Seeds of Discourse: A Multilingual Corpus of Direct Quotations from African Media on Agricultural Biotechnologies

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Abstract

Direct quotations play a crucial role in journalism by substantiating claims and enhancing persuasive communication. This makes news articles a rich resource for opinion mining, providing valuable insights into the topics they cover. This paper presents the first multilingual corpora (English and French) featuring both manually annotated (1,657) and automatically extracted (102,483) direct quotations related to agricultural biotechnologies from a curated list of Africa-based news sources. In addition, we provide 665 instances annotated for Aspect-Based Sentiment Analysis, enabling a fine-grained examination of sentiment toward key aspects of agricultural biotechnologies. These corpora are freely available to the research community for future work on media discourse surrounding agricultural biotechnologies.

1 Introduction

Climate change presents novel challenges and has spurred significant debate regarding how to ensure global food security while maintaining environmental sustainability. One technological tool that animates these debates is agricultural biotechnology. Often referred to as genetically modified organisms (GMO), agricultural biotechnologies are crop varieties that have been bred using the tools of modern molecular biology to alter a plant's genetic composition. For some, these technologies are a powerful means to address severe events like drought and pest infestation. Others, however, question their connections to large agribusiness conglomerates, arguing that agricultural biotechnologies are good for business, but not necessarily the environment.

Debates regarding the potential benefits of biotechnology unfold in media outlets. Agribusiness companies have placed ads for their products in newspapers (Nestle, 2019; Glover, 2010), activists have penned op-eds, and investigative journalists have uncovered vast networks of influence amongst agribusiness and non-profits.[1] More recently, initiatives seeking to bring GM crops to African farmers have explicitly developed and funded media organizations as a core part of their work (Rock and Schurman, 2020). This indicates that proponents of GM crops see the media as an essential component of crop development and promotion.

Given the importance of media for both civic debates and the development of agricultural biotechnologies, academics have examined how networks amplify messages around GM crops (Calabrese et al., 2019), asked if and how misinformation spreads within the media (Lynas et al., 2022), and analysed social media networks (Crossland-Marr et al., 2023).

Understanding the use of media in a complex space like agricultural biotechnology is a task well-suited for combining tools of data and social science. Data science allows for the retrieval and analysis of millions of articles, while social science offers the contextual knowledge required to conduct deep analysis. Our main contributions include: (1) the first multilingual corpora (in English and French), featuring both manually annotated (1,657) and automatically extracted (102,483) direct quotations from news media on agricultural biotechnologies, (2) along with 665 instances annotated for Aspect-Based Sentiment Analysis (ABSA) that is freely available to the research community.

[1] https://tinyurl.com/gov-pesticides

2 Related Work

Quotation extraction. Quotations play a key role in news articles by supporting claims and enhancing persuasive communication. While many works focus on building resources for direct quotations (Pouliquen et al., 2007; O'Keefe et al., 2012; Zhang and Liu, 2021), some also explore indirect and mixed quotations (Pareti et al., 2013; Zhang et al., 2023; Petersen-Frey and Biemann, 2024). In this paper we are focusing on direct quotations due to their traceability and informativeness, which enhance credibility, authority, and transparency (Esser and Umbricht, 2014).

Aspect-Based Sentiment Analysis. The widespread availability of textual data from social media and online news platforms has opened up new opportunities to analyse public sentiment towards various topics (Wankhade et al., 2022). ABSA, in particular, offers a more fine-grained approach by examining sentiment towards different aspects of an entity in a text (Pontiki et al., 2014). However, existing ABSA corpora are mostly limited to domains such as restaurant and e-commerce reviews, highlighting a need for broader coverage (Chebolu et al., 2023). In this work, we build on the corpus proposed by Chiril et al. (2024), which includes 1,553 English language instances pertaining to agricultural biotechnologies.

3 Data and Annotation

3.1 Data Collection

To build our dataset, we relied on a subset of 1.2M articles from the available corpus collected by Chiril et al. (2024). This dataset comprises nearly 2M news articles published over a 26-year period,[2] and were sourced from the Dow Jones premium publication archive using the Factiva Snapshots API.[3] We further refine this collection by selecting only articles from a curated list of Africa-based publishers, allowing us to focus specifically on discourse originating from, and disseminating within, the continent. This resulted in a corpus comprising 804,000 English and 300,000 French news articles.

