



SoK: Automated TTP Extraction from CTI Reports – Are We There Yet?

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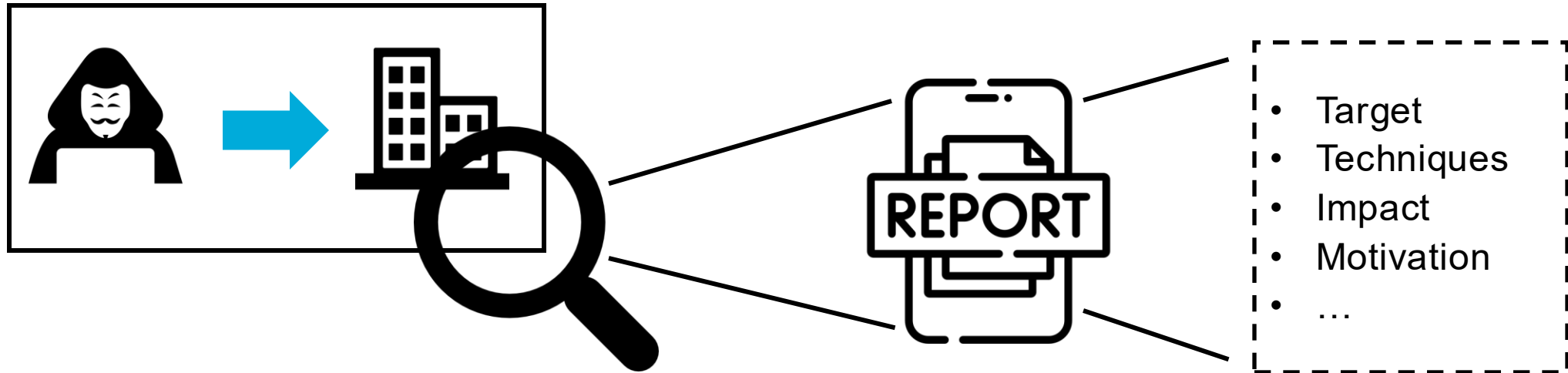
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Cyber Threat Intelligence (CTI)

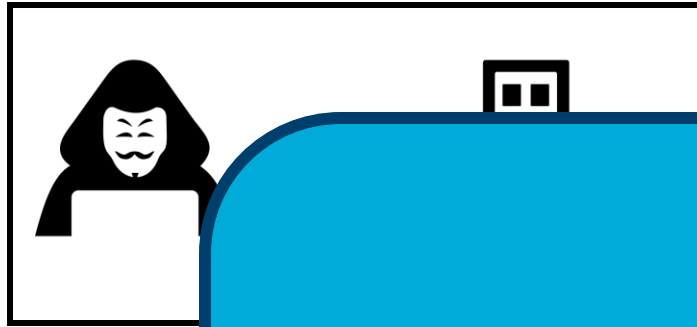


CTI reports containing important information about recent cyber attacks...

Cyber Threat Intelligence (CTI)



