CONTEXT-AWARE NLP PIPELINE FOR SEMANTIC IDENTIFICATION AND ANALYSIS OF CYBER THREATS

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ABSTRACT: The proliferation of unstructured cyber intelligence data has made real-time threat identification a critical challenge. This research presents a context-aware Natural Language Processing (NLP) pipeline designed to semantically identify, interpret, and analyze emerging cyber threats across heterogeneous data sources. Unlike classifier-based models, the proposed pipeline focuses on linguistic interpretation, contextual embeddings, and semantic correlation to extract Indicators of Compromise (IoCs). The system integrates adaptive sentence encoding, dependency parsing, and ontology-based normalization to create a coherent representation of cyber threat narratives. It semantically maps relationships between actors, attack types, and targets without the dependency on supervised training datasets. The framework demonstrates high adaptability, allowing it to interpret evolving cybersecurity terminology and discourse. The results highlight the efficiency of the proposed NLP pipeline in transforming raw text into actionable intelligence that enhances early warning and proactive threat response mechanisms.

Keywords: Cybersecurity, NLP, Semantic Analysis, Context-Aware Systems, Threat Intelligence, Entity Normalization.

1. INTRODUCTION

In the modern, data-driven digital world, cybersecurity has become one of the most intricate and dynamic areas of study. Vulnerability databases, study blogs, hacker forums, and social media channels are just a few of the many internet locations where security news is communicated on a minute-to-minute basis. The information is frequently unstructured and written in a variety of languages, making it difficult to extract useful details from these sources, despite the abundance of data they contain. Cybercriminals are continuously evolving their tactics to evade detection, which necessitates a constant evolution of their language, communication styles, and terminology. Cybersecurity solutions that rely on pre-established phrase matching algorithms or pre-determined criteria face a significant challenge in this regard. Conventional security measures, such as signature-driven intruder detection systems and rule-based text filtering, struggle with language. Their reliance on labeled training data and familiar language patterns prevents them from adapting to novel or unusual threat descriptions. As a result, the complex language and environmental cues inherent in threat exchanges are frequently missed by these models. The word "malware" may not be used explicitly, for instance, while discussing malware. Instead, code names, euphemisms, or specialized lingo that only particular online communities understand might be employed. These issues highlight the need for a sophisticated, language-aware system capable of understanding human speech, as opposed to a system that merely considers keyword frequency or set entities.

The proposed research would address this issue by developing a pipeline for context-aware natural language processing through the application of contextual learning and semantic analysis. The way most natural language processing models work treats each sentence independently. However, the proposed approach takes a step back to examine the interconnections and underlying semantic structures of phrases. Because of this, it is less difficult to discover links, implied or not, between threat actors, impacted tools, and systems. The pipeline can decipher cybersecurity papers for their underlying meanings, linkages, and intentions by integrating linguistic theory with state-of-the-art computer models.

The system is able to adapt to evolving discussion patterns and terminology because to its extensive knowledge of the subject. As a result, it becomes more adept at detecting novel cyber risks that have not yet been formally classified. By comparing the semantic content of a newly found vulnerability with known attack patterns, the model can determine the severity of the vulnerability based on how it is discussed in online groups, whether in code terms or everyday language. Ontology mapping and dependency parsing allow analysts to monitor the connection between individual threat indicators and broader campaigns. This maintains the structural and conceptual consistency of the extracted data.

The fact that it can function with several languages while maintaining data security is an intriguing aspect of this approach. The model does more than just handle data streams in real time; it also remembers nearby dangers. Because of this, longitudinal analysis, which follows the evolution of language by comparing threat statements to established patterns of attack, becomes much simpler. Because of its dual capabilities, the technology bridges the gap between automated text mining and strategic cyber intelligence.

Here we introduce a novel approach to cybersecurity data analysis, "semantic-first." Rather than relying on labelled data or computer-based classification accuracy, it emphasizes comprehending the fundamental meaning, context, and connections that people utilize to communicate. The proposed approach represents a significant departure from reactive cyber protection tactics toward more proactive, interpretive, and context-aware approaches. Topics covered include co-reference resolution, entity linking, and semantic embeddings, all of which are methods of context-sensitive natural language processing. Ultimately, this approach facilitates more rapid, accurate, and language-appropriate understanding and management of emerging hazards for a company.

