AI for Cybersecurity: Current Status and the Role of GPT-4

Peng Liu

College of IST

pliu@ist.psu.edu

4 takeaway messages

- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- ChatGPT (and other LLMs) seems the biggest X factor

Outline

- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- ChatGPT (and other LLMs) seems the biggest X factor

A lot of progress has been made in cybersecurity during the past 30 years!

- Example 1: today, most messages are encrypted
- Example 2: two-factor authentication
- Example 3: Windows security
- Example 4: App security

However, a few "broken heart" findings are fundamentally concerning.

The “building a secure system” vision researchers had 30 years ago is NOT achieved!

Broken heart #1

The Principle of Least Privilege is a most fundamental principle in building secure systems.

Example: privilege escalation attacks

However, no commodity systems (Windows, Linux, Android, iOS) achieve least privilege.

Broken heart #2

TEEs (Trusted Execution Environments) are trapped into an arms race w/ side channels

Example:

-- Spectre attack

-- Side channels against SGX

Is there a practical way to implement “root of trust”?

Broken heart #3

The "explicit information flow control" vision hinted by HiStar (OSDI 2006) has limited adoption in the real world

-- MAC is a fundamentally important concept in building secure systems

Example: Antivirus software data exfiltration

30 years have passed, we still don't know how to build a commodity computer system we can trust

Outline

- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- ChatGPT (and other LLMs) seems the biggest X factor

A pragmatic view of cybersecurity

First, let's stop building a computer system we can fully trust

Second, let's systematically deploy defense measures for the known attacks

-- Firewalls, encryption, EDR, IAM (Identity and Access management), TEEs, backups
-- Provably security can still be very useful when its assumptions are True

Third, let's be adaptive when dealing with unknown attacks

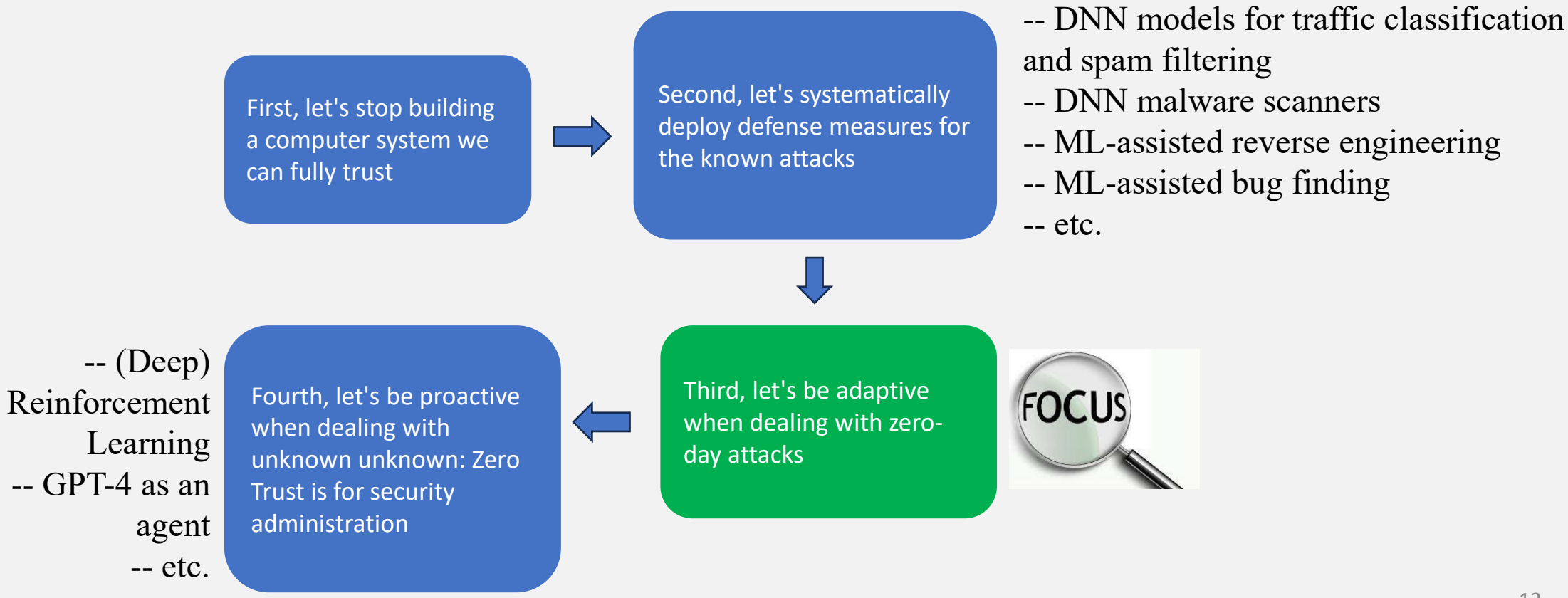
Fourth, let's be proactive when dealing with unknown unknown: Zero Trust is for security administration