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TTPs

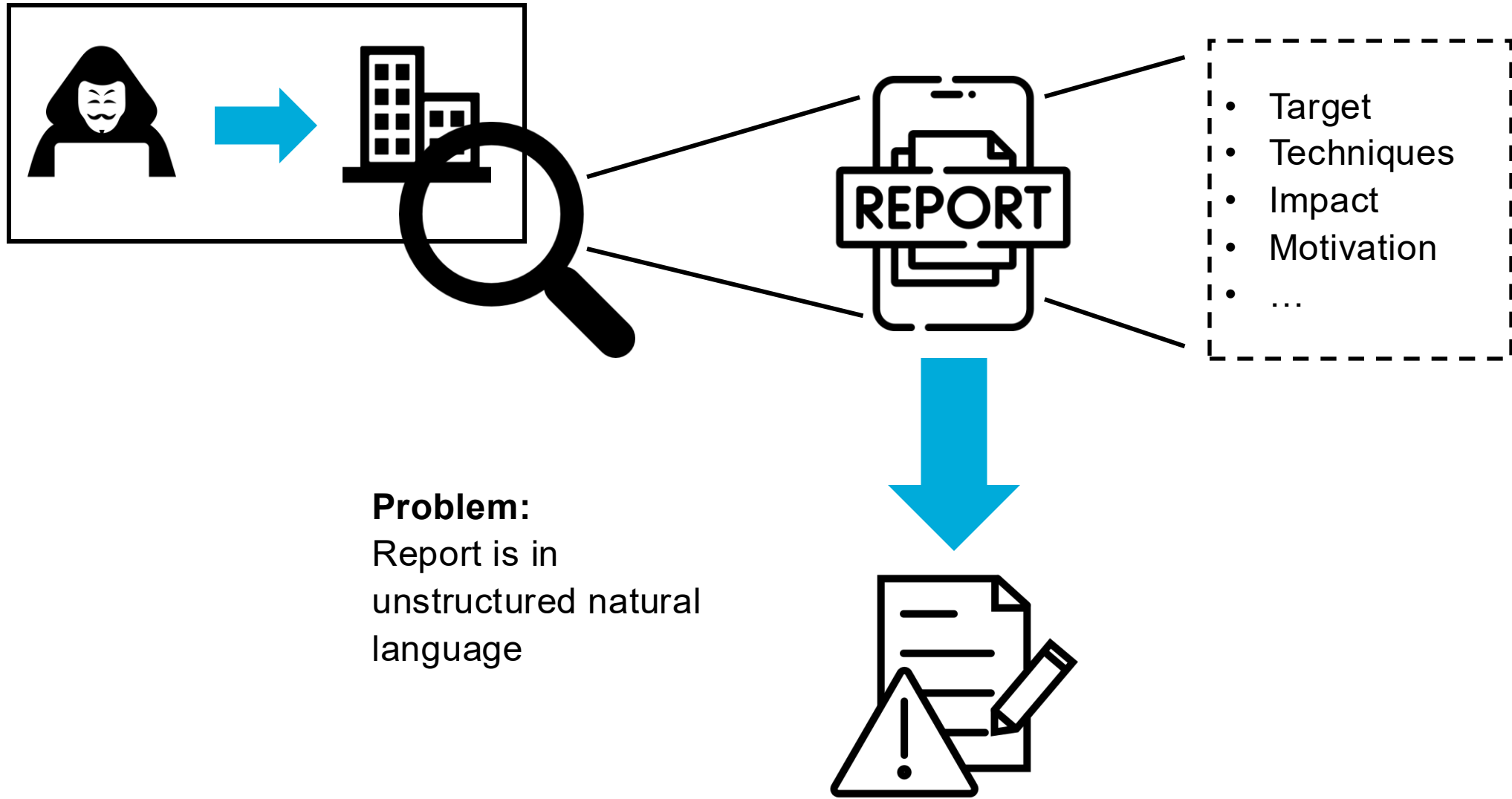
Tactics: describe the high-level goals

Techniques: How they attempt to achieve the high-level goals

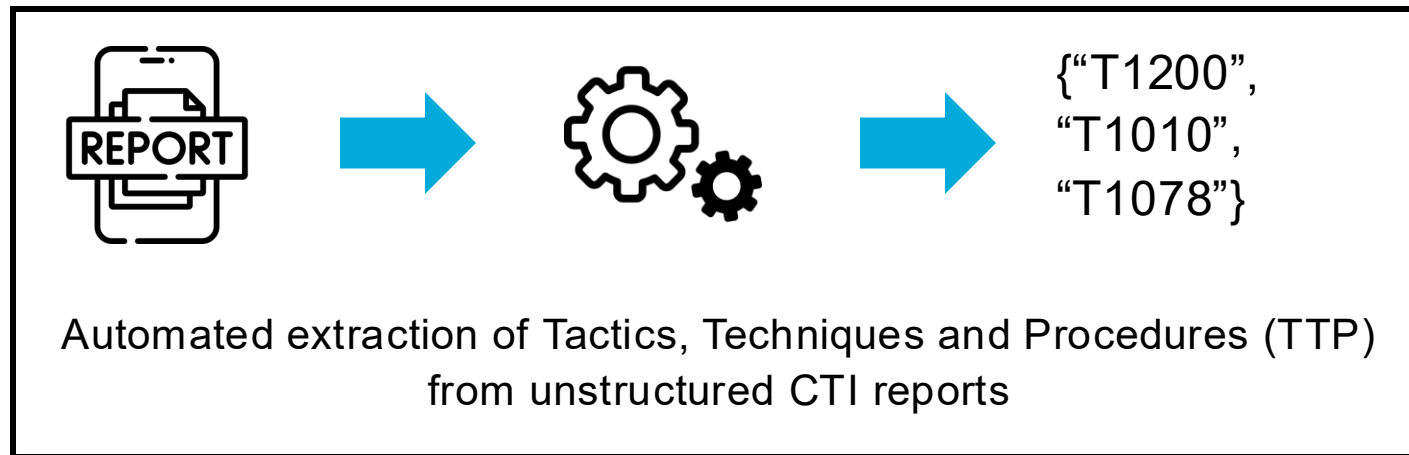
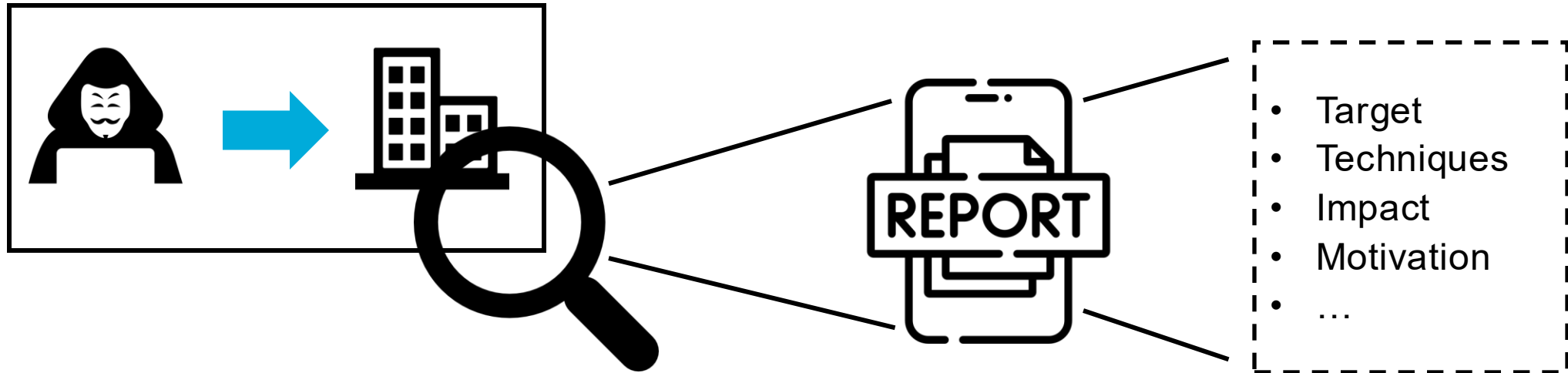
Procedures: Specific methods and tools they employ to carry out their objectives

- Target
- Techniques
- Impact
- Motivation
- ...

Cyber Threat Intelligence (CTI)



Cyber Threat Intelligence (CTI)



The MITRE **ATT&CK**[®] Ontology

- De-facto standard for categorizing TTPs
- A globally accessible knowledge base of TTPs based on real-world observations
- Unique IDs for Tactics and Techniques
- Creates a common language for security professionals and enables automated processing