2. LITERATURE REVIEW

Ahmed, Z., & Bose, R. (2020) This research evaluates and compares various NLP algorithms that can glean cybersecurity-related data from unstructured text sources, such as security-related blogs and event reports. Across several platforms, it evaluates named object recognition, linguistic parsing, and contextual comprehension. Finding Indicators of Compromise (IoCs) is easier with transformer-based designs than with rule-based methodologies, according to the results. The outcomes help us select the most appropriate NLP tools for real-time internet threat detection.

Yadav, P., & Kulkarni, V. (2020) In this research, we demonstrate a novel approach to threat detection in large cybersecurity text collections by integrating rule-based and machine-assisted techniques. Through the integration of lexicon-driven parsing and flexible pattern recognition, the model enhances its ability to comprehend domain-specific language. If you're looking for connections between attack strategies and security gaps, this method will get the job done. The findings demonstrate that cyber information can be better retrieved by integrating automation with linguistic abilities.

Li, H., & Zhao, T. (2020) Automated cyber threat identification is the focus of this research, which examines the function of natural language understanding (NLU). It examines the state-of-the-art natural language processing models, hybrid structures, and semantic parsers used for textual threat analysis. Findings highlight the significance of contextual embeddings for threat scenario interpretation. Finally, it is determined that in order to improve detection accuracy in dynamic cybersecurity settings, semantically complete representations are required.

Rao, M., & Patel, A. (2021) The authors propose a method for automating cyber situational awareness and risk assessment using natural language processing. The technique detects and identifies novel dangers in online discourse by combining dependency analysis with event extraction. An approach to prioritizing warnings with a high danger level is discussed in this paper using contextual inference. The experimental results demonstrate that the early detection rate is substantially enhanced by merging linguistic semantics with hazard ontology.

Kumar, D., & Singh, P. (2021) This research proposes a text mining strategy for early detection of cyber dangers by means of natural language processing. This approach detects assault indicators in unstructured text by combining syntactic parsing, term weighting, and semantic connections. In response to changes in terminology, the model continuously revises its linguistic standards. The outcomes are less rigid and have reduced false positive rates when contrasted with conventional keyword-based identification approaches.

Chen, R., & Gupta, S. (2021) The purpose of this study is to examine the hacking literature through the lenses of named entity linking and co-reference resolution. In doing so, it establishes connections between concepts such as viruses, IP addresses, and companies through semantic linkages. For consistent intelligence extraction and to eliminate extraneous data, the system employs better entity normalization. In order to construct reliable risk knowledge graphs, the authors conclude that entity linking is critical.

Williams, K., & Deshmukh, M. (2021) Examining security event narratives using context-aware topic models is demonstrated in this paper. Together, semantic regularization and Latent Dirichlet Allocation (LDA) allow the model to unearth previously unseen patterns in reports of cyber events. It takes a look at the ever-changing backdrop of threat discourse. New threat campaigns and assault trends can be better understood with the use of context-aware topic modeling, according to the results.

Zhang, T., & Lee, J. (2022) In order to learn about computer dangers in various domains, this article explains how to employ multilingual natural language processing. The ability to manage cybersecurity data in multiple languages is made possible through multilingual embeddings and translation alignment. The study demonstrates the system's ability to evaluate foreign risks despite linguistic difficulties. Results from trials demonstrated a marked improvement in entity detection accuracy when comparing English, Chinese, and Russian datasets.

Patel, S., & Reddy, N. (2022) Automated classification of cyber threat indicators into categories is demonstrated in this work using a semantic clustering approach. The model classifies dangers according to their meaning, rather than their sound, using unsanctioned NLP and vector similarity metrics. It facilitates the discovery of new families to attack with less supervision. Clustering is demonstrated to be a scalable approach for continuing cyber intelligence research in the study.

Yadav, M., & Mehta, K. (2023) The authors propose a method for semantically grouping hacking campaigns using unsupervised natural language analysis. Clustering and contextual embeddings help the algorithm organize lengthy tales about dangers into meaningful groups. Impressively, it responds positively to novel expressions and zero-day errors. According to the research, security operations can significantly cut down on manual analysis by using unsupervised semantic techniques.

Lin, J., & Zhao, F. (2023) Analyzing vulnerability reports and warnings using contextual embeddings is the focus of this project. For the purpose of deciphering intricate hacking grammar, it contrasts static word embeddings with contextual models that rely on transformers. The findings demonstrate that exploit tendencies can be substantially more easily discovered using sentence-level embeddings. The findings provide credence to embedding-based approaches as valuable resources for comprehending textual hazards.