Outline

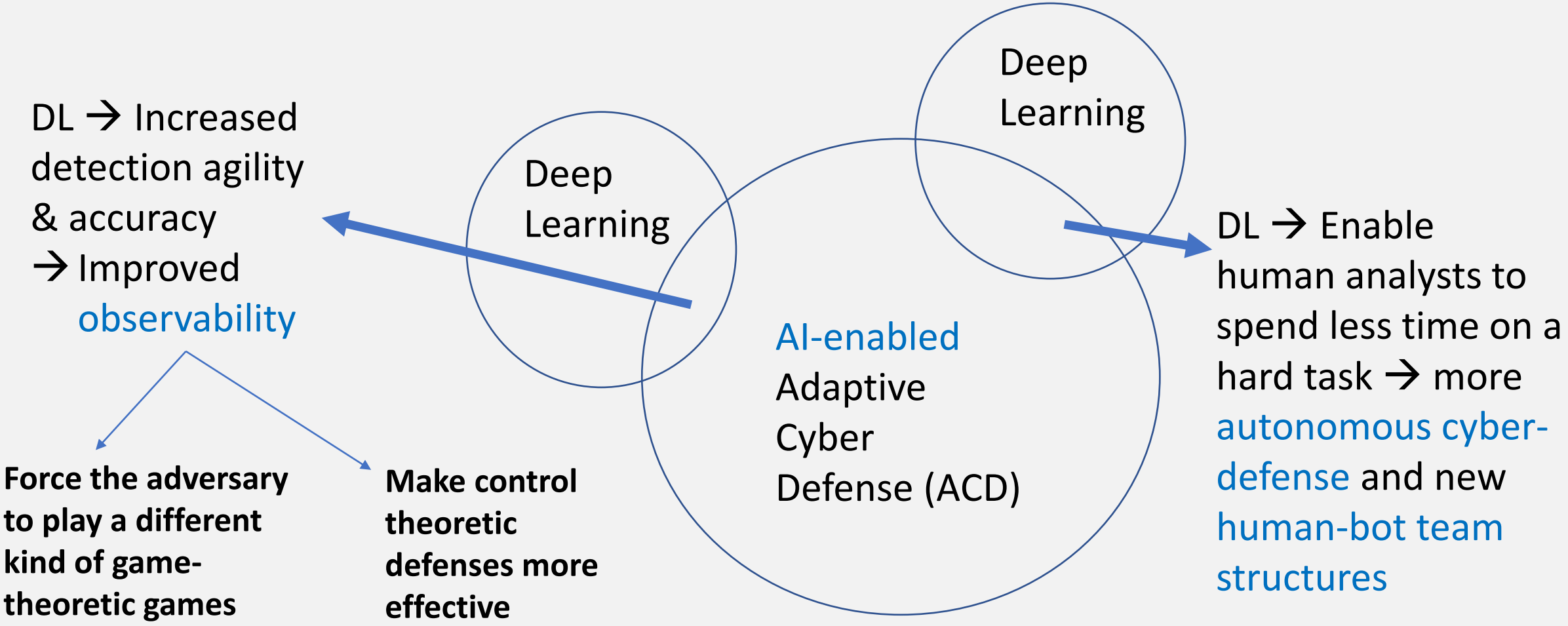
- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- ChatGPT (and other LLMs) seems the biggest X factor