3.2 Methodology

For the task at hand (i.e., quotation extraction), we experimented with several models that have shown remarkable performance on various NLP tasks (Qiu et al., 2020). To this end, we fine-tune the following models: `distilBERT` (Sanh et al., 2019), `BERT-base-multilingual` (Devlin et al., 2019), and `XLM-RoBERTa` (Conneau, 2019)[4] on the dataset proposed by Zhang and Liu (2021).[5] Given the sequence length limitation of these models, we segment each article into individual paragraphs (based on the presence of two consecutive newline characters),[6] and use these smaller text segments as our test set. In this manner, over 5,000 quotations were extracted from articles for labelling.

The main drawback of these models, is their need for large amounts of training data. Inspired by recent advancements in NLP, where Large Language Models (LLMs) have evolved to manage increasingly complex language generation tasks,[7] we include a `LLaMA` model (Dubey et al., 2024)[8] for comparison.

In addition to quotation extraction, our interest extends to attributing these statements to their corresponding speakers and identifying how the speakers are introduced to the reader. Consider the following direct quotation:

> *"You can't build a peaceful world on empty stomachs and human misery."*

this quote takes on additional significance when associated with the speaker, Nobel Peace Prize laureate Dr. Norman Ernest Borlaug (i.e., the identity of the speaker can amplify the impact and urgency of the message conveyed (Gagich et al., 2014)). In simple cases, attribution follows clear syntactic patterns, where the speaker is explicitly mentioned (e.g., SPEAKER *said* QUOTATION). However, more complex scenarios can oc-

[2] From January 1, 1997, to March 13, 2023.

[3] The material was collected using a set of representative keywords (e.g., *crop names*, *organizations involved in the development of GM crops*) and it originates from a diverse range of sources, including non- and for-profit media outlets, as well as government media.

[4] To train the models, we used their HuggingFace PyTorch implementations (Wolf et al., 2019), with default parameters.

[5] This corpus consists of 19,706 text segments extracted from news articles, with manually annotated quotation spans and corresponding speakers.

[6] While it is possible for a quotation to span multiple paragraphs (e.g., in literary works, academic writing), this is less frequent in news articles, where journalists often break up lengthy quotations by paraphrasing or summarizing a speaker's statements.

[7] For a comprehensive overview of LLM capabilities see Guo et al. (2023) and Chang et al. (2024).

[8] `https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct`

cur, such as when the speaker is indirectly referenced through pronominal anaphora (e.g., *"he said"*, cf. Figure 1) or nominal anaphora (e.g., *"the farmer said"*). To handle these challenges, we leverage the capabilities of the LLaMA model: instead of processing only a single paragraph, we provide the entire article and prompt the model to extract all the direct quotations along with their corresponding speakers, accounting for cases where the reference is indirect or distant. The pipeline used for creating our corpus is presented in Figure 1.

3.3 Annotation Protocol

Assessment of Extracted Quotes' Quality. The primary goal of this annotation task is to evaluate the performance of a suite of models on the task of quotation extraction and attribution. Each instance is evaluated and assigned one of three labels based on the performance of the quotation extraction model: *perfect*, *good* (the extracted span is missing at most two words), and *poor* (the extracted span is missing more than two words, or the model completely failed to capture the quotation). For instances labelled as good or poor, annotators were further required to manually select the correct span. In addition, for assessing the quality of the LLaMA model performance on quotation attribution, annotators reviewed 100 (full) articles and evaluated the accuracy of the extracted speakers.[9]

Aspect-Based Sentiment Analysis. To better understand *what* is being discussed and *how*, the main purpose of this annotation task is assigning a polarity (*positive*, *neutral*, *negative*, *conflict*) to each of the aspect categories (entity-attribute pairs) identified within the quotation. To this end, we extend the English corpus (along with the annotation guidelines) proposed by Chiril et al. (2024) to also include a small set of French data. The entities considered for the task at hand include: *crops, organizations, agricultural practices, natural resources, geographic locations, technology, legal aspects & politics, environmental conditions, economic factors, programs & initiatives*, and *other*. The attributes can be assigned one of the following nine labels: *resistance, consumer perception, safety, food security, productivity, economic impact, research development, environmental & ethical concerns*, and *miscellaneous*.

