslingual, medical entity recognition, entity linking, large medical annotated dataset

1. Introduction

The field of natural language processing (NLP) has witnessed significant advancements due to the availability of large, annotated corpora. These corpora serve as valuable resources for training and evaluating machine learning models, enabling the development of robust and accurate NLP applications such as Named Entity Recognition (NER). However, creating high-quality annotations for large datasets is a time-consuming and resource-intensive task. Manual annotation requires domain experts, which can be particularly challenging when dealing with specialized domains.

To address this challenge, researchers have explored automated and semi-automated methods for generating annotations, aiming to reduce the human effort involved in the annotation process. One promising approach is annotation projection, which involves transferring annotations from one language to another. By leveraging the existing annotations in a different language, it provides an efficient way of creating annotated datasets in languages where such annotations are limited or nonexistent.

2. Related works

2.1 Crosslingual annotation projection

Several studies have explored the use of crosslingual annotation projection techniques to save annotation time, ensure comparability across languages, and create valuable multilingual resources.

Bentivogli and Pianta (2005) proposed an approach to create linguistically annotated resources based on aligned parallel corpora. By transferring annotations from a source language to a target language using a bilingual knowledge-intensive word aligner, they were able to reduce human effort and exploit existing annotated resources to create new ones. This is exemplified in the creation of the MultiSemCor corpus, an English-Italian semantically annotated parallel corpus based on translations of the English SemCor corpus.

Previous contributions used crosslingual annotation projection, either to create a new multilingual resource or to perform NER. The methods are based on the use of a Machine Translation (MT) system, followed by variants of string matching: Ehrmann et al. (2011), Jain et al. (2019) and Miranda-Escalada et al. (2022) respectively used consonant signature matching (i.e., a variant of string matching but with vowels removal), phonetic similarity, and lemmatized string matching. Alternatively, Abacha et al. (2013) projected annotations using MOSES (Koehn et al. 2007), a word alignment tool based on a statistical model. The evaluation of the projected annotations is indirectly done quantitatively through the evaluation of the final NER task.

Furthermore, annotation projections have been applied to other tasks such as Semantic Role Labeling and Part-of-Speech Tagging (Padó and Lapata 2009; Van der Plas et al. 2011, 2014; Huck et al. 2019; Aminian et al. 2019; Daza and Frank 2020). Knowledge-based annotation projection have also been proposed: Padó and Lapata (2009) used FrameNet (Baker 2017) to create an English-German parallel corpus with high-quality annotations, with minimal human effort. Van der Plas et al. (2011) generated semantic role annotations for the French language using PropBank (Kingsbury and Palmer 2002), an English corpus annotated with semantic propositions.

To the best of the authors' knowledge, no previous work has utilized a Transformer-based annotation projection to produce a new annotated dataset. While these previous studies have demonstrated the feasibility of crosslingual annotation projection techniques, the creation of French annotated medical corpora through annotation projection remains largely unexplored.

2.2 Available French medical NER data

The French research community has previously collected and distributed clinical and biomedical datasets for NER.

One such dataset is CAS corpus (Grabar et al. 2018), a collection incorporating clinical cases originating from French scientific literature. Annotated with demographic attributes (age, gender) and clinical features (origin of visit, outcome), the corpus encompasses 717 clinical documents, comprising approximately 231'662 tokens.

A subset of CAS, known as DEFT, emerged within the 2020 DEFT challenge (Cardon et al. 2020). Comprising 167 cases, DEFT integrates 13'493 annotations with 13 different clinical entity types.

The QUAERO dataset features a French biomedical NER Gold Standard (Névéol et al. 2014). Drawing from PubMed article titles and European MEdicines Agency (EMEA) documents, it boasts manual annotations encompassing ten clinical entity categories, all linked to the Unified Medical Language System (UMLS) Metathesaurus. Spanning 1'688 files, this corpus accommodates 26'409 UMLS-linked annotations.

The European Clinical Case Corpus (E3C) (Magnini et al. 2021) stands out as a multilingual resource encompassing English, French, Italian, Spanish, and Basque. It offers annotated clinical narratives, aligning clinical entities (disorders) with the UMLS terminology and incorporating temporal information. Comprising 81 French documents with 29'256 tokens, E3C comprises 1'327 annotated entities, with 1'085 linked to UMLS concepts.

Kors et al. (2015) introduces the MANTRA corpus, a multilingual resource comprising French texts extracted from EMEA, MEDLINE, and biomedical patent claims. This freely accessible corpus, with a total size of 7'206 words in the French subset, is annotated with UMLS semantic groups.

Campillos et al. (2018) releases MERLOT, a clinical corpus of 500 anonymized clinical notes and reports sourced from French health institutions. This resource has a size of 148'476 tokens and is richly annotated with 44'740 UMLS entities and 26'478 relations. Unfortunately, due to the sensitive nature of the data, the resource is not freely available.

Finally, Miranda-Escalada et al. (2022) presented DISTEMIST, a Spanish corpus comprising 1'000 synthetic clinical cases annotated with diseases linked to SNOMED-CT (SNOMED International 1999). They produced a multilingual dataset by employing a lemmatized string-matching based annotation projection method across six languages, including French. However, the evaluation of the projections' quality is limited.

While these datasets collectively provide a rich foundation for advancing clinical natural language processing, the number of very large French clinical NER datasets available to the public is limited.

3. Contributions of this study

This paper builds upon this existing line of research and presents a novel methodology for generating translated versions of annotated datasets using a language-independent BERT-based approach (Devlin et al. 2018). The proposed annotation projection methodology offers several advantages: (i) it does not require any ontology or lexical resource, (ii) it is applicable to multiple languages, including low-resource ones, and (iii) publicly available fine-tuned BERT models are used for crosslingual annotation projection.

As a practical application of our methodology, the focus is on creating a French annotated corpus, named FRASIMED, through MT and annotation projection. FRASIMED originates from two Spanish annotated corpora consisting of synthetic cases: the first corpus, CANTEMIST, includes oncological cases (Miranda-Escalada et al. 2020), while the second corpus, DISTEMIST, contains annotated diseases (Miranda-Escalada et al. 2022). An example of annotation from the original CANTEMIST corpus is presented in Figure 1.