Key Observation

- AI/ML techniques are well aligned with the pragmatic view of cybersecurity

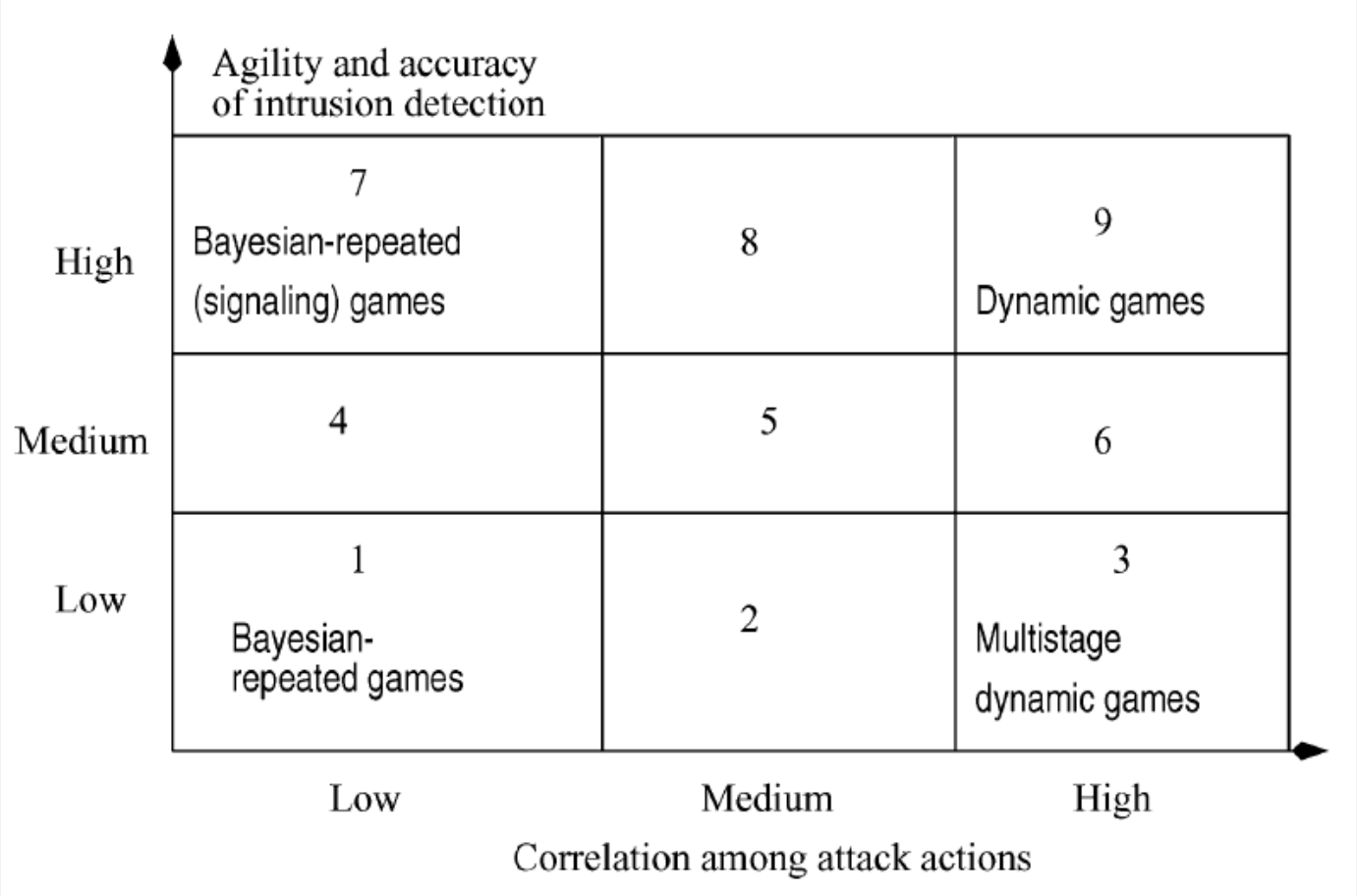


Two opportunities provided by Deep Learning in Adaptive Cyber Defense



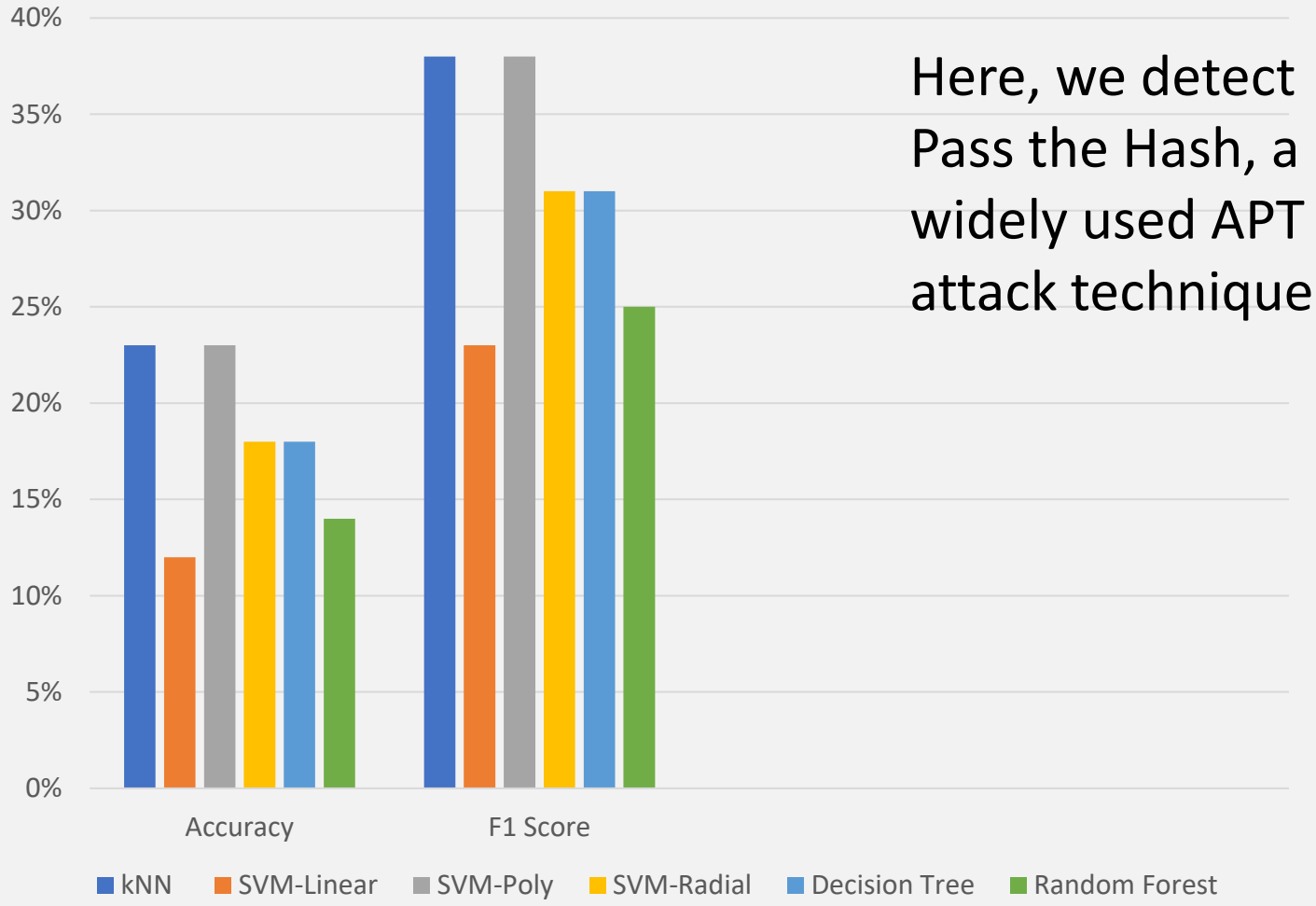
Impact of detection agility and accuracy on game-theoretic defenses

