

Translating Cybersecurity Descriptions into Interpretable MITRE Tactics using Transfer Learning

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Introduction

- Intrusion logs and threat intelligence reports have been developed to assist security analysts
- Description in these logs and reports, however, can be cryptic and not easy to interpret. Thus:

We ask:

Given a description of cyberattack techniques, how to interpret the intended effects (MITRE Tactics [1])?

- E.g.,1,** Initialization scripts can be used to perform administrative functions, which may often execute other programs or send information to an internal logging server.

- E.g.,2,** Custom Outlook forms can be created that will execute code when a specifically crafted email is sent.

Privilege Escalation? Persistence? Both?

Related Works

PATRL (Pseudo-Active Transfer Learning) [2]

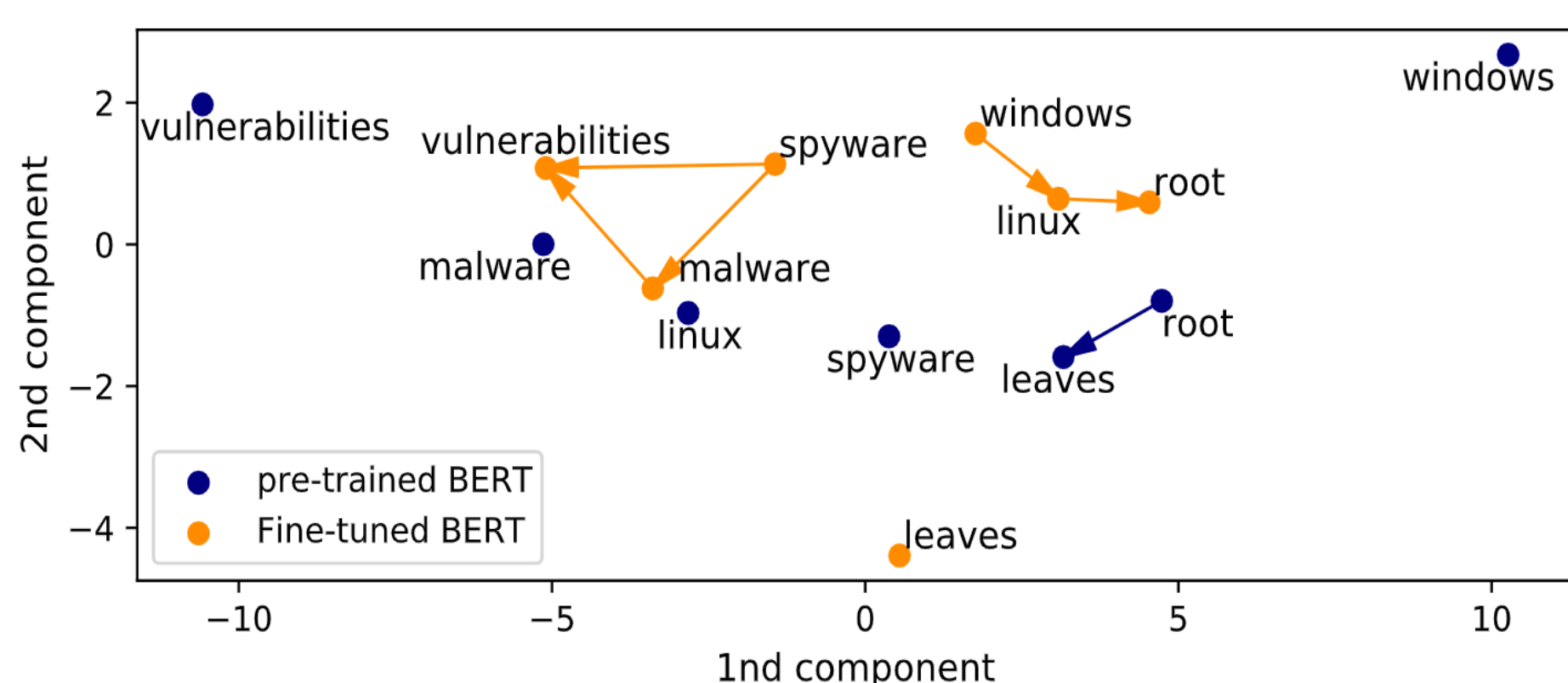
- A semi-supervised process leveraging ULMFiT [3] to determine the attack stage of IDS alert signatures

BERT [4]

- A Transfer Learning technique to uncover the semantic information conveyed in a sentence

ExBERT [5]

- A framework that applies Transfer Learning to BERT to predict exploitability
- Word embedding for the pre-trained and fine-tuned BERT with cybersecurity words