The contributions of this work are summarized as follows:

- A novel pipeline for generating translated versions of annotated datasets using a language-independent crosslingual annotation projection approach, available at https://github.com/JamilProg/crosslingual_bert_annotation_projection.
- A novel corpus, FRASIMED, composed of synthetic clinical cases for French NER and Entity Linking freely available (https://zenodo.org/record/8355629), making it the largest open annotated corpus for oncological concepts in French.
- A set of extensive experiments to evaluate the annotation projection quantitatively and qualitatively.

4. Methodology

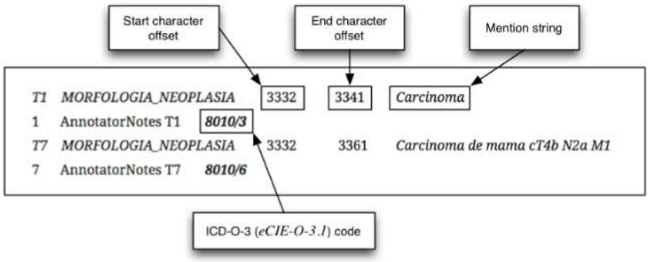
In this section, we introduce our methodology which consists of the following steps, illustrated in Figure 2:

- First, we use an existing document-level MT system to get the translated version of the textual content, as detailed in Section 4.2.

- Next, an automatic annotation projection pipeline is run to generate the annotation files for the translated text. Also, we produce a TSV file gathering the projected annotations, explained in Section 4.3.
- Then, using this report we semi-automatically detect badly projected annotations by going through this report - presented in Section 4.4.
- Finally, we manually correct these badly projected annotations, as discussed in Section 4.5.

4.1 Datasets

We produce a French version of a dataset made available through CANTEMIST (CANcer TExt Mining Shared Task), a shared task focusing on NER and Entity Linking of Spanish clinical texts in oncology (Miranda-Escalada et al. 2020). Through a publicly available corpus of 1’301 annotated synthetic cases, the task aims to automatically detect mentions of tumor morphology terms, as well as linking them to a medical terminology. As illustrated in Figure 1, each entity in this dataset is associated with a morphology code from the International Classification of Diseases for Oncology (ICD-O-3.1) (WHO 2013).



```
T1  MORFOLOGIA_NEOPLASIA    3332   3341   Carcinoma
1   AnnotatorNotes T1   8010/3
T7  MORFOLOGIA_NEOPLASIA    3332   3361   Carcinoma de mama cT4b N2a M1
7   AnnotatorNotes T7   8010/6
```

Figure 1: An example of CANTEMIST annotation

Moreover, in addition to the CANTEMIST dataset, we also include a subset from a dataset named DISTEMIST (DISease TExt Mining Shared Task). This subset consists of 750 cases, and it is annotated with diseases (Miranda-Escalada et al. 2022), with linkages to the July 31, 2021 release of SNOMED-CT. The combination of these two datasets, CANTEMIST and DISTEMIST, allows us to create a more comprehensive French annotated corpus for medical NLP tasks. Also, by including the DISTEMIST dataset, we can conduct a comparative analysis between our methodology and the annotation projection method employed by the original authors.

4.2 Document-level MT

Based on previous works (Läubli et al. 2018; Sun et al. 2022), it has been established that document-level translation is a more effective approach in comparison to sentence-level translation. This is primarily attributed to its capacity to capture the contextual nuances and overall coherence of a document. Nevertheless, the adoption of this approach comes at the expense of losing the information pertaining to sentence alignment. Document-level translation takes into consideration the broader context encompassing themes, subject matter, and intended meaning of the entire document. The precise reason for the superiority of document-level neural MTs compared to those involving isolated sentences remains unclear: Kim et al. (2019) discovered that most improvements are not readily interpretable.

In our study, we use DeepL Pro to translate Spanish documents into French. This step has been applied to CANTEMIST. However, for DISTEMIST, we opt to directly use the semi-automatically translated French texts provided by the original authors.