In the context of defending multi-stage attacks in enterprise networks…



P. Liu, et al., "Incentive-Based Modeling and Inference of Attacker Intent, Objectives, and Strategies," ACM TOPS, 2005

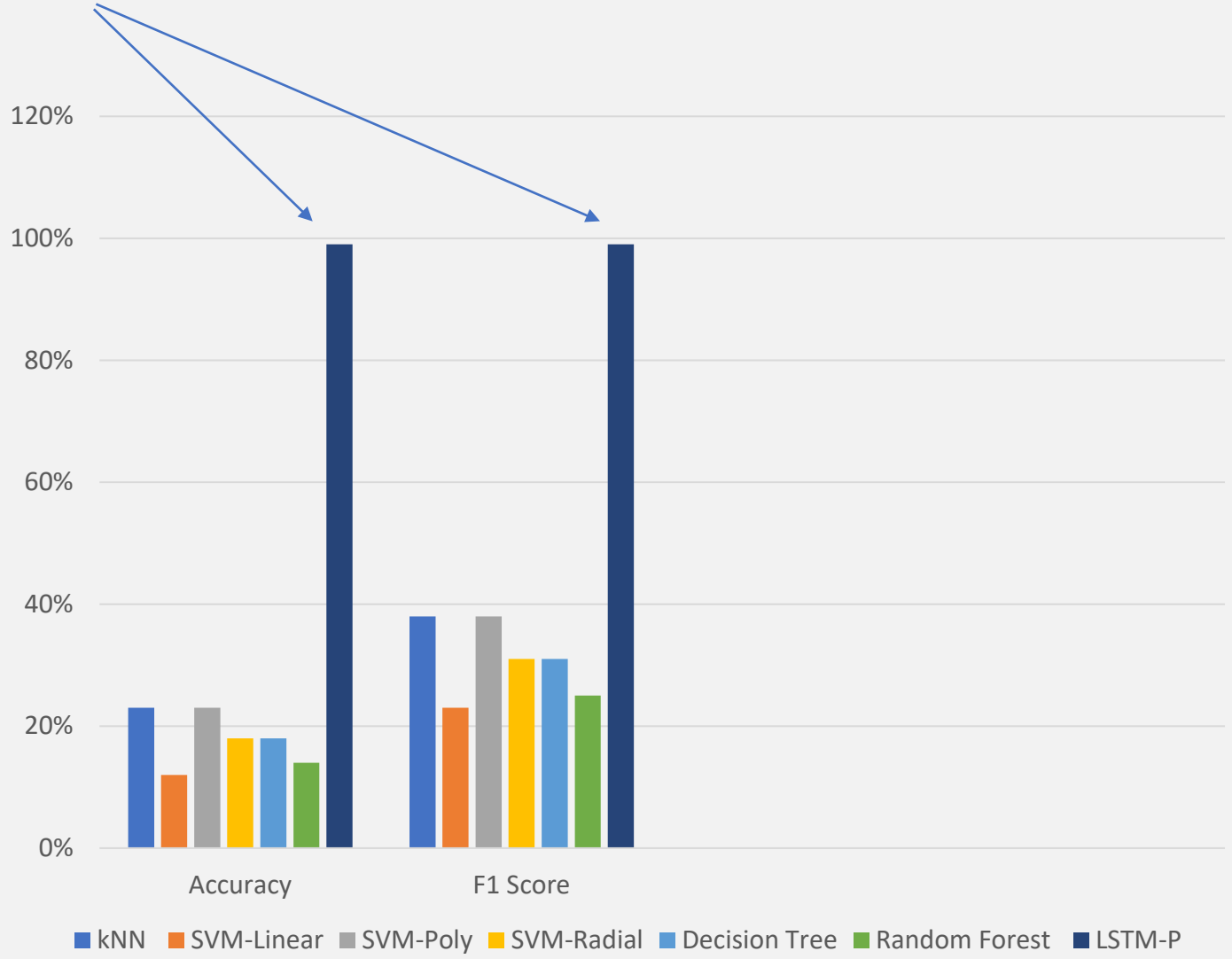
Traditional Machine Learning is not very effective in detecting attacks



Here, we detect Pass the Hash, a widely used APT attack technique

- **Heavily dependent on feature engineering**
- **Requires a lot domain knowledge (e.g., the relation of the features to the attacks of interest)**

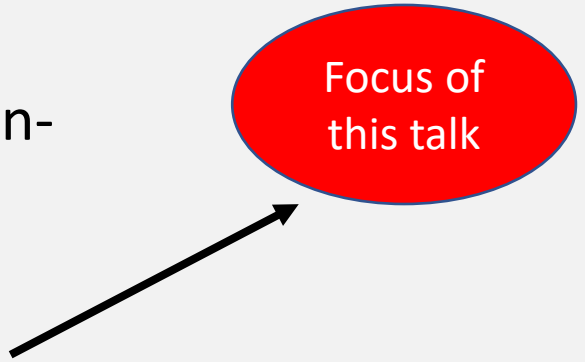
DL makes a difference



- One major advantage of DL is that it makes learning algorithms less dependent on feature engineering
- Another major advantage of DL is that it could achieve high classification accuracy with minimum domain knowledge

Importance of logic-flaw-exploiting network attacks

- APT attacks leverage 5 main categories of **R2L** (remote to local) techniques
  - Spear Phishing
  - Cross-site scripting and Drive-by download
  - Memory corruption attacks (e.g., buffer overflow, return-to-Libc, ROP)
  - Backdoor (SolarWinds)
  - **Logic-flaw-exploiting (LFE) network attacks (e.g., PtH)**



However, it is very challenging to detect LFE network attacks!

Traditional network attack detection techniques

- Signature-based
- Rule-based

} Need constant updates & May not always be available

- Anomaly detection-based → Tend to raise false alarms

Public network attack data sets

KDD99, NSL-KDD, UNSW-NB15, CICIDS2017, CICIDS-2018, etc.

They are not very suitable for applying DL in detecting LFE network attacks!

- Do not include LFE attacks
- Unbalanced
- Lack of variations
- Coarse labeling

A new opportunity:

Deep learning could be applied to achieve **accurate**, **signature-free**, and **low-false-alarm-rate** detection!