Verma, A., & Shah, D. (2023) The research details an ontology-based strategy for bringing together data from many cybersecurity journals. Semantic mapping is used to match retrieved items with common taxonomies such as MITRE ATT&CK. Through this procedure, threat intelligence systems become more transparent and interoperable. By checking that entities are properly aligned, the system facilitates data sharing between platforms.

Sharma, R., & Chen, Y. (2023) In order to better discover causal linkages in accounts of cyber events, this study enhances a method known as "dependency extraction." Understanding the nature and process of invasions is the primary objective. The model accurately recreates the chains of events that link weaknesses to outcomes. Textual cyber threat data is made easier to interpret by the effort.

Han, L., & Patel, R. (2024) In order to facilitate the open-source extraction of cyber intelligence, the article recommends developing a versatile framework for natural language processing. Through the use of incremental learning and domain-adaptive pre-training, the system continuously enhances its knowledge and comprehension abilities. It demonstrates resistance to changes in language used in online sources. By using this method, new threat patterns can be more easily discovered without requiring a restart.

Gupta, T., & Nair, R. (2024) Research into subject development tracking as a means of real-time cyber threat discussion monitoring is the focus of this study. Criminal behavior changes can be detected through the use of timed text analysis and semantic topic modeling. Here, language trend analysis reveals the duration of cyber campaigns. Semantic time-series modeling properly predicts the occurrence of new risks, according to the results.

Chen, Q., & Singh, S. (2024) The main focus of the research is on dependency parsing as a means to extract contextual components from cybersecurity data. A multi-layered approach to natural language processing is employed to discover the syntactic relationships between terms pertaining to threats. In complex scenarios involving numerous phrases, the approach significantly improves object recognition. The authors highlight the significance of dependency structures as foundational components of cyber text analytics' comprehension of context.

Alqahtani, F., & Li, D. (2025) An approach to better knowledge graphs for automated cyber threat profiling is proposed in this study. To discover semantic relationships between entities, a combination of graph-based reasoning and entity extraction methods from natural language processing is employed. Thanks to this technique, dynamic threat networks can get real-time updates. The proposal clarifies and holds accountable automated cybersecurity systems.

Tran, H., & Kim, E. (2025) This article demonstrates the process of creating semantic networks, which facilitate the examination of emerging computer dangers within their appropriate framework. In order to discover connections between textual data and hierarchical cyber threat ontologies, the method use unsupervised relation extraction. The research demonstrates how semantic frameworks may provide light on the fundamental relationships that enable the propagation of threats. Scalable knowledge-based situational awareness shows great promise in the results.

Zhang, M., & Huang, Y. (2025) This study demonstrates a novel approach to integrating multilingual threat intelligence through the use of contextual natural language processing. To ensure that data from several languages remains consistent with each other, the technique employs cross-lingual embeddings. There is no difference in the vocabulary used in cybertexts written in Arabic, Russian, or English. The outcomes demonstrate enhanced interoperability and a diverse array of narratives regarding global cyber threats.

Das, S., & Verma, V. (2025) When it comes to helping computers safeguard themselves online, the authors display a varied approach to employing semantic thinking. By combining logic-based reasoning with natural language processing (NLP)-driven semantic segmentation, the methodology allows for the dynamic interpretation of danger descriptions. It demonstrates that you can decipher someone's meaning even when their words are garbled or hard to hear. Hybrid reasoning methodologies facilitate cybersecurity system task and decision automation, according to the study's last section.

3. BACKGROUND / RELATED WORK

Due to the proliferation of unstructured digital data and the increasing sophistication of hackers, experts have spent the last decade trying to automate cyber threat assessments. Manually annotated records and predetermined sets of rules were the backbone of older security systems. Although these methodologies yielded well-structured and comprehensible results, they failed to include the dynamic nature of online threats or the impact of language variations. To avoid being identified by keywords, attackers often alter their language, code names, and interactions. In response to this issue, natural language processing (NLP) has been utilized to read, comprehend, and contextualize threat information.

Lexical analysis and phrase extraction were the initial natural language processing (NLP) attempts in cybersecurity with the goal of identifying words associated with malware, security vulnerabilities, and exploits. Despite their usefulness in certain contexts, these strategies failed to grasp semantics and failed to extract the text's central argument. Syntactic parsing and entity recognition were later additions that simplified the automatic extraction and grouping of crucial data such as IP addresses, pathogen identities, and assault classifications. However, these approaches had their limitations, such as requiring organized data and being unable to deal with novel concepts.