4.3 Annotation projection pipeline

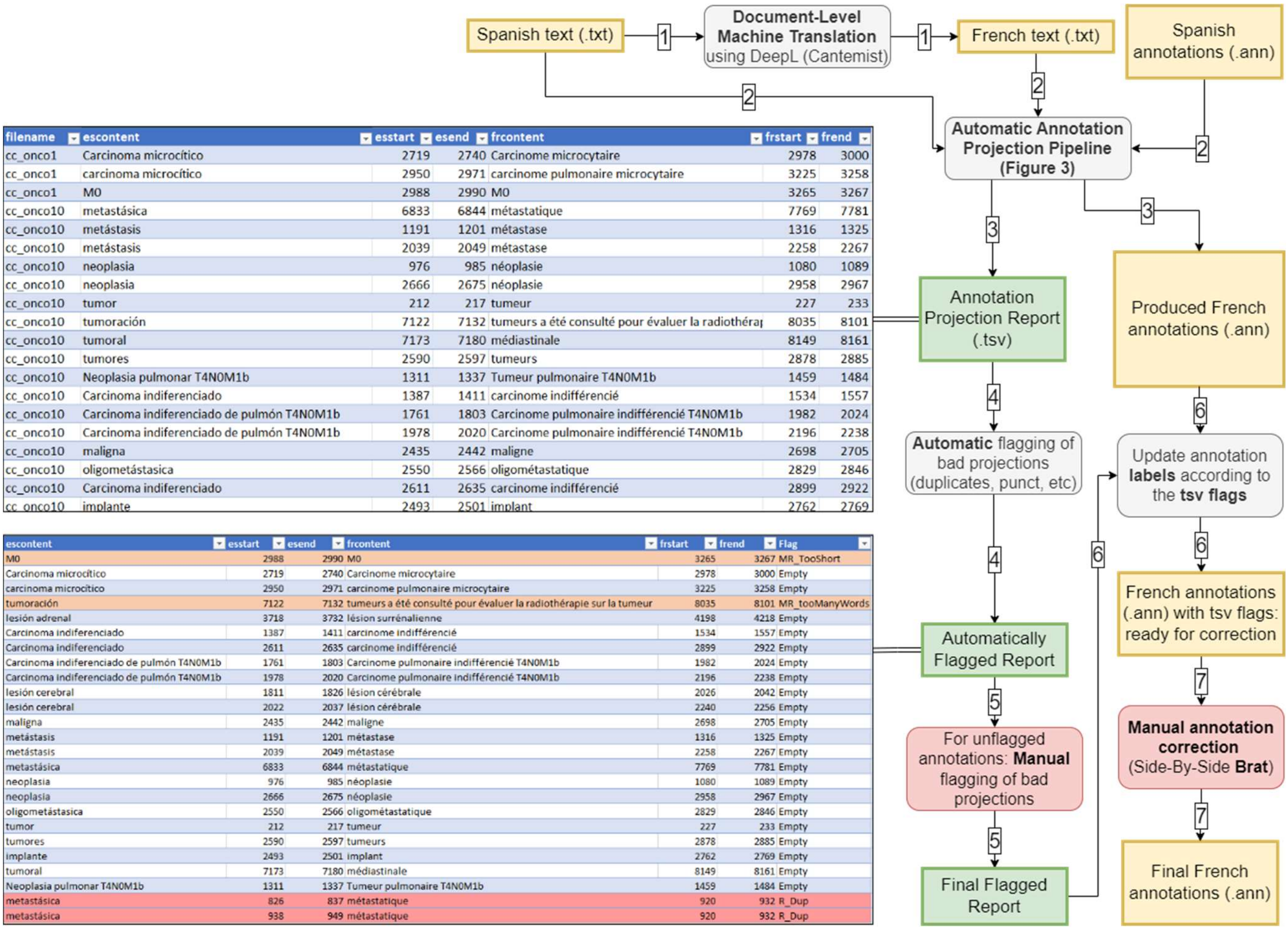
After having obtained the translated version of the unannotated text, we launch a pipeline that aims to project annotations from one language to another. As illustrated in Figure 3, the process begins with a textual document, its translated version, and its annotation file.

Sentence-level pipeline: Firstly, the Spanish document and its corresponding French translation are split into individual sentences. To represent each sentence effectively, a Language Agnostic BERT Sentence Embedding (LABSE) (Feng et al. 2022) is employed[1]. This BERT model is trained on both monolingual and bilingual corpora, employing Masked Language Modeling (MLM) and Translation Language Modeling (TLM) as pre-training objectives. MLM requires the model to predict the [MASK] token in the context of surrounding tokens, while TLM extends this objective to a bilingual context by inputting a concatenated translation pair. With support for over 109 languages, this model has achieved state-of-the-art performance in bi-text retrieval. Notably, LABSE surpasses multilingual BERT in generating superior crosslingual sentence embeddings, primarily due to TLM's focus on sentence-level objective. By comparing the sentence representations using similarity measures, sentence alignment is established, determining which sentences correspond between the two languages (Liu and Zhu 2023). The code aligning bilingual sentences using LABSE is publicly available on GitHub[2].

Word-level pipeline: Once the sentence alignment is established, the focus shifts to word-level alignment. Each pair of aligned sentences is further processed by splitting the words. The word alignment is then computed by encoding the words using multilingual BERT and measuring the cosine similarity between them: each word in the source sentence is aligned with the closest word in the target one. To account for the one-to-many relationships between words, the word alignment is applied bidirectionally (Figure 4). This means that the alignment is performed both from Spanish to French and from French to Spanish, ensuring comprehensive coverage of the annotations.

[1] https://github.com/bojone/labse

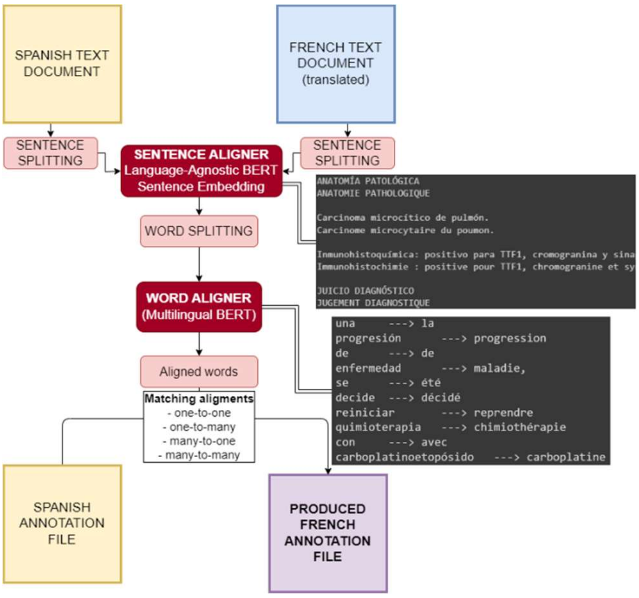
[2] https://github.com/bfsujason/bertalign


Spanish text (.txt)
1
Document-Level Machine Translation using DeepL (Cantemist)
1
French text (.txt)
Spanish annotations (.ann)
2
2
2
Automatic Annotation Projection Pipeline (Figure 3)
3
3
Annotation Projection Report (.tsv)
Produced French annotations (.ann)
4
6
Automatic flagging of bad projections (duplicates, punct, etc)
Update annotation labels according to the tsv flags
4
6
6
Automatically Flagged Report
French annotations (.ann) with tsv flags: ready for correction
5
7
For unflagged annotations: Manual flagging of bad projections
Manual annotation correction (Side-By-Side Brat)
5
7
Final Flagged Report
Final French annotations (.ann)

