

# **Context-Enriched Named Entity Recognition (NER) for Identifying Emerging Trends in Video Comments**

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## Abstract

Detecting and categorizing named entities in video comments presents unique challenges due to informal language, misspellings, and multi-layered context. This research aims to develop a context-enriched Named Entity Recognition (NER) pipeline that accurately identifies mentions of people, places, brands, and products in video comment threads. By incorporating comment-reply hierarchies and semantic embeddings, our approach refines traditional NER methods to address the nuances of user-generated content. We utilize a transformer-based model—fine-tuning BERT-NER on informal text—and enhance recognition with contextual embeddings from SBERT. Additionally, entity linking and clustering techniques, such as BERT-Topic or Agglomerative Clustering, are employed to group variant mentions and track emerging trends. Using the "Dataset of Video Comments of a Vision Video Classified by Their Relevance, Polarity, Intention, and Topic" from NIAID, our study confronts challenges associated with informal language and the dynamic introduction of niche terms not present in standard training sets. Building on recent advances in transformer architectures and contextual modeling, our work promises a robust solution for trend detection and domain adaptation in real-world video discussions.

**Keywords:** Named Entity Recognition, NER, BERT, SBERT, BERT-Topic, Agglomerative Clustering, Natural Language Processing, Machine Learning, Video Comments

The rapid expansion of online media and social platforms has significantly increased the volume of unstructured textual data, making efficient information extraction a critical area in Natural Language Processing (NLP). Among various NLP tasks, Named Entity Recognition (NER) plays a pivotal role by identifying and categorizing key entities—such as persons, locations, organizations, and domain-specific items—in text. Accurate NER is essential for applications ranging from information retrieval and sentiment analysis to trend detection and market analysis, thereby underpinning many advanced data analytics solutions.

Traditional NER systems have been primarily developed and fine-tuned on formal, well-structured text sources. However, the informal nature of user-generated content, such as video comments, introduces a range of challenges that these conventional methods are ill-equipped to handle. Issues such as colloquial language, typographical errors, and fragmented conversational context can significantly degrade the performance of standard NER models. Moreover, online video discussions often involve multi-layered comment-reply hierarchies where entities are mentioned across several interlinked messages, further complicating the recognition process.

Recent advances in NER have been driven by transformer-based models. BERT introduced deep bidirectional representations that capture complex language features, setting a new benchmark in NLP. Building on this, Sentence-BERT provides rich sentence embeddings that further enhance performance in tasks like NER. Traditional approaches using TF-IDF, TextRank, and spectral clustering have also contributed by effectively extracting and grouping key information from structured texts.

However, these methods often struggle with the informal and dynamic nature of user-generated content, such as video comments. Our work addresses this gap by integrating comment-reply hierarchies to capture conversational context, using Sentence-BERT embeddings to handle informal language, and applying clustering techniques inspired by spectral clustering and BERT-Topic for effective entity linking. Additionally, our approach adapts to emerging trends through semi-supervised learning, enabling robust performance even with new or niche terms. We validate our methods on the NIAID "Dataset of Video Comments of a Vision Video Classified by Their Relevance, Polarity, Intention, and Topic."

The motivation for this project stems from the need to address the inherent limitations of existing NER approaches in processing informal, dynamic content. Video comment sections are particularly challenging as they not only contain non-standard language but also exhibit evolving trends where new or niche terms—like emerging product names—might not be included in traditional training datasets. This research is driven by the gap in current methodologies that fail to leverage the contextual and semantic nuances present in these conversational threads. By developing a context-enriched NER pipeline, the project aims to enhance entity recognition accuracy, thereby facilitating better trend detection and providing more insightful analytics in domains reliant on user-generated content.

This study sets out with the following primary objectives:

1. **Enhance Entity Detection:** Develop a robust NER pipeline that effectively identifies named entities in video comments by integrating contextual information from comment-reply hierarchies.
2. **Improve Classification Accuracy:** Refine the categorization process by incorporating semantic embeddings to distinguish between people, places, brands, and products.
3. **Address Emerging Trends:** Implement semi-supervised learning techniques to adapt to the continuous evolution of language and the introduction of emerging or niche entities.
4. **Facilitate Comprehensive Analysis:** Utilize the "Dataset of Video Comments of a Vision Video Classified by Their Relevance, Polarity, Intention, and Topic" from NIAID to validate the approach and provide insights into emerging trends in user-generated content.