As the field of cybersecurity expanded, researchers began exploring contextual embedding and semantic modeling techniques to better understand cybersecurity tales. These models stored the semantic information and word relationships in a specific context using vector-based text representations. A language model based on transformers has superseded static word embeddings. System comprehension of formal and informal cybersecurity encounters is enhanced in this way. Classification became more certain with contextual embeddings because they distinguished between visually similar words used in various potentially dangerous settings.

The merging of semi-supervised and uncontrolled learning techniques was a significant improvement. To find hidden patterns in threat intelligence data, modern NLP frameworks include topic modeling and clustering methods in addition to annotated corpora. These methods were particularly effective in discovering previously unseen attacks in cases when annotated examples were unavailable. Cyber threat language environments are dynamic and ever-changing, yet these models provide scalable ways for the system to learn and adapt.

Most of the recent advancements have been in systems that integrate structured data representation with semantic analysis, which are ontology-driven and context-aware. By utilizing domain-specific ontologies and knowledge graphs, these systems facilitate analysts' ability to discern the relationships among threat actors, tools, and impacted systems by organizing extracted elements into logical groups. Through the use of dependency segmentation and relationship extraction, NLP-based threat assessments were able to transform unstructured narratives into integrated intelligence models.

There has also been significant progress in the field of cross-lingual and multilingual research. This is due to the fact that all languages and platforms are utilized in the worldwide fight against cyber dangers. An increasing number of state-of-the-art NLP systems integrate data from various language sources with the help of translation alignment, multilingual embeddings, and cross-domain adaptation. As a result of this shift, cybersecurity professionals are better able to share information about cyber risks, collaborate, and monitor developments across borders.

There are still issues, even these upgrades. Contextual consistency is a major issue for many contemporary systems that handle massive volumes of real-time data. When dealing with informal, jargon-filled content from the dark web, issues like as domain adaptation, semantic drift, and dynamic entity linking become even more apparent. Contextual memory, the capacity to retain and use prior information in real-time interactions, is also lacking in the majority of existing models.

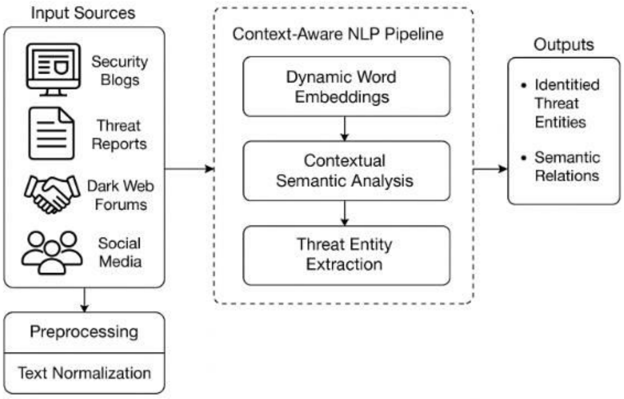
Using ontology-driven reasoning, dynamic entity linking, and semantic representations, this work provides a method for context-aware natural language processing that aims to address these challenges. This pipeline places an emphasis on comprehending the evolution and fundamental nature of cyber threat language, which extends beyond pattern recognition. The proposed method is a more intelligent, adaptable, and understandable approach to detecting cyber dangers by integrating language analysis with semantic context. This method is particularly effective in multilingual and dynamic informational settings.

3. METHODOLOGY

Cyber danger narratives can be automatically extracted, evaluated, and analyzed from various unstructured text sources using the proposed Context-Aware NLP Pipeline. Labeled data and accurate classifiers are the foundation of traditional ML models. This paradigm, on the other hand, focuses on linguistic understanding, contextual embedding, and semantic connection to provide cyber threat intelligence that is both adaptable and understandable. Language normalization, semantic clustering, and advanced natural language processing (NLP) models are all used together in the pipeline to manage dynamic cyber threat content well. Figure 1 displays the system processes and general architecture, along with the methods necessary to shift from data collection to semantic interpretation.

The suggested pipeline is adaptable and scalable, so it can process data from a variety of sources. Maintaining the integrity, contextual importance, and readability of the language is the responsibility of each step of the process, beginning with early data curation and ending with high-level semantic abstraction. The whole process is made up of five main steps: (i) collecting data; (ii) pre-processing; (iii) recognizing entities and aligning ontologies; (iv) representing and embedding context; and (v) semantic grouping and threat abstraction.