filename	escontent	esstart	esend	frcontent	frstart	frend
cc_onco1	Carcinoma microcítico	2719	2740	Carcinome microcytaire	2978	3000
cc_onco1	carcinoma microcítico	2950	2971	carcinome pulmonaire microcytaire	3225	3258
cc_onco1	M0	2988	2990	M0	3265	3267
cc_onco10	metastásica	6833	6844	métastatique	7769	7781
cc_onco10	metástasis	1191	1201	métastase	1316	1325
cc_onco10	metástasis	2039	2049	métastase	2258	2267
cc_onco10	neoplasia	976	985	néoplasie	1080	1089
cc_onco10	neoplasia	2666	2675	néoplasie	2958	2967
cc_onco10	tumor	212	217	tumeur	227	233
cc_onco10	tumoración	7122	7132	tumeurs a été consulté pour évaluer la radiothéraı	8035	8101
cc_onco10	tumoral	7173	7180	médiastinale	8149	8161
cc_onco10	tumores	2590	2597	tumeurs	2878	2885
cc_onco10	Neoplasia pulmonar T4N0M1b	1311	1337	Tumeur pulmonaire T4N0M1b	1459	1484
cc_onco10	Carcinoma indiferenciado	1387	1411	carcinome indifférencié	1534	1557
cc_onco10	Carcinoma indiferenciado de pulmón T4N0M1b	1761	1803	Carcinome pulmonaire indifférencié T4N0M1b	1982	2024
cc_onco10	Carcinoma indiferenciado de pulmón T4N0M1b	1978	2020	Carcinome pulmonaire indifférencié T4N0M1b	2196	2238
cc_onco10	maligna	2435	2442	maligne	2698	2705
cc_onco10	oligometástasica	2550	2566	oligométastatique	2829	2846
cc_onco10	Carcinoma indiferenciado	2611	2635	carcinome indifférencié	2899	2922
cc_onco10	implante	2493	2501	implant	2762	2769

escontent	esstart	esend	frcontent	frstart	frend	Flag
M0	2988	2990	M0	3265	3267	MR_TooShort
Carcinoma microcítico	2719	2740	Carcinome microcytaire	2978	3000	Empty
carcinoma microcítico	2950	2971	carcinome pulmonaire microcytaire	3225	3258	Empty
tumoración	7122	7132	tumeurs a été consulté pour évaluer la radiothérapie sur la tumeur	8035	8101	MR_tooManyWords
lesión adrenal	3718	3732	lésion surrénalienne	4198	4218	Empty
Carcinoma indiferenciado	1387	1411	carcinome indifférencié	1534	1557	Empty
Carcinoma indiferenciado	2611	2635	carcinome indifférencié	2899	2922	Empty
Carcinoma indiferenciado de pulmón T4N0M1b	1761	1803	Carcinome pulmonaire indifférencié T4N0M1b	1982	2024	Empty
Carcinoma indiferenciado de pulmón T4N0M1b	1978	2020	Carcinome pulmonaire indifférencié T4N0M1b	2196	2238	Empty
lesión cerebral	1811	1826	lésion cérébrale	2026	2042	Empty
lesión cerebral	2022	2037	lésion cérébrale	2240	2256	Empty
maligna	2435	2442	maligne	2698	2705	Empty
metástasis	1191	1201	métastase	1316	1325	Empty
metástasis	2039	2049	métastase	2258	2267	Empty
metastásica	6833	6844	métastatique	7769	7781	Empty
neoplasia	976	985	néoplasie	1080	1089	Empty
neoplasia	2666	2675	néoplasie	2958	2967	Empty
oligometástasica	2550	2566	oligométastatique	2829	2846	Empty
tumor	212	217	tumeur	227	233	Empty
tumores	2590	2597	tumeurs	2878	2885	Empty
implante	2493	2501	implant	2762	2769	Empty
tumoral	7173	7180	médiastinale	8149	8161	Empty
Neoplasia pulmonar T4N0M1b	1311	1337	Tumeur pulmonaire T4N0M1b	1459	1484	Empty
metastásica	826	837	métastatique	920	932	R_Dup
metastásica	938	949	métastatique	920	932	R_Dup

Figure 2: The comprehensive workflow describing our methodology (green and yellow squares depicts the TSV file, and the corpus respectively, red, and grey rounded boxes are automatic and manual tasks respectively).



```
ANATOMÍA PATOLÓGICA
ANATOMIE PATHOLOGIQUE

Carcinoma microcítico de pulmón.
Carcinome microcytaire du poumon.

Inmunohistoquímica: positivo para TTF1, cromogranina y sina
Immunohistochimie : positive pour TTF1, chromogranine et sy

JUICIO DIAGNÓSTICO
JUGEMENT DIAGNOSTIQUE
```

```
una      ---> la
progresión       ---> progression
de       ---> de
enfermedad       ---> maladie,
se       ---> été
decide  ---> décidé
reiniciar        ---> reprendre
quimioterapia   ---> chimiothérapie
con      ---> avec
carboplatinoetopósido   ---> carboplatine
```

Figure 3: Automatic annotation projection pipeline.

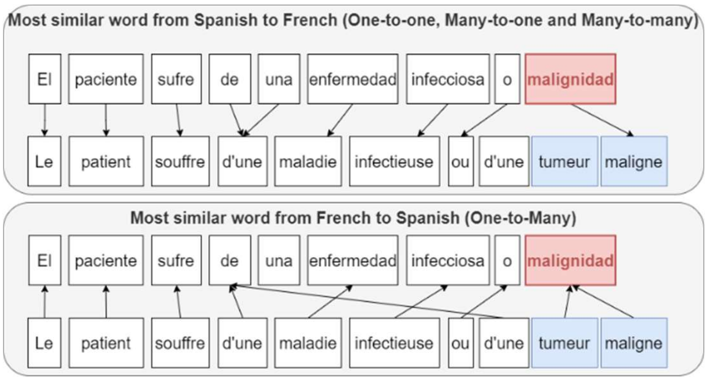


Figure 4: Word alignment using cosine similarity.

The code aligning words from a bilingual sentence pair using multilingual BERT is also publicly available on GitHub[3].