Goal: Map *'The attacker modified the Windows Registry'* -> **ATT&CK ID T1112**

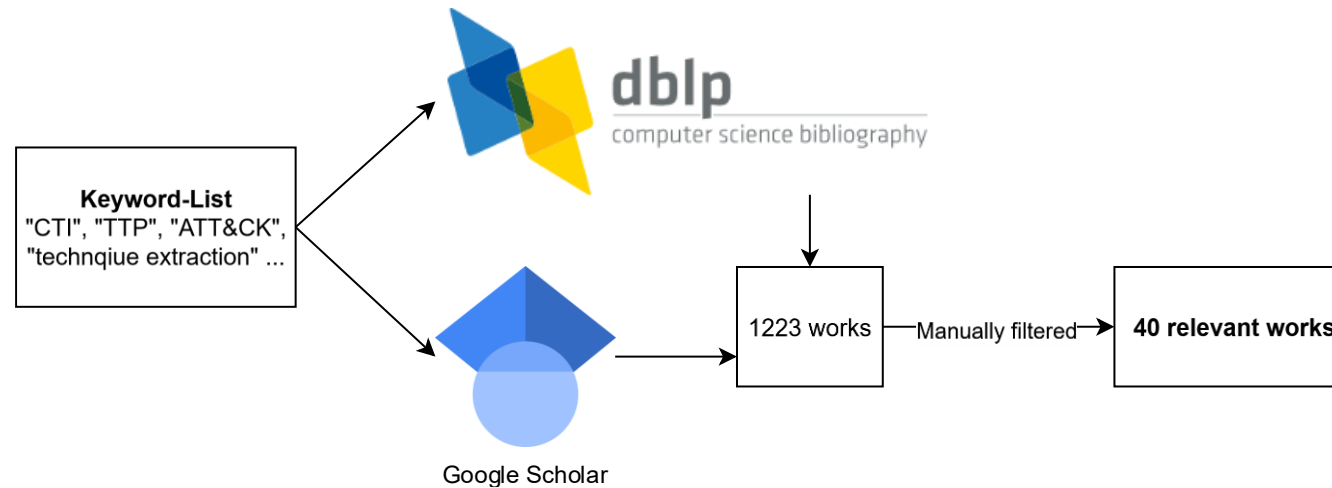
Literature Review

Objective: To systematize all existing NLP-based solutions for automatic TTP extraction.

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Process:



Our Systematization of Knowledge

- **40 relevant works published**



Named Entity Recognition (NER): Advanced rule-base "word search"



Classification: Data-driven classification approach (often BERT-like models)



Generation: Generative Large Language Model (LLM)

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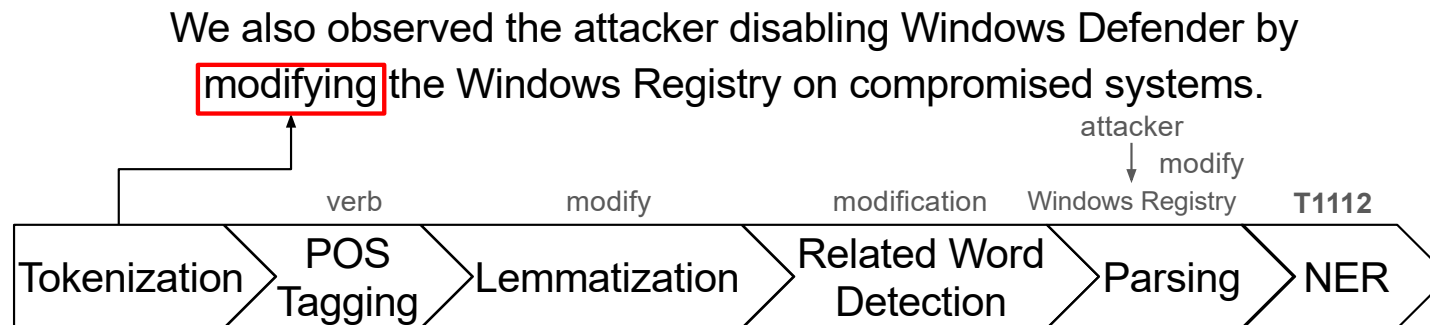
Generation: Generative Large Language Model (LLM)

- **Identified 16 fundamental Natural Language Processing (NLP) methods**

Approach Methods NER

Each work consists of a composition of NLP methods within the general approach.

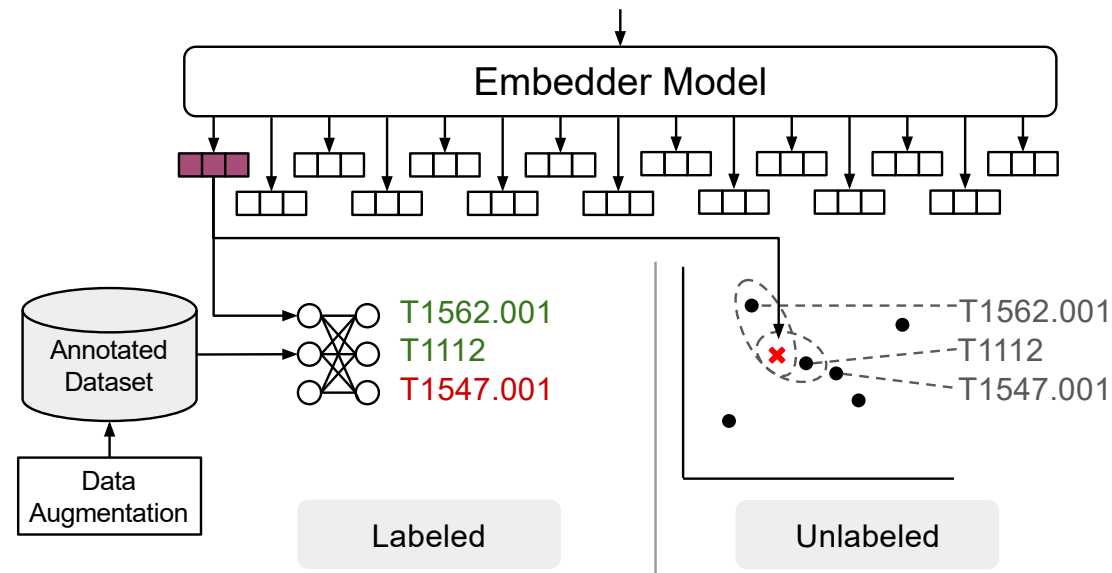
NER Approach Example:



Approach Methods Classification

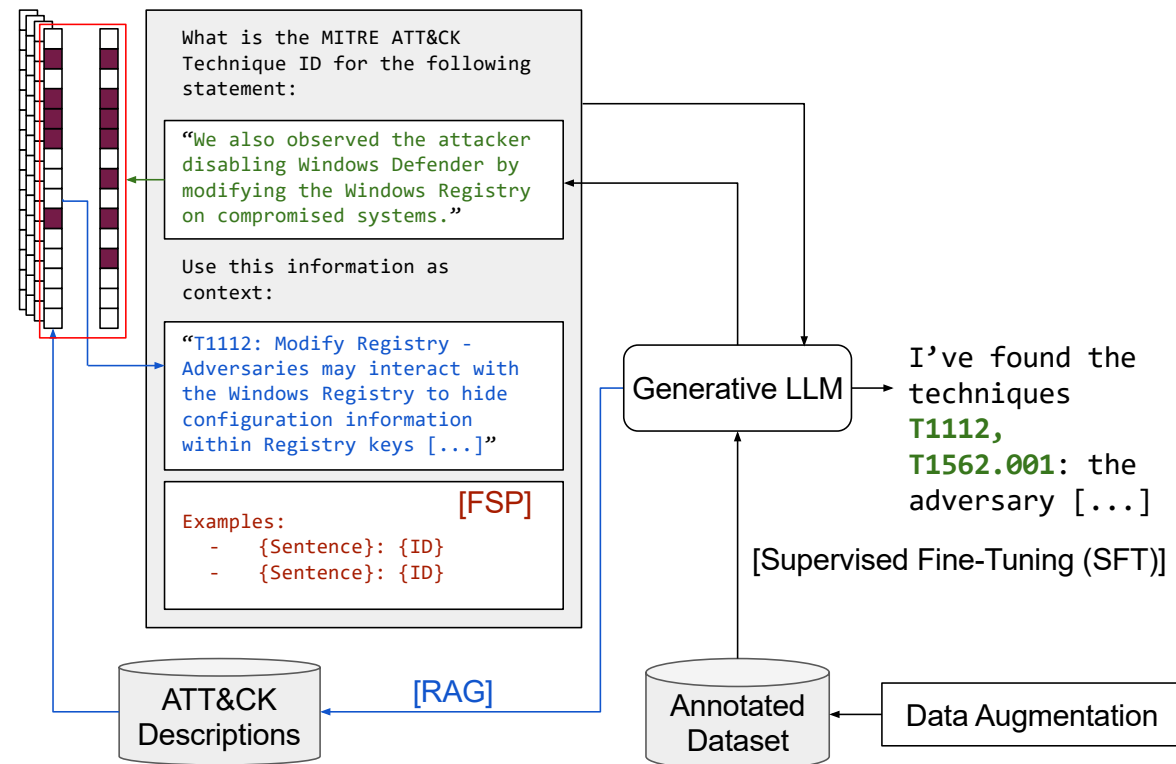
Structure Classification Approach:

We also observed the attacker disabling Windows Defender by modifying the Windows Registry on compromised systems.



Approach Methods Classification

Structure Generation Approach:



Literature Trends - NER

Table 1: Components implemented by related work.