3.4 Annotation Results

The annotation process was conducted in multiple stages. During the initial pilot phase, we aimed to refine the annotation scheme, and ensure task understanding and annotation consistency. In this phase, we used a total of 150 quotations . Following this stage, the eight annotators,[10] worked on small sets of quotations, with any arising issues being discussed on a weekly basis. The inter-annotator agreement for a set of 200 quotations, measured in terms of F1-score (a common alternative to Cohen/Fleiss kappa for NER/spans), is 100% and 99.5% for quotation extraction, 83.7% and 70.8% for the identification of entity type, 83.3% and 76.7% for the attribute, and 78.2% and 61.6% for tuples of the form (entity-attribute pair, sentiment), in English and French, respectively.[11] Given the amount of data to label, the students were each assigned distinct subsets of the corpus for annotation, using the open-source platform LabelStudio (Tkachenko et al., 2020-2022).[12] After this phase was completed, the two senior annotators reviewed and corrected the annotated instances. The final corpus consists only of instances where minimum two annotators reached consensus, totalling 1,657 direct quotations (1,299 in English and 358 in French). Of these, 665 (357 in French and 308 in English) quotes were labelled for ABSA, containing 1,719 relevant entities. Table 1 presents examples of the annotation of various aspects within quotations in both English and French.

3.5 Quantitative Results

For evaluating the quotation extraction model, we rely on two different metrics: *exact match* and an *overlap metric* (Pareti et al., 2013). The annotation procedure revealed that the quotation extraction model perfectly identified quotes in 11.9% of the

[9] Many of the manually labelled paragraphs included speakers referenced indirectly. While transformer models are capable of correctly identifying these speakers, an additional step (i.e., coreference resolution) would have been necessary to resolve the mentions.

[10] Six students (three proficient in English, three in French/four females and four males) and two of the paper's authors.

[11] The labelling tasks varied widely in difficulty. For some labelling tasks, we observed moderate inter-annotator agreement, highlighting the complexity of the task. For others, near perfect agreement is reflective of the straightforward nature of the task.

[12] The corpora containing all the annotated instances, as well as the new annotation guidelines, will be made available to the research community upon acceptance.

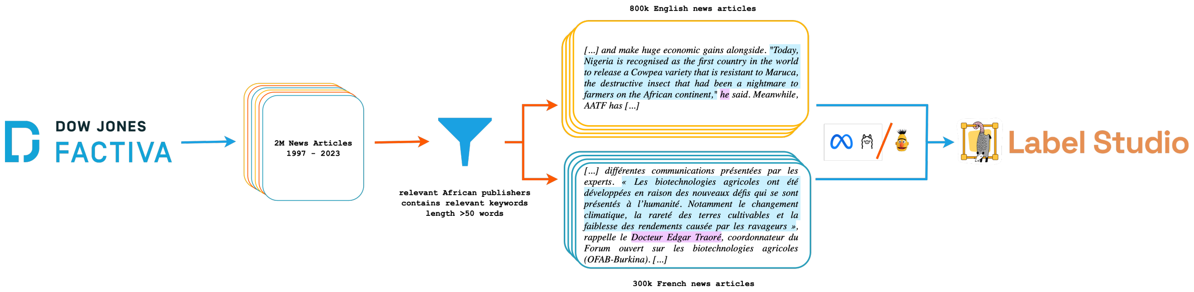
DOW JONES
FACTIVA
2M News Articles
1997 - 2023
relevant African publishers
contains relevant keywords
length >50 words
800k English news articles
[...] and make huge economic gains alongside. "Today, Nigeria is recognised as the first country in the world to release a Cowpea variety that is resistant to Maruca, the destructive insect that had been a nightmare to farmers on the African continent," he said. Meanwhile, AATF has [...]
[...] différentes communications présentées par les experts. « Les biotechnologies agricoles ont été développées en raison des nouveaux défis qui se sont présentés à l'humanité. Notamment le changement climatique, la rareté des terres cultivables et la faiblesse des rendements causée par les ravageurs », rappelle le Docteur Edgar Traoré, coordonnateur du Forum ouvert sur les biotechnologies agricoles (OFAB-Burkina). [...]
300k French news articles
Label Studio

Figure 1: Pipeline for the creation of the corpus.