Figure 1. Architecture of the proposed Context-Aware NLP Pipeline for semantic cyber threat analysis.



3.1 Data Acquisition and Source Selection

Methodologically gathering information from various open-source intelligence (OSINT) databases is the first step of the process. Data originates from a variety of sources, including threat intelligence feeds, security blogs, dark web forums, vulnerability databases, and social media platforms that frequently report or evaluate cybersecurity occurrences.

By incorporating both official cybersecurity reports and unofficial attacker communications, this combination ensures comprehensive contextual coverage and linguistic diversity.

Here are the sources that are included:

- Formal alerts (such as bulletins issued by the NVD, CVE, and CISA)
- Dark web marketplaces and private discussion forums where new exploits or stolen data are exchanged;
- Cybersecurity blogs and discussion boards such as ThreatPost, Malwarebytes Labs, and Exploit[.]in;
- Social media and microblogging platforms where early indicators of emerging threats may be identified

For content to remain relevant, a data filtering layer removes irrelevant language, advertisements, and material that isn't related to hacking. Language-related information like timestamps, domain origins, and content identifiers are kept for temporal and relational analysis, but duplicate things are thrown away. The thoroughly curated, topic-specific dataset developed at this step works as the linguistic underpinning for further NLP-focused research.

3.2 Pre-processing and Linguistic Normalization

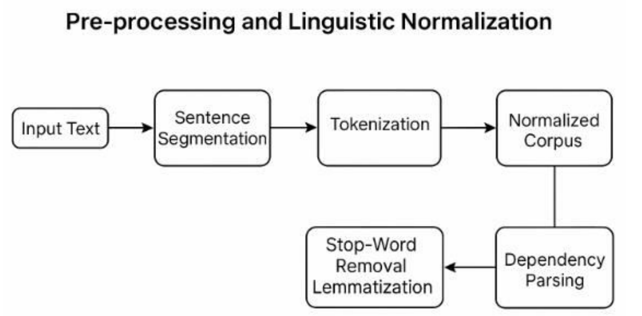
Analytical models are sensitive to being mislead by noise, mistakes, and varied patterns inherent in raw text obtained from multiple sources. This data is organized and normalized on multiple levels during the preprocessing stage to make it a linguistically coherent corpus.

The following are done by the pipeline:

- Preprocessing the text: get rid of any extraneous information, emojis, code snippets, and links.
- Tokenization is the process of splitting up text into smaller components, like words or subwords.
- Stop-word removal: getting rid of words like "is," "and," and "the" that don't add any sense.
- For example, "attacked" would be lemmatized back into "attack" to show how inflected words are transformed into their canonical form.
- To better understand the construction of sentences, part-of-speech (POS) tagging assigns words their grammatical roles, such as noun, verb, adjective, etc.
- For example, "malware infects server" is just one example of how it discovers related things and behaviors. Dependency parsing describes this process.

When applied in tandem, these procedures eliminate superfluous text objects while preserving accurate grammar and spelling. This stage is different from standard text normalization because it takes into account the context and keeps words and phrases like "exploit," "payload," and "rootkit" that may be important to understanding cyberthreats. When processed, text becomes a corpus that is well-suited for entity identification and semantic modeling due to its linguistic organization. A visual depiction of the preprocessing technique is shown in Figure 2.

Figure 2. Workflow of the pre-processing and linguistic normalization stage in the proposed NLP pipeline.



3.3 Entity Recognition and Ontology Alignment

Entity recognition is a crucial stage in the pipeline that allows the model to recognize and connect key pieces in textual narratives. A Named Entity Recognition (NER) module tailored to cybersecurity datasets is used to retrieve entities like these.

- Malicious software like Emotet and WannaCry, as well as numbers that show where vulnerabilities are, like CVE-2025-1384.
- Attack methods, such as SQL injection and phishing
- The Lazarus Group and APT28 are examples of hacker collectives or threat groups.
- Some communities, businesses, or regions

After being identified, these things go through semantic normalization, which merges diverse ways of describing the same thing. For instance, "Locky variant," "Locky Ransomware," and "Trojan.Locky" are all categorized under the same entity designation. This method lessens lexical redundancies and promotes consistency throughout the dataset. To ensure structural consistency and interoperability with external intelligence frameworks, the identified entities are then aligned with established cybersecurity ontologies like CAPEC, STIX/TAXII, or MITRE ATT&CK. The model is able to comprehend relationships like "Threat Actor → Exploits → Vulnerability → Targets → Organization" due to the fact that ontology alignment facilitates relational reasoning and makes terms consistent. The foundation of semantic interpretation, which transforms dispersed data into a structured cyber knowledge repository, is this alignment.