Two major challenges:

--- datasets

--- neural network architecture search space is large

New method (JCS 2021)

- We propose an end-to-end approach to detect the LFE network attacks
  - The end-to-end approach means it starts with acquiring data and ends with detecting attacks using the trained neural networks.
- We address two challenges:
  - Data generation: **penetration testing + protocol fuzzing** → a new approach
  - Neural network training: identify fields of interest and do model selection

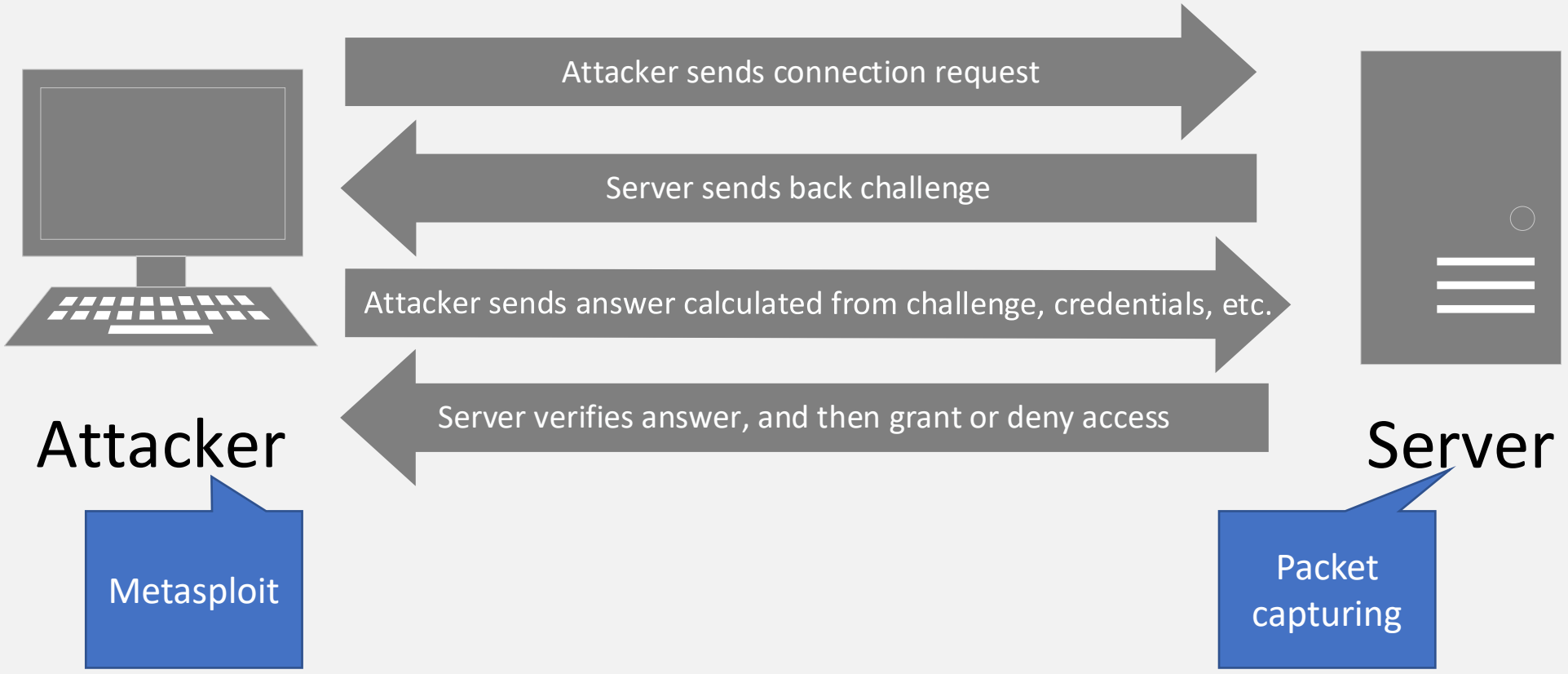
New approach for data generation

Our approach combines penetration testing and protocol fuzzing

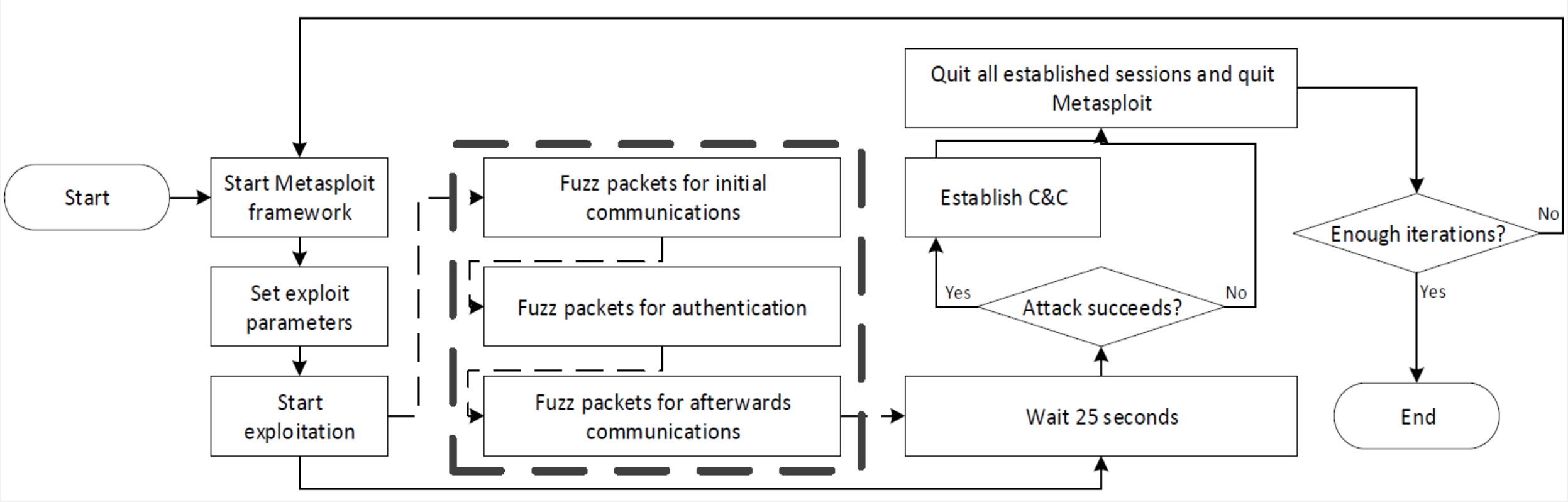
- Fuzzing inside Metasploit → change the contents of network packets → the values of some fields in the packets
- Find out which fields are able to be fuzzed
- ARP poisoning, DNS cache poisoning, PtH.

```
Result: BList, which stores fields to fuzz
input AList of all available fields;
initialize an empty BList to store fields to fuzz;
foreach field in AList do
    fuzz field;
    fuzz all fields in BList;
    launch the attack for hundreds of times;
    count successful attacks and calculate success rate;
    if attack success rate is over 50% then
        add field to BList;
    end
end
```