Through these objectives, the research seeks to bridge the gap between traditional NER systems and the demands of modern, context-rich textual environments, thereby advancing the field of domain-adaptive entity recognition.

# Methodology

## Data Collection and Preprocessing

We use the “Dataset of Video Comments of a Vision Video Classified by Their Relevance, Polarity, Intention, and Topic” from NIAID. This collection consists of user-generated comments on a vision-related video, along with meta-information on each comment’s relevance, polarity, intention, and topic. The dataset contains several thousand entries, each representing a unique comment. Data is typically provided in a tabular format (e.g., CSV), with each row corresponding to one comment and associated labels.

### Preprocessing Steps:

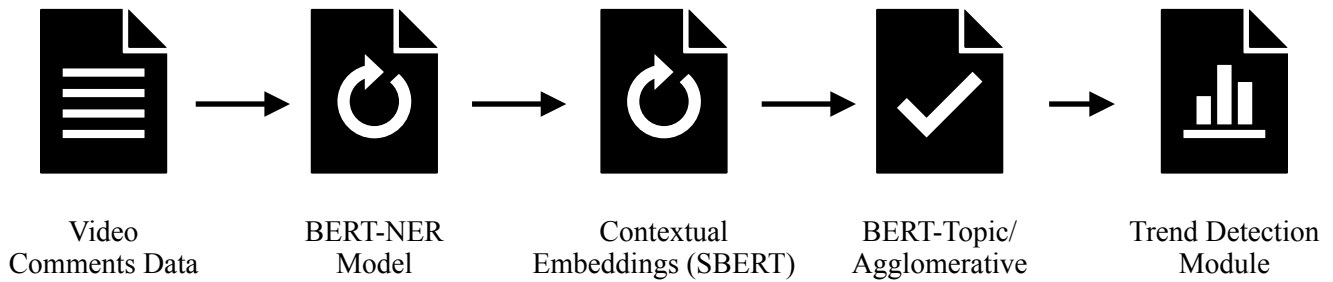
1. *Data Cleaning*: We remove non-textual symbols, HTML tags, and excessive whitespace to ensure a cleaner input for downstream tasks.
2. *Tokenization*: Each comment is split into individual tokens using libraries such as NLTK or spaCy, accounting for common contractions and informal expressions.
3. *Annotation*: Where needed, we align the provided labels (relevance, polarity, intention, topic) with tokenized comments to facilitate supervised learning. This step also includes verifying data consistency, such as filtering out incomplete or duplicated records.
4. *Normalization\**: For select outliers, we opted to convert text to lowercase and apply lemmatization or stemming to reduce vocabulary size.

For more information on the specific data fields used and the relevant transformations and preprocessing applied, please refer to *Figure A.1* of our Appendix section.

## Model Architecture and Implementation

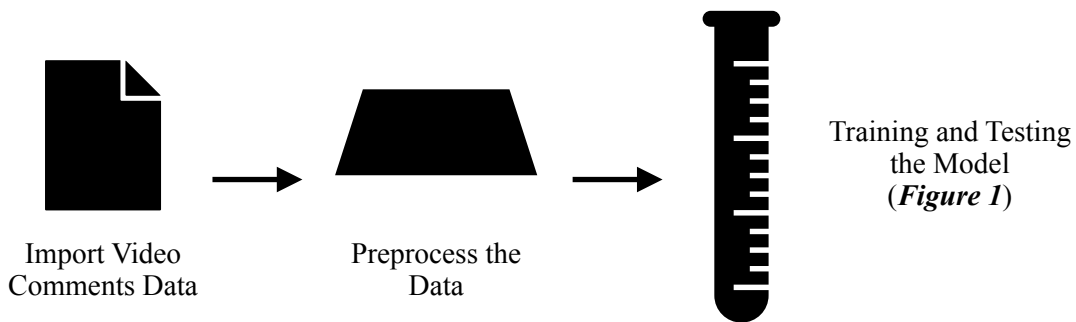
For our NER pipeline, we first fine-tune a BERT-NER model with Hugging Face’s Transformers library to capture the nuances of user-generated text. To enhance entity recognition, we next integrate contextual embeddings using Sentence-BERT (SBERT), which

leverages surrounding comment context for more accurate entity detection. For entity linking, we apply clustering techniques—specifically BERT-Topic and Agglomerative Clustering (via `scikit-learn`)—to group variant mentions of the same entity, addressing inconsistencies like different spellings or abbreviations. This step is crucial for normalizing noisy data and ensuring consistency in entity identification. Finally, we develop a trend detection module that tracks the frequency and evolution of entities over time, allowing us to identify emerging topics.