Type	Approach	Tok.	POS	Lem.	Rel.	Par.	NER	Data	Ontology
Semantic	AttackKG [58]	○	○	○	×	○	●	Custom	Custom
	Extractor [85]	●	●	●	○	●	●	[20, 66]	Custom
	TTPDrill [38]	●	●	×	●	○	●	Custom	Custom
Hybrid	ActionMiner [39]	○	○	×	×	○	●	Custom	Custom
	CASIE [86]	○	○	○	×	●	●	Custom	Custom
	CyberEntRel [3]	○	×	×	○	×	●	Custom	Custom
	EX-Action [103]	●	○	×	×	○	●	Custom	ATT&CK
	Ghazi et al. [32]	○	○	×	×	×	○	Custom	Custom
	ThreatKG [27]	●	×	×	×	●	●	Custom	Custom
	TIMiner [106]	○	×	○	●	○	●	Custom	Custom

× action is not present or not mentioned. Tok. = Tokenization Rel. = Related word detection
 ○ action is present, but not domain-specific. POS = Part-of-Speech Par. = Parsing
 ● action is present and domain-specific. Lem. = Lemmatization NER = Named Entity Recognition

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Literature Trends - Classification

Table 2: Classification approaches for TTP extraction.

	Paper	Model	Augment.		Mult.	Ont.	CTRs	Data	Gran.
			Art.	OOD					
Labeled	rcATT [52]	Word2Vec [65]	×	×	●	ATT.	●	Custom	Doc.
	Ayoade et al. [7]	None	×	×	●	ATT.	●	Custom	Doc.
	SeqMask [30], Ge et al. [31]	FastText [12]	×	×	●	ATT.	●	Custom	Doc.
	TRAM [82,99]	SciBERT [11]	×	×	●	ATT.	●	[82]	Sent.
	Liu et al. [61]	Custom	×	×	●	ATT.	●	Custom	Doc.
	TTPHunter [79]	BERT-based [22]	×	×	×	ATT.	●	Custom	Sent.
	TIM [101]	SBERT [81]	×	×	×	ATT.	×	Custom	Sent.
	Tang et al. [91]	BERT [22]	×	×	×	ATT.	●	Custom	Sent.
	Alves et al. [6]	BERT-based [22,84]	×	×	×	ATT.	×	Custom	Sent.
	Yan et al. [98]	BERT [22]	×	×	●	ATT.	●	Custom	Sent.
	Kim et al. [45]	None	●	×	●	ATT.	×	[82], Cust.	Doc.
	TTPXHunter [80]	SecureBERT [2]	●	×	×	ATT.	●	Custom	Sent.
	You et al. [100]	CTI-BERT [75]	×	●	●	ATT.	×	[82], Cust.	Sent.
	ALERT [77]	SciBERT [11]	×	×	×	ATT.	×	Custom	Sent.
	Li et al. [56]	BERT-based [22,84]	×	×	●	ATT.	×	[82], Cust.	Sent.
	CTI-to- MITRE [72]	Multiple [60,65]	×	×	●	ATT.	●	[82], Cust.	Both
	HMCAT [35]	SecureBERT [2]	●	×	×	ATT.	×	Custom	Both
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Kumarasinghe et al. [49]		SentSecBERT [49]	-	-	●	ATT.	×	[82], Cust.	Sent.
Abdeen et al. [1]		ATTACK-BERT [1]	-	-	●	ATT.	×	Custom	Sent.

Legend: (●) Element is present. (×) Element is not present or unclear from text. (-) Element does not apply. (Augment.) Data Augmentation. (Mult.) Multi-label. (Ont.) Ontology. (CTRs) TTP extraction from real-world CTI reports. (Gran.) Granularity. (Doc.) Document-level. (Sent.) Sentence-level.

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Literature Trends - Generation

Table 3: Generative approaches for TTP extraction.

Title	LLM Model	Ontology	SFT	FSP	RAG	CTRs	Doc.	Data
aCTIon [88]	GPT-3.5 _{Turbo}	ATT&CK	×	×	×	●	×	Cust.
CTINexus [15]	GPT-4	MALOnt	×	●	●	●	●	Cust.
AECR [14]	ChatGLM3 _{6B}	ATT&CK	●	×	×	●	×	Cust.
Fayyazi et al. [24]	GPT-3.5	ATT&CK	×	×	●	×	×	Cust.
Fengrui et al. [102]	Llama2	ATT&CK	●	×	×	×	×	Cust.
IntelEX [97]	GPT-4o _{mini}	ATT&CK	×	×	●	●	●	Cust.
Kumarasinghe et al. [49]	Multiple	ATT&CK	×	●	×	×	×	Cust.
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Fieblinger et al. [26]	Multiple	Custom	●	●	×	●	×	Cust.