PtH introduction



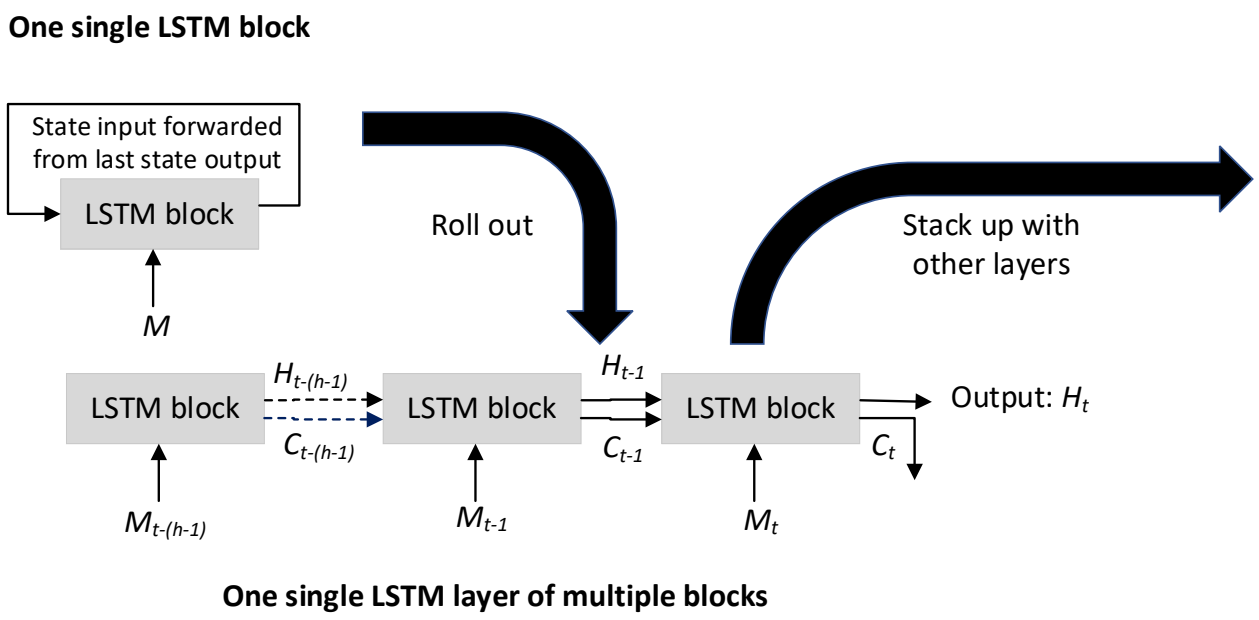
PtH data generation

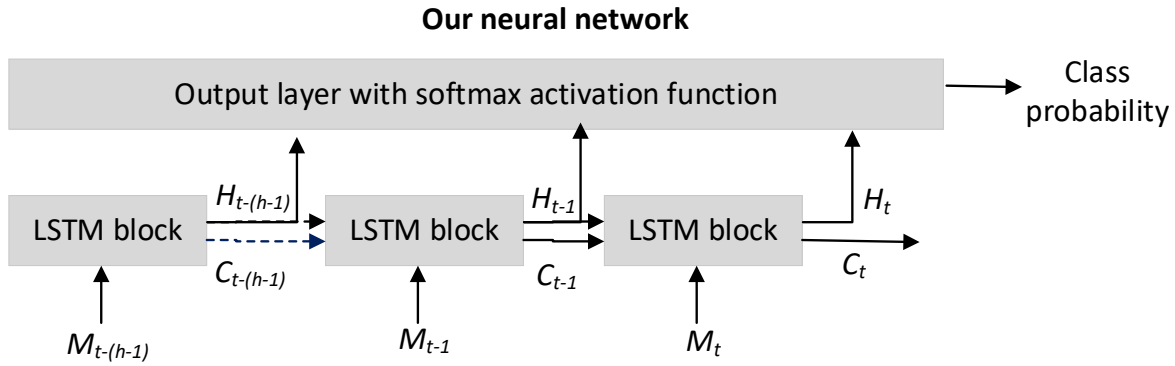


PtH detections – key insights

- Each data sample should be **a sequence of packets**, rather than an individual packet
- Differences between benign and malicious exist in the **field values** of the SMB/SMB2 layer

LSTM model for PtH detection





M stands for input; H stands for each LSTM block's output; and C stands for each LSTM block's state output. Subscripts stand for the time points, in which h stands for the window size.

Model selection

Ground truth \ Model classification	Positive (malicious)	Negative (benign)
Positive (malicious)	True positive (TP)	False negative (FN)
Negative (benign)	False positive (FP)	True negative (TN)

$$Acc = \frac{TP + TN}{TP + FN + FP + FN}$$

$$F1 = \frac{TP}{TP + 0.5 * (FP + FN)}$$

$$DR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

Metrics:

- Accuracy (Acc), F1 score (F1), detection rate (DR), and false positive rate (FPR)
- Best-performing: $P = \frac{Acc+F1}{2}$
- Best-detecting: $D = \frac{DR+1-FPR}{2}$ or $D = DR$ (if there is no negative data sample and FPR cannot be calculated)

Data set description

- Fuzzing data set: **80% as the training set, and 20% as the test set**.
  - **4-fold cross-validation** to avoid over-fitting.
- Unfuzzed data set (**real attack set**) → verify whether trained detection models can detect real attacks.