Annotation projection: Finally, leveraging the results of the word alignment, the French annotation file is constructed from the original Spanish annotation file. In cases where the resulting annotation projection exhibits discontinuity, a gluttonous strategy is employed: this approach involves annotating all the words intervening between the fragmented annotations to form a cohesive and continuous annotation. This approach aims to prevent fragmented annotations while favoring the recall.

4.4 Identification of badly projected annotations

Upon the successful execution of the automated annotation projection pipeline, a report is generated in TSV format, enumerating the crosslingual annotation projections that were conducted. The purpose of this report is to present a comprehensive examination of potential errors that may arise during the annotation projection process and facilitate their identification.

To aid manual correction of annotations, an initial phase involves discerning distinct error patterns that may manifest. These patterns include, among others:

- instances of duplicate annotations.
- presence of punctuation in projected annotations while it was originally absent.
- annotations of excessively short length.
- undesirable words such as coordinating conjunctions and determiners appearing at the beginning or end of the annotations.
- absence of alphanumeric characters in the projected annotations.
- a relatively higher word count in the projected annotations compared to the original ones.

The subsequent phase involves the identification of annotations that appear only once throughout the entire corpus, rendering them initially questionable. The aim is to manually review these suspicious annotations to either validate or disprove the uncertainty. For both datasets, which encompassed a total of 24'097 projected annotations, this methodology proved efficient.

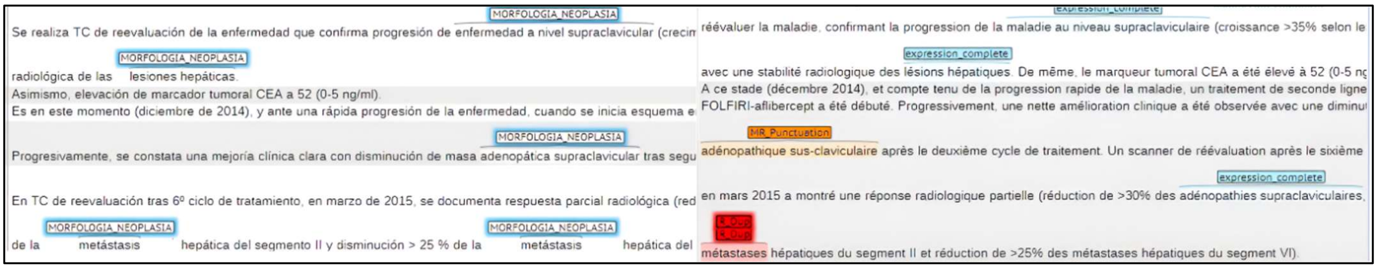
Lastly, the generated annotation files' tags are adjusted based on the outcomes from the TSV file, as a preparation step for the manual correction of these annotations.

4.5 Manual annotation correction

Using the tags obtained from the error identification of projections detailed in the preceding section, it becomes feasible to perform a manual correction of the corpus in an efficient manner.

We establish an annotator guideline encompassing the tag meanings and instructions to handle complex annotation projections. For instance, it addresses scenarios caused by the translation phenomena, such as revealing the subject in French that was initially hidden in Spanish.

The manual correction process is carried out employing Brat (Stenetorp et al. 2012), a web-based tool specifically designed for textual annotation. Moreover, Brat enables the side-by-side display (Figure 5), considerably expediting the correction of crosslingual annotation projections. The correction of CANTEMIST and DISTEMIST datasets required 28 and 20 hours of annotations, respectively.



Se realiza TC de reevaluación de la enfermedad que confirma progresión de enfermedad a nivel supraclavicular (crecim
radiológica de las lesiones hepáticas.
Asimismo, elevación de marcador tumoral CEA a 52 (0-5 ng/ml).
Es en este momento (diciembre de 2014), y ante una rápida progresión de la enfermedad, cuando se inicia esquema e
Progresivamente, se constata una mejoría clínica clara con disminución de masa adenopática supraclavicular tras segu
En TC de reevaluación tras 6º ciclo de tratamiento, en marzo de 2015, se documenta respuesta parcial radiológica (red
de la metástasis hepática del segmento II y disminución > 25 % de la metástasis hepática del

réévaluer la maladie, confirmant la progression de la maladie au niveau supraclaviculaire (croissance >35% selon le
avec une stabilité radiologique des lésions hépatiques. De même, le marqueur tumoral CEA a été élevé à 52 (0-5 ng
A ce stade (décembre 2014), et compte tenu de la progression rapide de la maladie, un traitement de seconde ligne
FOLFIRI-aflibercept a été débuté. Progressivement, une nette amélioration clinique a été observée avec une diminu
adénopathique sus-claviculaire après le deuxième cycle de traitement. Un scanner de réévaluation après le sixième
en mars 2015 a montré une réponse radiologique partielle (réduction de >30% des adénopathies supraclaviculaires,
métastases hépatiques du segment II et réduction de >25% des métastases hépatiques du segment VI).

Figure 5: Brat in side-by-side display mode. The Spanish annotation file is displayed on the left, and the French version on the right. The red / orange label means the annotation is false / suspicious, respectively.