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Literature Trends

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PROBLEM

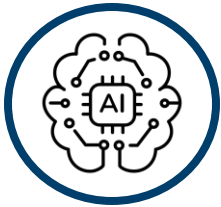
- Custom datasets
- Not open-source
- Different TTP ontologies
- Handcrafted optimizations

Empirical Study



Evaluation:

- Unified framework



Source Code:

- Re-Implementation of all 16 identified NLP components



Experiments:

- Lab Scenarios, Real-World Scenarios

PROBLEM

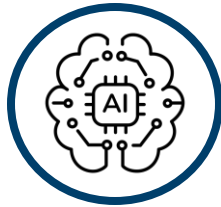
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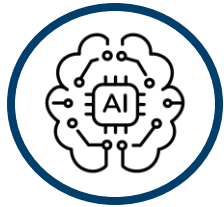
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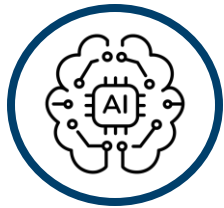
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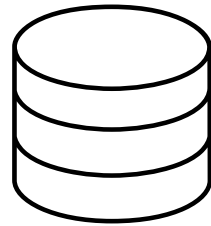
PROBLEM

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A Framework for Fair Comparison: Datasets

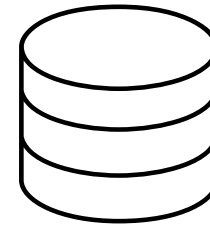
Datasets:

We used two public, real-world CTI datasets with sentence-level ATT&CK labels for training and testing.



MITRE TRAM2

150 reports
50 most common unique TTPs



Bosch AnnoCTR

120 reports
118 unique TTPs

A Framework for Fair Comparison: Scenarios

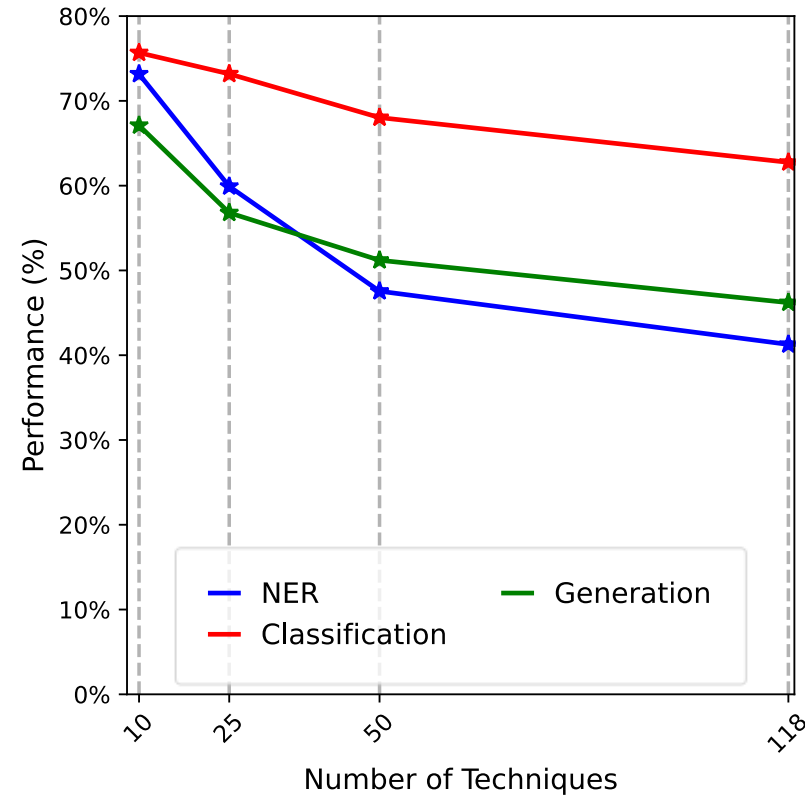


Closed-Set: Simulates a lab environment where the set of possible TTPs is known beforehand. This is how most papers evaluate their work.