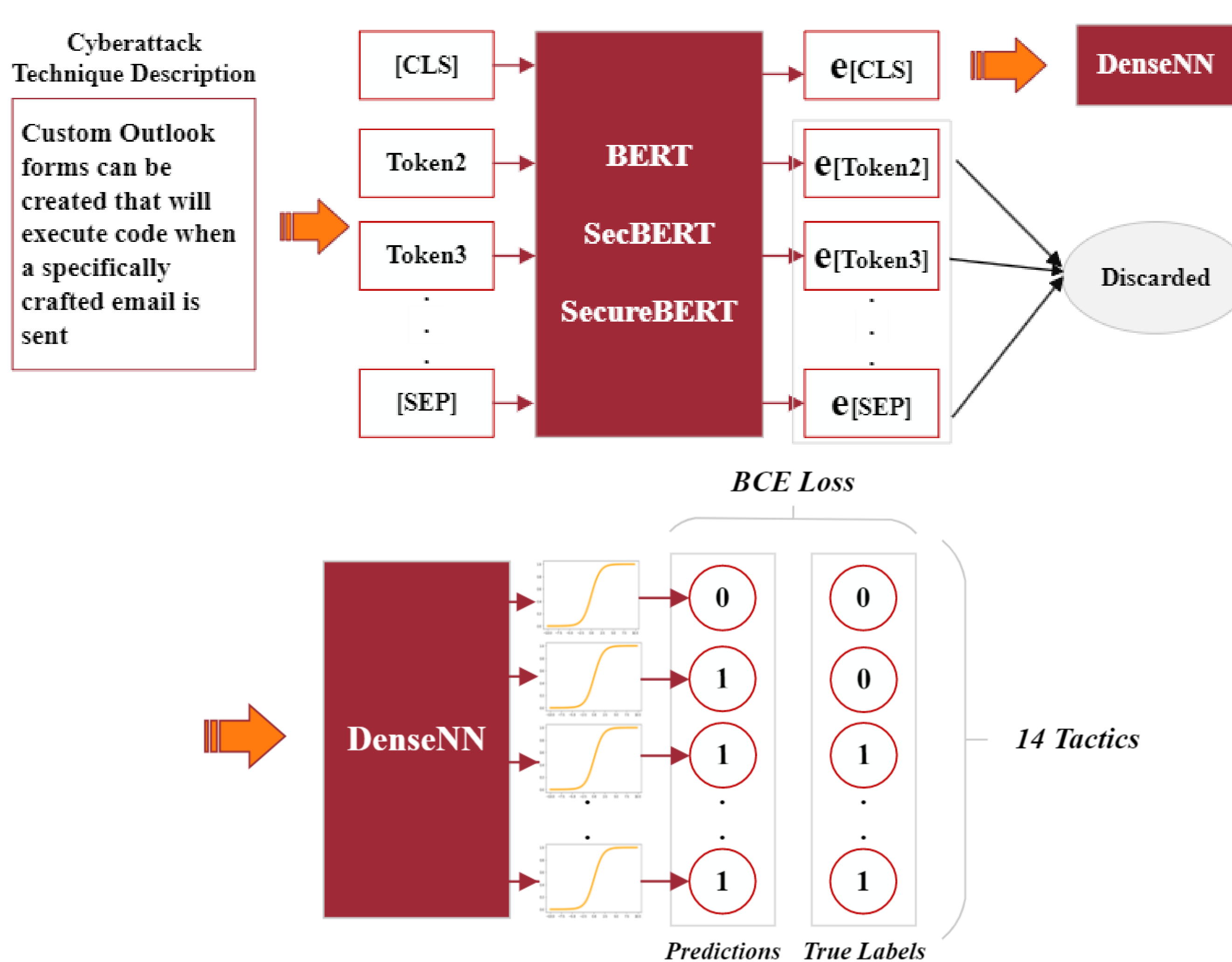
SecBERT [6]

- A BERT model trained on cybersecurity texts

SecureBERT [7]

- A language model based on RoBERTa [8] that is trained on cybersecurity texts

Methodology



- Multi-Label Classification for the total of 14 MITRE Tactics
- Total of 4500+ Descriptions with their corresponding tactic(s)