[3] https://github.com/andreabac3/Word_Alignment_BERT

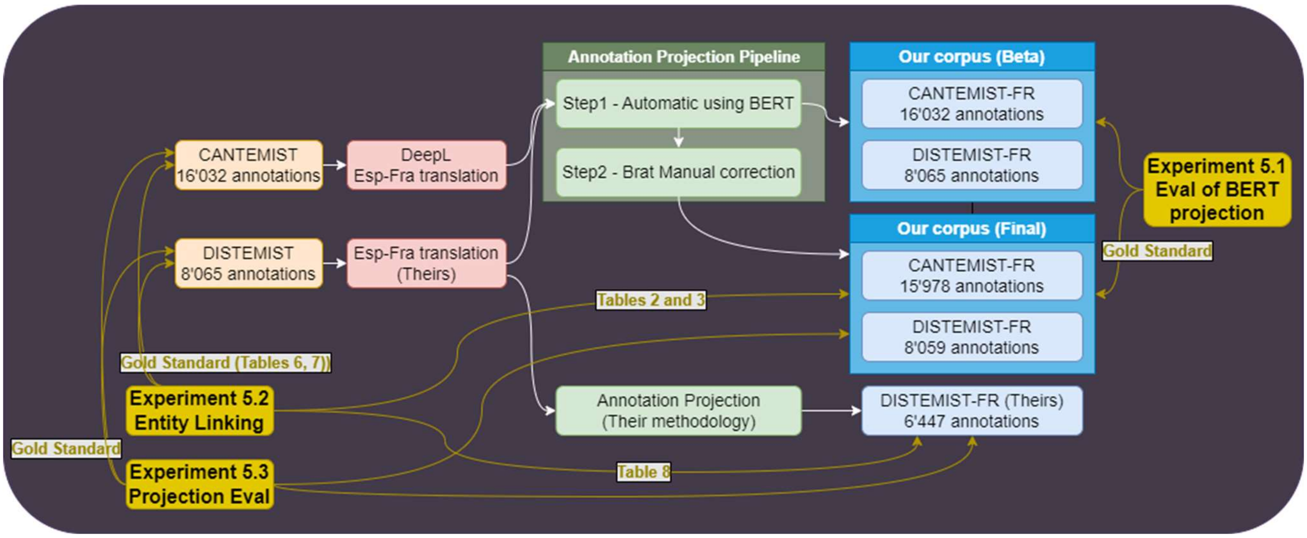

Annotation Projection Pipeline
Step1 - Automatic using BERT
Step2 - Brat Manual correction
Our corpus (Beta)
CANTEMIST-FR 16'032 annotations
DISTEMIST-FR 8'065 annotations
Our corpus (Final)
CANTEMIST-FR 15'978 annotations
DISTEMIST-FR 8'059 annotations
Experiment 5.1 Eval of BERT projection
Gold Standard
CANTEMIST 16'032 annotations
DeepL Esp-Fra translation
DISTEMIST 8'065 annotations
Esp-Fra translation (Theirs)
Tables 2 and 3
Gold Standard (Tables 6, 7)
Experiment 5.2 Entity Linking
Annotation Projection (Their methodology)
DISTEMIST-FR (Theirs) 6'447 annotations
Gold Standard
Experiment 5.3 Projection Eval
Table 8

Figure 6: Summary of experiments (golden arrows and nodes are experiments-related, while white arrows refer to the pipeline's process flow. Orange and blue nodes are Spanish and French annotated corpora, resp.)

5. Experiments and results

We provide a comprehensive overview of our experimental approach by encapsulating the entire paper's workflow in the Figure 6. This figure illustrates the strategic allocation of experiments across various stages of the workflow, allowing for a concise representation of our research methodology and the specific components targeted by each experiment.

5.1 Quality of the automatic annotation projection pipeline

To evaluate the performance of our automatic annotation projection pipeline, we conduct a comparative analysis between the annotation files generated by the pipeline before manual correction and the manually corrected versions (i.e., the gold standard). The evaluation metrics used in this analysis include:

- CORRECT: Entities identified in both sets, with matching annotation indices.
- PARTIAL: Cases where entities are partially identified (non-matching annotation indices).
- MISSING: Instances where the system fails to identify an expected entity, present in the gold standard.
- SPURIOUS: Incorrect identification of entities, i.e., when the system identifies a word or phrase as an entity erroneously, absent in the gold standard.

The Table 1 shows that CORRECT annotations are the most prevalent, followed by PARTIAL annotations. Given that several PARTIAL annotations involve minor corrections such as punctuations or single-character differences, we also introduce a relaxed version of Precision, Recall, and F1-Score to consider these annotations as valid along with the CORRECT ones. The presence of SPURIOUS and MISSING annotations underscores the importance of the manual correction procedure.

	CANTEMIST	DISTEMIST
CORRECT	13'404 (83.8%)	5'991 (74.3%)
PARTIAL	2'701 (16.9%)	2'376 (29.5%)
MISSING	770 (4.8%)	333 (4.1%)
SPURIOUS	424 (2.6%)	228 (2.8%)
PRECISION (Relaxed) [CORRECT+PARTIAL] / [CORRECT+PARTIAL+ SPURIOUS]	97.4%	97.3%
RECALL (Relaxed) [CORRECT+PARTIAL] / [CORRECT+PARTIAL+ MISSING]	95.4%	96.1%
F1-SCORE (Relaxed)	96.4%	96.8%
PRECISION (Strict) [CORRECT] / [CORRECT +PARTIAL+ SPURIOUS]	81.1%	69.6%
RECALL (Strict) [CORRECT] / [CORRECT +PARTIAL+MISSING]	79.4%	68.8%
F1-SCORE (Strict)	80.2%	69.2%

Table 1: Evaluation results of BERT projection against the manual correction as the gold standard

5.2 Quality of entity linking

In this experiment, we examine the quality of entities linked to medical terminologies in various datasets, including:

- Our French version of CANTEMIST (Table 2)
- Our French version of DISTEMIST (Table 3)
- The original Spanish CANTEMIST (Table 6 in the Appendix)
- The original Spanish DISTEMIST (Table 7 in the Appendix)
- The French version of DISTEMIST created by the original authors through their annotation projection method (Table 8 in the Appendix)

ICD-O	ICD-O Concept description	Count	Most occurrent
8000/6	Neoplasm, metastatic	5721	métastases
8000/1	Neoplasm, uncertain whether benign or malignant	2805	tumeur
8000/3	Neoplasm, malignant	966	cancer
8140/3	Adenocarcinoma, NOS (not otherwise specified	487	adénocarcinome
8010/3	Carcinoma, NOS	223	carcinome
8500/3	Infiltrating duct carcinoma, NOS	214	carcinome canalaire infiltrant
8140/6	Adenocarcinoma, metastatic, NOS	212	métastase d'adénocarcinome
8720/3	Malignant melanoma, NOS	166	mélanome
8010/9	Carcinomatosis	135	carcinomatose
8001/1	Tumor cells, uncertain whether benign or malignant	131	cellules tumorales

Table 2: Top 10 concepts in the French CANTEMIST dataset, with the most occurrent annotation found.