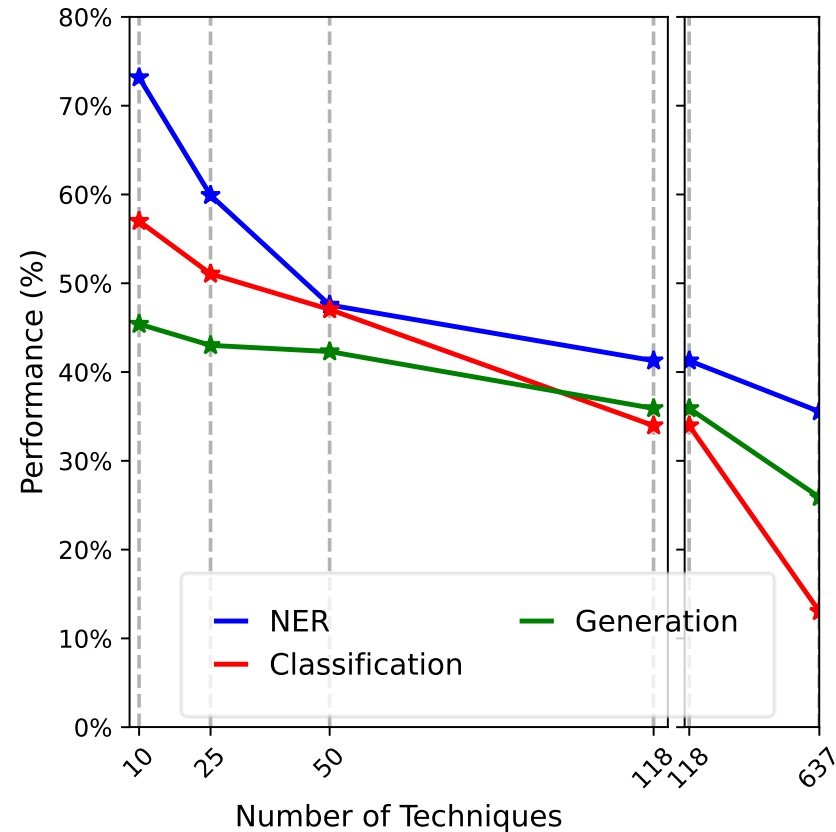
Open-Set: Simulates a realistic scenario where any TTP from the entire ATT&CK framework could appear. Models cannot be specifically tuned for the test data.

Key Finding 1: Closed-Set



In a controlled lab environment, modern, data-hungry models like LLMs and BERT-based classifiers are the top performers.

Key Finding 2: Open-Set



We tested on the AnnoCTR dataset against an increasing number of possible TTPs. This is where the results turn. The “older” traditional NER approach outperforms both newer data-driven approaches.

Key Finding 3: What are the bottlenecks?

The Dataset Bottleneck:

- Progress is fundamentally limited by the lack of large, high-quality, manually annotated public datasets.
- Existing datasets are small, cover only a fraction of ATT&CK techniques, and are highly imbalanced.
- Data augmentation techniques provide only marginal benefits.

Key Finding 3: What are the bottlenecks?

The Ontology Bottleneck (Label Confusion):

- The ATT&CK framework itself can be ambiguous. Many techniques are subtly different and hard to distinguish from a single sentence, even for a human expert.
- Example: T1547.001 (Boot or Logon Autostart Execution: Registry Run Keys) vs. T1112 (Modify Registry). Both involve modifying the registry, but the intent is different. Distinguishing them requires broader context.

Conclusion: Are We There Yet?

No. Automated TTP extraction is still an open research problem. Current approaches are not yet reliable enough for fully automatic practical use.

Conclusion: Are We There Yet?

The Path Forward is Not (Just) Better Models:

- The community's focus on novel NLP models is hitting a point of diminishing returns.
- Obstacles are the lack of high-quality data and the inherent ambiguities in the TTP definitions.

Recommendations:

- For Practitioners: A high-recall NER system can be a good assistant for analysts, while a fine-tuned classifier can work well for a known, closed set of TTPs.
- For Researchers: The community urgently needs to shift focus towards creating larger, high-quality, and more comprehensively annotated datasets.

Thank you!



Paper



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