Aspect Category Entity # Attribute	Polarity	Example
CROPS # CONSUMER PERCEPTION CROPS # PRODUCTIVITY	positive positive	*"the beauty of the bt variety is the quality of the yarn produced from it. It is better and the yield is higher so why would we stick to the old variety that doesn't give the quality and quantity the bt variety gives?"*
LEGAL ASPECTS & POLITICS # SAFETY	positive	*"Text and pictures advertising health warnings shall appear together and shall occupy no less than 75% of the packet display. All tobacco products should conform to the regulations"*
ENVIRONMENTAL CONDITIONS # PRODUCTIVITY ENVIRONMENTAL CONDITIONS # ECONOMIC IMPACT	negative negative	*"Exacerbées par les impacts du conflit, la sécheresse de 2018 et les inondations survenues en 2019 ont été catastrophiques pour les petits exploitants agricoles, les empêchant de cultiver de vastes parcelles de terres ou de constituer des surplus de stocks de semences qui pourraient ensuite être utilisés lors des prochaines plantations. Ce qui a également perturbé les marchés locaux."* *("Exacerbated by the impacts of the conflict, the 2018 drought and the floods of 2019 were catastrophic for smallholder farmers, preventing them from cultivating large areas of land or building surplus seed stocks that could later be used for future planting. This also disrupted local markets.")*
ENVIRONMENTAL CONDITIONS # SAFETY	negative	*"Des pluies torrentielles ont depuis la mi-septembre causé des dégâts considérables dans l'ensemble du pays. Ces inondations sont les pires au Bénin depuis plus d'un siècle."* *("Since mid-September, torrential rains have caused considerable damage throughout the country. These floods are the worst in Benin in over a century.")*
ENVIRONMENTAL CONDITIONS # ECONOMIC IMPACT	negative	*"D'ici 2050, le changement climatique entraînera une augmentation de 25 % du prix des céréales, en comparaison avec un scénario sans le facteur de changement climatique."* *("By 2050, climate change will lead to a 25% increase in cereal prices, compared to a scenario without the climate change factor.")*

Table 1: Examples of annotated quotations in the corpus that reference various aspect categories.

cases and exhibited good performance in 82.1% of the cases. Table 2 shows the performance for the task (cf. Section 3.2). Surprised by the relatively poor performance of LLaMA, we performed a manual error analysis, and identified several issues: the model occasionally splits quotations, extracts a quotation followed by a substring of said quotation, or, in rare cases, includes mentions (i.e., a scientific term placed in quotes). Based on this analysis, we implemented filters to exclude quotations that are substrings of another quotation, quotations without an identified speaker, and quotations shorter than 4 words.

Model	Language (# of instances)	
	English (1,302)	French (314)
distilBERT	96.5	–
BERT-base-multilingual	96.6	98.1
XLM-RoBERTa	96.3	98.6
llama-3.1-8B	88.6	90.3

Table 2: Quotation extraction results.

We then repeat the same experiments on a larger set of articles, including only the quotations on which all models reached consensus in the final dataset, resulting in a total of 102,483 instances (59,501 and 42,982 quotations in French and English, respectively).

maybe the next paragraph we put as a footnote and we add the stuff in an anonymous repo Table **??** presents the number of annotated instances per aspect category in the corpus. These initial results provide valuable insights into public discourse surrounding agricultural biotechnologies.

4 Conclusion and Perspectives

In this paper, we have presented the first multilingual corpora which includes direct quotations and ABSA annotations pertaining to agricultural biotechnologies. A model trained on this data, combined with quotation attribution, could enable a comprehensive analysis of media representations of agricultural biotechnologies in Africa, uncovering connections between news outlets and quoted sources, while examining the sentiment expressed in these quotations. Although the broader applications of such analysis lie beyond the scope of this article, we believe that our corpora will be a valuable resource for future work in analysing media representations of GM crops, and exploring the discourse structure surrounding agricultural biotechnologies.

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