For the FRASIMED corpora (Tables 2 and 3), we observe proper alignment and consistency between concepts and the most frequently occurred annotations. These tables closely resemble their Spanish counterparts (Tables 6 and 7), with identical top 10 concepts.

SNOMED	SNOMED Concept description	Count	Most occurrent
417163006	Traumatic or non-traumatic injury (disorder)	146	lésion
38341003	Hypertensive disorder, systemic arterial (disorder)	94	hypertension artérielle
55342001	Neoplastic disease (disorder)	78	tumeur
157670007	Injury NOS (disorder)	51	lésions
30746006	Lymphadenopathy (disorder)	46	adénopathie
77176002	Smoker (finding)	41	fumeur
441457006	Cyst (disorder)	34	kyste
40733004	Infectious disease (disorder)	33	infection
128462008	Metastatic malignant neoplasm (disorder)	30	métastase
44054006	Diabetes mellitus type 2 (disorder)	26	diabète sucré de type 2

Table 3: Top 10 concepts in our French DISTEMIST dataset, with the most occurrent annotation found.

Furthermore, we compare our French DISTEMIST dataset with the one created by the original authors through a lemmatization-based projection of annotations. Table 8 in the Appendix highlights that the most frequent concept has a remarkably higher occurrence count, and its most occurred annotation is inconsistent. This is likely caused by the translation and lemmatization of the word "HTA", leading to "et", a French coordinating conjunction.

Additionally, the top 10 concepts do not align with the Spanish dataset, suggesting that the authors likely detected additional SNOMED concepts and missed those already present in the original Spanish corpus.

5.3 Comparison and evaluation of the full projection pipeline

5.3.1 Quantitative Evaluation

In this comparative study, we evaluate the quantitative aspects of entities and codes linked to medical terminologies across five datasets (Table 4).

Our analysis focuses on the original datasets and their projected counterparts. Both versions of CANTEMIST demonstrates that all entities were appropriately linked to an ICD-O code, signifying the preservation of entity-code associations through our annotation projection methodology. The slight difference in entity and code quantities between the original and projected dataset was expected due to manual corrections.

We also examine the French versions of the DISTEMIST dataset, namely DISTEMIST-FR (Miranda-Escalada et al. 2022), and DISTEMIST-FR (FRASIMED), in comparison to the original Spanish DISTEMIST-ES dataset. Like the CANTEMIST-FR dataset, our annotation projection methodology maintains consistency by retaining entities and codes from the original DISTEMIST-ES dataset and DISTEMIST-FR (FRASIMED). In contrast, the original DISTEMIST authors' alternative approach, using string-matching with translation and lemmatization, overlooked some entities. However, their method identified novel links to SNOMED terminologies, indicating a trade-off between entity coverage and new code associations.

Dataset	# Entities	# Codes
CANTEMIST-ES (Miranda-Escalada et al. 2020)	16’032	16’032
CANTEMIST-FR (ours)	15’978	15’978
DISTEMIST-ES (Miranda-Escalada et al. 2022)	8’065	5’136
DISTEMIST-FR (Miranda-Escalada et al. 2022)	6’447	6’445
DISTEMIST-FR (ours)	8’059	5’132

Table 4: Quantitative comparison between datasets

5.3.2 Qualitative Evaluation

The Table 5 presents the results of the qualitative evaluation conducted on 640 annotation projection pairs extracted from both our annotation projection pipeline and the one used by the original DISTEMIST authors. The choice of this sample size was deliberate, ensuring a sufficient level of statistical robustness with a 99% interval confidence and a margin of error of 5%.

During the qualitative analysis, a trained medical student was engaged to meticulously assess and analyze instances of poor annotation projections within these pairs. The evaluation specifically aimed to identify and categorize various types of problematic projections, shedding light on both the strengths and weaknesses of the two approaches.

Dataset created with projections	**Bad projections**	**Bad translations caused by abbreviations**	**Other bad translations**
CANTEMIST (ours)	11 (1.72%)	22 (3.44%)	31 (4.84%)
DISTEMIST (Miranda-Escalada et al. 2022)	**2 (0.31%)**	**2 (0.31%)**	**9 (1.41%)**
DISTEMIST (ours)	7 (1.09%)	7 (1.09%)	35 (5.5%)

Table 5: Qualitative evaluation of the projections, on 640 projection pairs for each dataset

The Table 5 reports the findings in three distinct categories:

Bad projections: These instances arise when the annotation projection results in semantically inaccurate associations between entities, often due to missing words in the projected annotations. The relatively low frequency of such occurrences attests to the effectiveness of both annotation projection algorithms in establishing accurate associations between entities. The primary cause of these omissions can be attributed to the limitations of MT in fully translating certain expressions.

Bad translations caused by abbreviations and **other bad translations:** In these cases, the annotation projection successfully establishes correct associations between entities. However, the translations are subpar due to the MT system's limitations in handling abbreviations or other factors unrelated to abbreviations, such as the use of unusual words in the clinical field or mistranslation of technical terms.

Comparing the annotation projection quality between the original authors of DISTEMIST and our approach, the original authors demonstrate superior annotation projection quality. Their string-matching based method prioritizes precision over recall, accurately detecting entities but potentially missing some in the process. Indeed, their approach results in fewer bad projections related to translation errors.

Conversely, in the case of FRASIMED, the alignment-based approach aims to match each concept, even if translations are suboptimal, leading to a higher number of mistranslated annotations. Instances of erroneous annotation projections, independent to mistranslations, constitute less than 2% of the total annotations.

6. FRASIMED Enrichment and Release

Data augmentation through ICD-O-3 to SNOMED-CT mappings. As SNOMED-CT is a versatile terminology with the ability to establish mappings with diverse international terminologies and classifications, we improve the French CANTEMIST dataset by adding the SNOMED-CT links. This is achieved through the mapping operation from ICD-O-3.1 to SNOMED-CT utilizing the UMLS Metathesaurus (Unified Medical Language System) as a pivotal terminological framework. This additional mapping allowed the addition of 15’457 new SNOMED codes (Table 9 in the Appendix). The whole dataset contains 24’037 annotations, with links to 15’978 ICD-O and 20’589 SNOMED codes.