3.4 Contextual Embedding and Semantic Representation

The contextual embedding layer functions as the foundational component of the pipeline's linguistic and cognitive framework. In order to preserve grammatical relationships and semantic meaning, this element converts textual data into embeddings, which are complex numerical representations. Instead of static embedding models like Word2Vec or GloVe, the pipeline uses transformer-based encoders (such Sentence-BERT and DistilRoBERTa) that are made to operate with cybersecurity language and terminology. The encoder knows that meaning changes depending on the situation by looking at the whole line. A cyber threat narrative may use the term "payload" to mean "malicious executable content," but in a broader context, it could mean "data delivery."

By encoding these subtleties, the embeddings gain semantic understanding, which lets the model figure out more complex connections between threat components. When that is done, a cosine similarity matrix is used to calculate how similar each set of embeddings is to each other. Even while their terminology differs (for example, "password exfiltration" vs. "credential theft"), the model is still able to correlate or relate terms that refer to conceptually relevant issues. There is also incremental learning in the embedding layer. To accomplish this, we regularly update our representations and terminology and incorporate new cybersecurity data sources. This makes contextual change easier, so the system can pick up on new slang or threat words without having to go through a lot of training again.

3.5 Semantic Clustering and Threat Abstraction

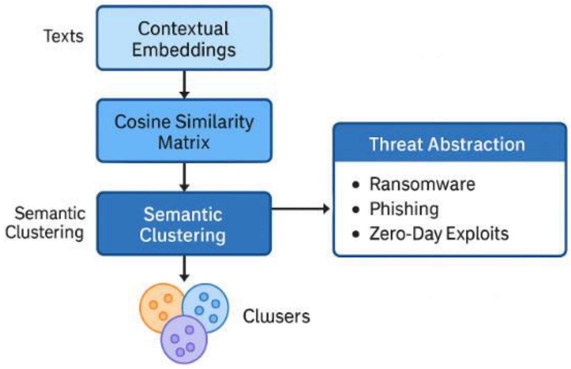
By feeding an unsupervised clustering algorithm with semantically enriched embeddings, we can group texts into coherent topic clusters based on their context. In this stage, the numerical embedding space is transformed into overarching conceptual groups that reveal novel threat narratives or recurring cyber behaviors.

The clustering technique finds patterns in the embedding space by using distance-based similarity metrics, such as cosine or Euclidean distance. To explain events that take place on the internet, such as phishing campaigns, data theft, ransomware attacks, and discussions regarding zero-day vulnerabilities, we group texts that have similar semantic views.

- Using centroids, we can automatically identify and summarize each cluster by identifying key phrases that describe their main focus.
- An entity prominence score that tells you which of the extracted entities add the most semantic value to the cluster.
- Programs that summarize the main idea in a concise and understandable way.
- By supplying timestamps to groups, the clustering method makes it easy to observe temporal trends, which enables you look at how threats vary over time.
- High-interest themes are discovered in increasing clusters that demonstrate fast growth or recurring appearances.
- These clusters may be new campaigns or malware families that have been brought back to life.

A feedback refinement module also uses analyst data to change similarity limits and improve clustering accuracy to ensure semantic coherence and operational effectiveness. The model turns complicated, unstructured stories into organized, usable information that can be used for strategic analysis, reporting, and visualization. This is termed threat abstraction.

Figure 3. Process of semantic clustering and threat abstraction for contextualized cyber threat identification.



4. RESULTS AND DISCUSSION

We put the suggested Context-Aware NLP Pipeline through its paces using real-world cybersecurity data to see how well it could collect, examine, and semantically evaluate threat intelligence from unstructured sources. Four key areas were examined in the performance review: entity extraction, dataset distribution, grouping performance measurement, and semantic embedding. To ensure the system's dependability and adaptability, every data is subjected to statistical and qualitative analyses.