Attacks	Set	Size	Benign to malicious ratio
PtH* (best-performing)	Training	3932	1.364:1
	Test	983	1.329:1
	Real attack	214	0:1
PtH* (best-detecting)	Training	2556	0.974:1
	Test	640	0.839:1
	Real attack	192	0:1

PtH: Best-performing models

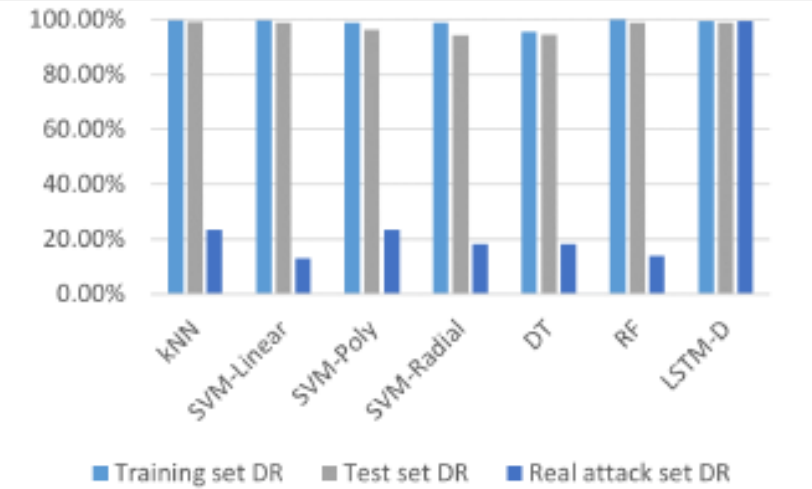
DL or ML	Model type	Training set		Test set		Real attack set	
		Acc	F1	Acc	F1	Acc	F1
DL	LSTM-P	98.45%	0.9865	98.07%	0.9831	98.96%	0.9948
ML	kNN	96.77%	0.9682	96.53%	0.9658	23.44%	0.3797
	SVM-Linear	96.89%	0.9694	96.72%	0.9674	13.02%	0.2304
	SVM-Poly	97.75%	0.9779	94.69%	0.9479	23.44%	0.3797
	SVM-Radial	98.07%	0.9810	93.72%	0.9378	18.23%	0.3084
	DT	94.70%	0.9467	95.44%	0.9533	18.23%	0.3084
	RF	100.00%	1.0000	97.99%	0.9798	14.06%	0.2466

DL models are substantially better than traditional ML models, especially on real attack set.

PtH: Best-detecting models

- LSTM model achieves highest DR.
- LSTM model achieves comparatively low FPR

DL models are better than ML models, especially on real attack set.



(b) PtH DR.

(e) PtH FPR.

Deep Learning for ACD: Challenges

- (C1) Imbalanced data
- (C2) Deep neural networks (DNN) are hard to explain
- (C3) Generalization ability cannot be taken for granted: people are **concerned** with using different neural networks to detect different network attacks
- (C4) DNN models have an extended attack surface: poisoning attack, adversary examples, etc.

We proposed “dual-threat adversary attack” in one ongoing work

- Opportunity A: Deep Learning (DL) improves observability in ACD

- Opportunity B: Deep learning enables human analysts to spend less time on a task

Why identify critical data in server programs

- ACD needs to defend not only control-flow hijacking, but also **data-oriented attacks**
- In data-oriented exploits, attackers use memory errors to modify the non-control, **security-critical data** to affect the program execution
- Turing complete attacks

```
1  int setup_env( ... ) { ...
2    aclp = login_check_limits(conf, FALSE, TRUE, &i); ...
3    if (c == NULL && aclp == 0) { ...
4      goto auth_failure;
5    } ...
6  }
7  // login_check_limits ->check_limit ->check_limit_deny
8  int check_limit_deny(config_rec *c, ...) { ...
9    if (check_user_access(c->subset, "DenyUser")) {
10     return 1;
11   } ...
12 }
```

Code 1: An example of critical data. `aclp` determines whether the program accepts current user authentication or not. Attackers may corrupt this variable to bypass blacklist.

Existing works heavily rely on human efforts

- Different from control data that are easy to detect based on the data type (e.g., function pointers) and instructions (e.g., jump, call and return), critical data are mainly defined using the program-specific, high-level semantics

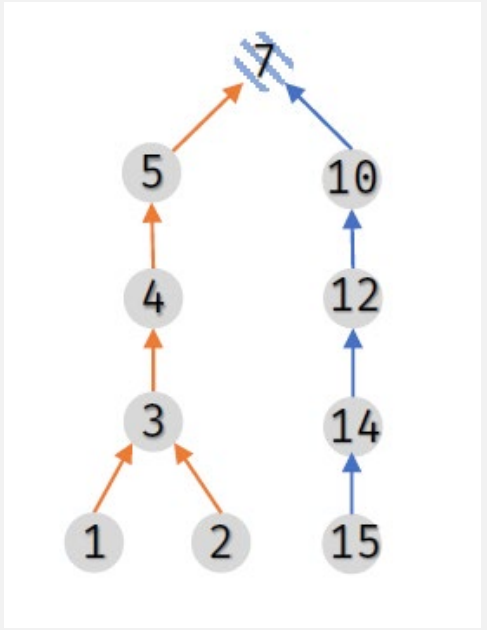
- Previous works on data-oriented exploits mainly rely on tedious human efforts to identify critical data

New method (arXiv:2108.12071)