Dissemination of FRASIMED. In a spirit of fostering research endeavors in French NLP, specifically in the domains of Clinical Medical Entity Recognition and Entity Linking to terminologies such as SNOMED-CT and ICD-O-3, we have made FRASIMED, encompassing the CANTEMIST and DISTEMIST datasets, accessible to the public. To the best of the authors’ knowledge, this is the first large French dataset annotated with ICD-O and SNOMED concepts that has been made publicly available. This initiative aims to catalyze advancements in the French NLP field and encourage researchers to make novel contributions.

7. Conclusions

In conclusion, this study has introduced a robust methodology centered around crosslingual annotation projection, facilitating the generation of translated versions of annotated datasets. Employing a language-agnostic BERT-based approach, this method not only offers an efficient solution for projecting annotations across diverse languages, including those with limited resources, but also presents a practical case for expediting the creation of annotated datasets with preserved semantic and domain-specific information.

Through the practical application of this methodology, exemplified by the development of FRASIMED, we have achieved notable efficiencies in terms of time and resources. The technique's ability to transfer annotations from a source language to a target language obviates the need for manual annotation from scratch, thereby highlighting its potential to create a large resource with minimal effort, including for low-resource languages.

Our extensive experimentation has thoroughly assessed the quality and efficacy of the crosslingual annotation projection approach. While mistranslations are hurdles, it is crucial to note that the methodology of our semi-automatic annotation projection pipeline remains independent from the MT system. Its applicability extends to any bilingual corpus. Hence, we posit that the efficacy of our approach would have been further pronounced if the bilingual sentence pairs were not produced through MT.

With the release of the French annotated resource, brought into existence via this methodology, this work does not only contribute to advancing crosslingual annotation projection as a valuable tool in NLP but also fosters advancements in linguistic research and applications in the clinical French NLP. With this resource as a starting point, we encourage researchers to make future contributions, particularly to the automatic detection of SNOMED-CT concepts in French free-text.

8. Code and Data Availability

FRASIMED, composed of clinical synthetic cases for French NER and Entity Linking, is freely available: https://zenodo.org/record/8355629. The code is also available on GitHub in the following link: https://github.com/JamilProg/crosslingual_bert_annotation_projection).

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Appendix: Tables for Experiment 5.2

ICD-O	ICD-O Concept description	Count	Most occurent
8000/6	Neoplasm, metastatic	5736	metástasis
8000/1	Neoplasm, uncertain whether benign or malignant	2811	tumor
8000/3	Neoplasm, malignant	974	malignidad
8140/3	Adenocarcinoma, NOS (not otherwise specified)	488	adenocarcinoma
8010/3	Carcinoma, NOS	223	carcinoma
8500/3	Infiltrating duct carcinoma, NOS	217	carcinoma ductal infiltrante
8140/6	Adenocarcinoma, metastatic, NOS	212	metástasis de adenocarcinoma
8720/3	Malignant melanoma, NOS	166	melanoma
8010/9	Carcinomatosis	136	carcinomatosis
8001/1	Tumor cells, uncertain whether benign or malignant	132	células tumorales

Table 6: Top 10 concepts in the Spanish CANTEMIST dataset, with the most occurrent annotation in the corpus

SNOMED	SNOMED Concept description	Count	Most occurrent
417163006	Traumatic or non-traumatic injury (disorder)	147	lesión
38341003	Hypertensive disorder, systemic arterial (disorder)	95	hipertensión arterial
55342001	Neoplastic disease (disorder)	78	tumor
157670007	Injury NOS (disorder)	51	lesiones
30746006	Lymphadenopathy (disorder)	46	adenopatías
77176002	Smoker (finding)	41	fumador
441457006	Cyst (disorder)	34	quiste
40733004	Infectious disease (disorder)	33	infección
128462008	Metastatic malignant neoplasm (disorder)	30	metástasis
44054006	Diabetes mellitus type 2 (disorder)	26	diabetes mellitus tipo 2

Table 7: Top 10 concepts in the Spanish DISTEMIST dataset, with the most occurrent annotation in the corpus

SNOMED	SNOMED Concept description	Count	Most occurrent
38341003	Hypertensive disorder, systemic arterial (disorder)	385	et
417163006	Traumatic or non-traumatic injury (disorder)	297	lésion
55342001	Neoplastic disease (disorder)	159	tumeur
157670007	Injury NOS (disorder)	107	lésions
128462008	Metastatic malignant neoplasm (disorder)	78	métastases
441457006	Cyst (disorder)	70	kyste
30746006	Lymphadenopathy (disorder)	60	adénopathies
385494008	Hematoma (disorder)	52	hématome
40733004	Infectious disease (disorder)	46	infection
77176002	Smoker (finding)	44	fumeur

Table 8: Top 10 concepts in the French DISTEMIST dataset released by the original authors.

SNOMED	SNOMED Concept description	Count	Most occurrent
14799000	Neoplasm, metastatic (morphologic abnormality)	5727	métastases
86251006	Neoplasm of uncertain behavior (morphologic abnormality)	2856	tumeur
1240414004	Malignant neoplasm (morphologic abnormality)	1004	cancer
1187332001	Adenocarcinoma (morphologic abnormality)	658	adénocarcinome
58477004	Infiltrating ductular carcinoma (morphologic abnormality)	332	carcinome canalaire infiltrant
1187425009	Carcinoma (morphologic abnormality)	307	carcinome
4590003	Adenocarcinoma, metastatic (morphologic abnormality)	228	métastase d'adénocarcinome
1162635006	Malignant melanoma (morphologic abnormality)	168	mélanome
1162767002	Squamous cell carcinoma (morphologic abnormality)	168	carcinome épidermoïde
307593001	Carcinomatosis (disorder)	135	carcinomatose

Table 9: Top 10 concepts in the French CANTEMIST dataset regarding the added SNOMED concepts