	PERSISTENCE	PRIV_ESC	DEF_EVA	COLLECTION	CRED_ACC	EXECUTION	LT_MOV	INI_ACC	DISCOVERY	C2	IMPACT	RECON	EXFILTRATION	RES_DEV	TOTAL #TACTIC
PERSISTENCE	235	356	185	0	17	57	13	39	0	0	0	0	0	0	847
PRIV_ESC	356	33	243	0	0	13	0	13	0	0	0	0	0	0	620
DEF_EVA	185	243	760	0	57	24	56	39	39	19	2	0	0	0	1377
COLLECTION	0	0	0	237	116	0	0	0	15	6	0	0	0	0	374
CRED_ACC	17	0	57	116	297	0	0	0	23	0	0	0	0	0	493
EXECUTION	57	13	24	0	0	234	12	0	0	0	0	0	0	0	332
LT_MOV	13	0	56	0	0	12	134	25	0	0	0	0	0	0	240
INI_ACC	39	13	39	0	0	0	25	179	0	0	0	0	0	0	269
DISCOVERY	0	0	39	15	23	0	0	0	243	0	0	0	0	0	320
C2	0	0	19	6	0	0	0	0	0	241	0	0	0	0	266
IMPACT	0	0	2	0	0	0	0	0	0	0	276	0	0	0	278
RECON	0	0	0	0	0	0	0	0	0	0	0	196	0	0	196
EXFILTRATION	0	0	0	0	0	0	0	0	0	0	0	0	95	0	95
RES_DEV	0	0	0	0	0	0	0	0	0	0	0	0	0	264	264
	 No Overlaps With Overlaps TOTAL: 5971														

- Pair-wise overlap for MITRE tactic descriptions
- Diagonal values correspond to the single-tactic descriptions
- Some descriptions match to two or more tactics. Hence, the total of 5971 instances are more than the curated descriptions

Results

Model:	BERT	SecBERT	SecureBERT
Avg. Training Loss	0.01	0.01	0.01
Avg. Test Loss	0.15	0.16	0.15
Abs. Accuracy	0.63	0.59	0.65
Micro Avg. F1 Score	0.75	0.72	0.76

Table.1. Results for running the three BERT models with 30 epochs using 5-fold cross-validation.

Per Tactic F1 Score:	BERT	SecBERT	SecureBERT
COLLECTION	0.68	0.63	0.68
C2	0.75	0.73	0.75
CRED_ACC	0.74	0.72	0.76
DEF_EVA	0.78	0.77	0.79
DISCOVERY	0.73	0.66	0.75
EXECUTION	0.72	0.64	0.71
EXFILTRATION	0.59	0.57	0.57
IMPACT	0.77	0.75	0.82
INI_ACC	0.64	0.62	0.65
LAT_MOV	0.57	0.56	0.59
PERSISTENCE	0.78	0.73	0.78
PRIV_ESC	0.72	0.72	0.74
RECON	0.89	0.83	0.88
RES_DEV	0.85	0.85	0.85

Table.2. Results for per-tactic F1 score for the three models to measure the differences in values for single-label and multi-label descriptions.

Observations & Future Works

Based on the Results:

- The 0.76 Micro F1 score in SecureBERT is promising in capturing semantic features of cybersecurity descriptions and dealing with multi-label data.
- The models could reasonably capture overlapping MITRE tactic descriptions

Future Works:

How to 1) better reflect the model's performance, 2) treat limited labeled data, 3) leverage label semantics, and 4) use a novel NSP-tuning approach to predict the intended consequences.

References

[1] "MITRE ATT&CK®." <https://attack.mitre.org/> (accessed Nov. 06, 2022).

[2] S. Moskal, S. Y.-2021 I. C. on, and undefined 2021, "Translating Intrusion Alerts to Cyberattack Stages using Pseudo-Active Transfer Learning (PATRL)," *ieeexplore.ieee.org*, Accessed: Sep. 13, 2022. [Online]. Available: <https://ieeexplore.ieee.org/abstract/document/9705037/>

[3] J. Howard and S. Ruder, "Universal Language Model Fine-tuning for Text Classification," *ACL 2018 - 56th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference (Long Papers)*, vol. 1, pp. 328–339, Jan. 2018, doi: 10.48550/arxiv.1801.06146.

[4] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, vol. 1, pp. 4171–4186, Oct. 2018, doi: 10.48550/arxiv.1810.04805.

[5] J. Yin, M. J. Tang, J. Cao, and H. Wang, "Apply transfer learning to cybersecurity: Predicting exploitability of vulnerabilities by description," *Knowledge-based systems*, vol. 210, Elsevier B.V., Dec. 27, 2020, doi: 10.1016/j.knsys.2020.106529.

[6] "SecBERT: pretrained BERT model for cyber security text, learned Cybersecurity Knowledge." <https://github.com/jackaduma/SecBERT> (accessed Oct. 02, 2022).

[7] E. Aghaei, E. Al-Shaer, X. Niu, and W. Shadid, "SecureBERT: A Domain-Specific Language Model for Cybersecurity Malware Deception View project Covert Communication using Network Behavioral Patterns", Accessed: Nov. 01, 2022. [Online]. Available: <https://github.com/ehsanaghaei/SecureBERT>

[8] Y. Liu *et al.*, "RoBERTa: A Robustly Optimized BERT Pretraining Approach," Jul. 2019, doi: 10.48550/arxiv.1907.11692.