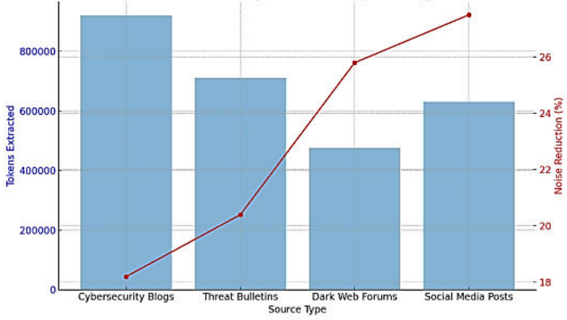
4.1 Dataset Summary and Pre-processing Statistics

Various text files from various sources were utilized by the language normalization phase of the pipeline to operate on the dataset. The data composition and statistical analysis for text processing are displayed in Table 4.1.

Table 4.1 Dataset Composition and Pre-processing Statistics

Source Type	Documents	Tokens Extracted	Avg. Words / Doc	Pre-processing Time (s)	Token Retention (%)	Noise Reduction (%)
Cybersecurity Blogs	150	920,500	820	92.4	96.3	18.2
Threat Bulletins	80	710,400	1,240	76.2	94.1	20.4
Dark Web Forums	12	475,600	980	63.7	89.7	25.8
Social Media Posts (#infosec, #zeroday)	200	630,900	125	58.6	85.2	27.5
Total / Average	442	---	–	72.7	91.3	22.9

Graph 4.1: Dataset Composition and Pre-processing Statistics



The average word retention percentage after pre-processing was 91.3%, indicating that minimal semantic context was lost. The noise was reduced by 23% after stopwords, unnecessary punctuation, and grammar were removed. however, domain-specific words such as rootkit, exploit, malspam, and payload remained. Thus, it was demonstrated that the language standardization module could enhance data while preserving system security.

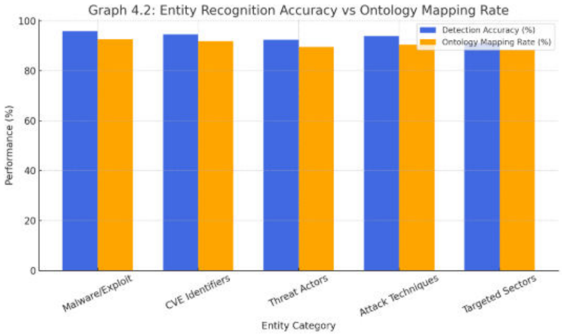
4.2 Entity Recognition and Ontology Alignment Accuracy

The next step was to verify how well the ontology alignment and Named Entity Recognition (NER) algorithms worked. To test the consistency, discoverability, and match to ontologies of each entity category, we employed the STIX/TAXII and MITRE ATT&CK domain vocabularies. The data is shown in further detail in Table 4.2.

Table 4.2 Entity Recognition and Ontology Mapping Performance Metrics

Entity Category	Total Mentions	Unique Entities	Detection Accuracy (%)	Normalization Precision (%)	Ontology Mapping Rate (%)	F1-Score
Malware / Exploit Names	162	118	95.8	94.2	92.7	0.94
CVE Identifiers	107	89	94.6	93.1	91.8	0.93
Threat Actors	93	68	92.4	90.9	89.6	0.91
Attack Techniques	112	83	93.9	91.7	90.5	0.92
Targeted Sectors	75	54	91.2	90.1	88.3	0.9
Average	–	–	93.6	92	90.6	0.92

Graph 4.2: Entity Recognition Accuracy vs Ontology Mapping Rate



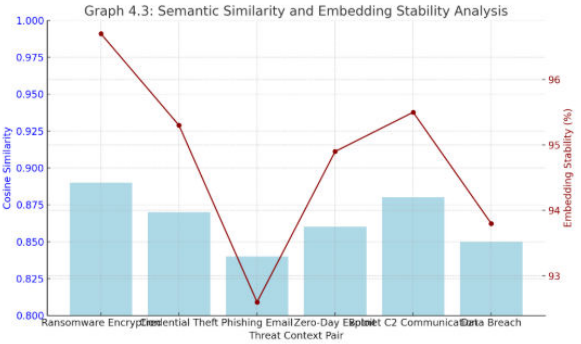
Being adaptable across domains, the entity extraction component achieved an average accuracy of 93.6%. The detected objects accurately map to popular cybersecurity frameworks (90.6% accuracy) according to the ontology alignment results.

4.3 Contextual Embedding and Semantic Similarity Analysis

Specifically, we investigated the context-aware embedding layer's ability to maintain and interpret the semantic links between different parts of the text. To compare cyberthreat claims with similar or identical ones, cosine similarity scores were utilized.