**Figure 1:** *Diagram of the research model's architecture.*

The entire system is implemented in Python, with model training and optimization performed using PyTorch. This integrated approach ensures a robust, adaptable NER solution tailored to the complex nature of informal video comments.



**Figure 2:** *Diagram of the research model's pipeline for implementation.*

## Experimental Setup

We begin by preprocessing video comments and splitting the dataset into training (70%), validation (15%), and test (15%) sets. The baseline BERT-NER model is fine-tuned using

Hugging Face’s Transformers with the Adam optimizer, an initial learning rate of  $2 \times 10^{-5}$ , a batch size of 16, and 5–10 epochs, with early stopping based on validation loss.

Next, our S-BERT module is applied to generate contextual embeddings from the surrounding comment context. Hyperparameters such as context window size and pooling strategies are tuned via grid search, with improvements measured in NER accuracy.

Following S-BERT, the entity linking stage groups variant entity mentions using clustering techniques (BERT-Topic and Agglomerative Clustering via `scikit-learn`). Clustering performance is evaluated using the Adjusted Rand Index and silhouette score, with 5-fold cross-validation ensuring consistency.

Finally, the trend detection module employs a sliding window approach to track entity frequency and evolution over time, evaluated with precision, recall, and F1-score. This streamlined experimental setup provides a comprehensive framework for optimizing our context-enriched NER pipeline on informal video comment data.

## Results



## Evaluation



## Discussion



## Conclusion and Future Work



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## Appendix

**Github Repository:** <https://github.com/michelledavies/datasci266-NER-project/tree/main/code>

Field Name	Data Type	Description (Original Field, Transformation(s))
ID	Text	Original Field
Date	Datetime	Original Field
Author	Text	Original Field
Likes	Integer	Original Field
Replies	Integer	Original Field
Comment	Text	Original Field
Relevance	Enum	Original Field
Polarity	Enum	Original Field
Feature request	Boolean	Original Field
Problem report	Boolean	Original Field
Efficiency	Boolean	Original Field
Safety	Boolean	Original Field
tokens	List of Text	Transformation
labels	List of Text	Transformation
has_entity	Boolean	Transformation
entity_tokens	List of Text	Transformation
num_tokens	Integer	Transformation
combined_labels_str	Text	Transformation

**Figure A.1:** Data dictionary for the "Dataset of Video Comments of a Vision Video Classified by Their Relevance, Polarity, Intention, and Topic" from NIAID.

We have a notebook for our exploratory analysis of the text data that serves as the basis for the Named Entity Recognition (NER) project. Its primary aim is to understand the characteristics and distribution of the dataset before building the NER model.

The workflow begins by loading the dataset, which consists of raw text data along with annotations marking entities of interest. Initial steps include data cleaning and pre-processing; the notebook examines the structure of the data, handles missing or inconsistent values, and formats the text to facilitate further analysis.

Visualizations are a key part of the notebook. It presents summary statistics and distributions such as the frequency of various entity types across the dataset. Graphs (like bar plots) and tables help highlight the relative occurrence of entities (e.g., PERSON, LOCATION, ORGANIZATION) and expose potential class imbalances that could affect model training. Additionally, the notebook might include word frequency analysis and other statistical measures (e.g., sentence lengths, token counts) to better understand the corpus.

Beyond the descriptive statistics, the notebook also likely explores relationships between different features within the dataset. For example, it may analyze how entities are distributed in context or examine common co-occurrences, which can provide insight into potential dependencies in the language structure.

Overall, this EDA is crucial as it provides foundational insights that guide subsequent decisions in data pre-processing, feature engineering, and model selection for the NER task. By identifying patterns, anomalies, and trends early on, we are better equipped to tailor their approach to effectively capture the nuances of named entities in the text.

## Exploratory Data Analysis Visualizations