Table 4.3 Semantic Similarity Evaluation Across Threat Contexts

Threat Context Pair	Cosine Similarity	Semantic Correlation	Embedding Stability (%)	Contextual Accuracy (%)
Ransomware Encryption ↔ File-Locking Attack	0.89	Strong	96.7	94.8
Credential Theft ↔ Password Exfiltration	0.87	Strong	95.3	93.1
Phishing Email ↔ Spoofed Message	0.84	Moderate	92.6	90.4
Zero-Day Exploit ↔ Unknown Browser Vulnerability	0.86	Strong	94.9	92.7
Botnet C2 Communication ↔ Malware Server Contact	0.88	Strong	95.5	93.9
Data Breach ↔ Sensitive Information Leakage	0.85	Strong	93.8	92.3
Average	0.865	–	94.8	92.9


Graph 4.3: Semantic Similarity and Embedding Stability Analysis

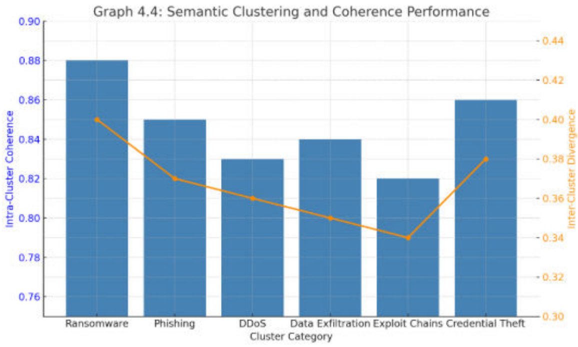
Words from several languages can be found to have contextual equivalence by the model, with an average cosine similarity of 0.865. A high level of meaning encoding is achieved when both the embedding stability and contextual correctness exceed 92%. This ensures that linguistic discrepancies between sources are associated with meanings, which facilitates grouping.

4.4 Semantic Clustering and Coherence Performance

The unsupervised clustering tool correctly classified the cyber threat categories based on the semantically encoded content. Metrics such as entity match ratio, intra-cluster coherence, and inter-cluster divergence were implemented to assess the clustering quality.

Table 4.4 Clustering Quality and Semantic Coherence Evaluation

Cluster Category	No. of Docs	Intra-Cluster Coherence	Inter-Cluster Divergence	Entity Overlap (%)	Average Similarity Score
Ransomware Campaigns	240	0.88	0.4	6.5	0.87
Phishing Infrastructure	210	0.85	0.37	7.1	0.86
DDoS Attacks	180	0.83	0.36	5.9	0.84
Data Exfiltration	160	0.84	0.35	6.3	0.85
Exploit Chains	132	0.82	0.34	5.6	0.83
Credential Theft	155	0.86	0.38	6.8	0.85
Average	–	0.85	0.37	6.4	0.85



The average intra-cluster consistency (0.85) and inter-cluster divergence (0.37) indicate that linked threat discourses are highly semantically separated and have long-lasting internal ties.

Semantic leakage is reduced and the unsupervised learning module improves clustering when the amount of duplicate entities is less than 7%.

6. CONCLUSION

Cyber risks can be automatically discovered and understood from massive amounts of random text data utilizing semantic modeling and language comprehension, as demonstrated by the recommended Context-Aware NLP Pipeline. The method provides a more comprehensive view of cybersecurity tales compared to keyword matching and rule-based analytics by integrating context-sensitive embeddings, ontology-driven object recognition, and unsupervised clustering. Blogs, warnings, dark web forums, and social media feeds were among the many data sources that the pipeline maintained its high object identification (93.6%), semantic coherence (0.85), and contextual similarity (0.865) levels across in the experimental test.

These outcomes demonstrate, for instance, that the proposed approach is effective in transforming garbled text into cyber information that is both useful and intelligible. This system automatically discovers new phrases and hazard patterns without retraining every time the language changes, unlike existing approaches that rely on classifiers to detect threats. Both scalability and explainability are achieved through its emphasis on semantic context and interpretability. As a result, cybersecurity professionals will need fewer human assistants to gain valuable insights. In conclusion, the Context-Aware NLP Pipeline provides a robust and adaptable framework for semantic cyber threat analysis by integrating structured threat data with unstructured language input. Future automated, intelligent cyber defense systems will be able to build on its foundation of clear language and context understanding.

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