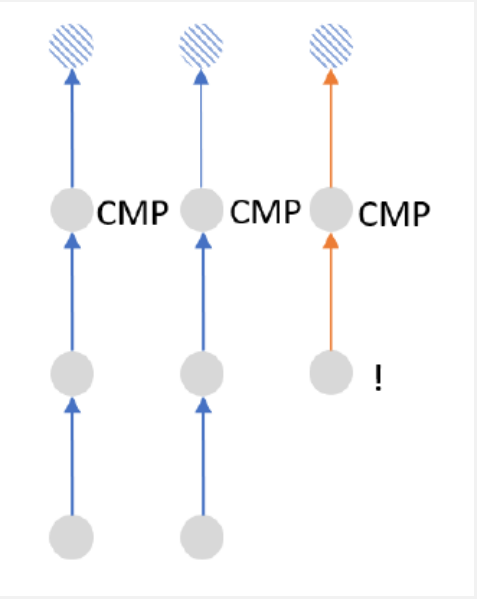
- It identifies critical data in an automated way
- It uses a deep neural model to identify critical data
  - Critical data are often associated with a particular data-flow pattern
  - Although a human analyst can write data-flow patterns to identify specific critical variables, such rules usually have very limited generalization ability, due to diversity among the data-flow patterns
  - In contrast, deep neural models have recently demonstrated remarkable generalization ability in recognizing useful patterns in several application domains such as computer vision and NLP
- It is the first work that applies DL to identify critical data in program binaries

New insights

- We found that traditional DFGs lead to low accuracy (62%, F1 score of 0.57), since the learned graph neural networks (GNN) can only learn “short” data-flow paths
  - The intuitive GNN models are not very capable
- Combination of newly defined data-flow trees and tree-LSTM enables one to learn “long” data-flow paths
  - The non-intuitive tree-LSTM models work well
- Measured control dependencies (i.e., how many basic blocks are influenced) are an important feature

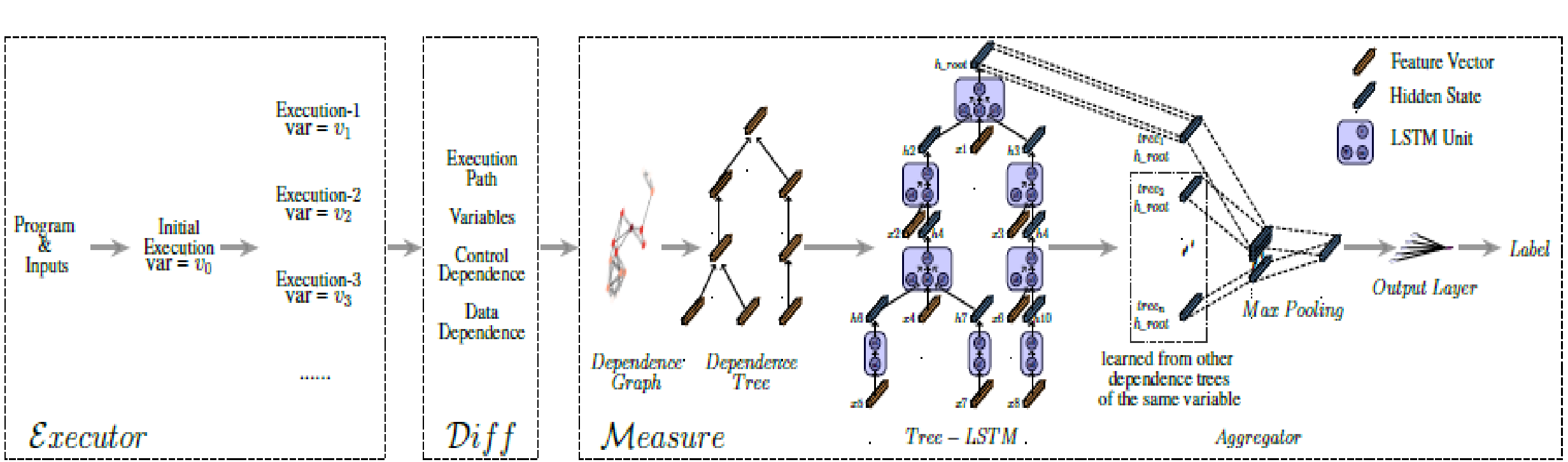


True Positive



True Negative

Workflow of the new method



Evaluation results

Dataset: 6,000 data-flow trees (each tree corresponds to a program dependency graph)

- 90% accuracy
- 8.2% false positive rate
- Discovers 80 critical variables in Google FuzzBench

Model	Accuracy	Precision	Recall	F1
RNN	0.7254	0.8287	0.6342	0.7185
LSTM	0.7465	0.8484	0.6871	0.7593
GGNN	0.6525	0.6987	0.3703	0.4818
ConvGNN	0.5465	0.5071	0.3580	0.4197
RGCN	0.6200	0.5849	0.5553	0.5698
GraphCodeBERT	0.6823	0.7058	0.8000	0.7499
SVM	0.6504	0.7472	0.5996	0.6653
Tree-LSTM (Ours)	**0.9032**	**0.9312**	**0.8919**	**0.9111**

Deep Learning for ACD: Additional Challenges

- (C5) Insights on “which data structure is most appropriate to represent the raw data” are hard to be automatically obtained or learned
- (C6) When recognizing sophisticated patterns, DL could suffer from quite a few false positives

Outline

- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- ChatGPT (and other LLMs) seems the biggest X factor

Why GPT-4 seems the biggest X factor?

The two fundamentally important aspects of cybersecurity:

Pattern Recognition

Reasoning

Before ChatGPT emerged

- DNN models had demonstrated strong pattern recognition abilities
  - However, they are very limited in reasoning
- Domain-specific models (e.g., a model trained with 1M malware samples) were viewed as the most promising direction for “AI for cybersecurity”
- Researchers had explored neural-symbolic AI: “An example is the Neural Theorem Prover, which constructs a neural network from an AND-OR proof tree generated from knowledge base rules and terms”
  - However, its reasoning ability is “jailed” by its knowledge base rules

After ChatGPT emerged

- Domain-specific models are no longer unanimously viewed as the most promising direction for “AI for cybersecurity”
- There are at least 3 alternative futures of “AI for cybersecurity”

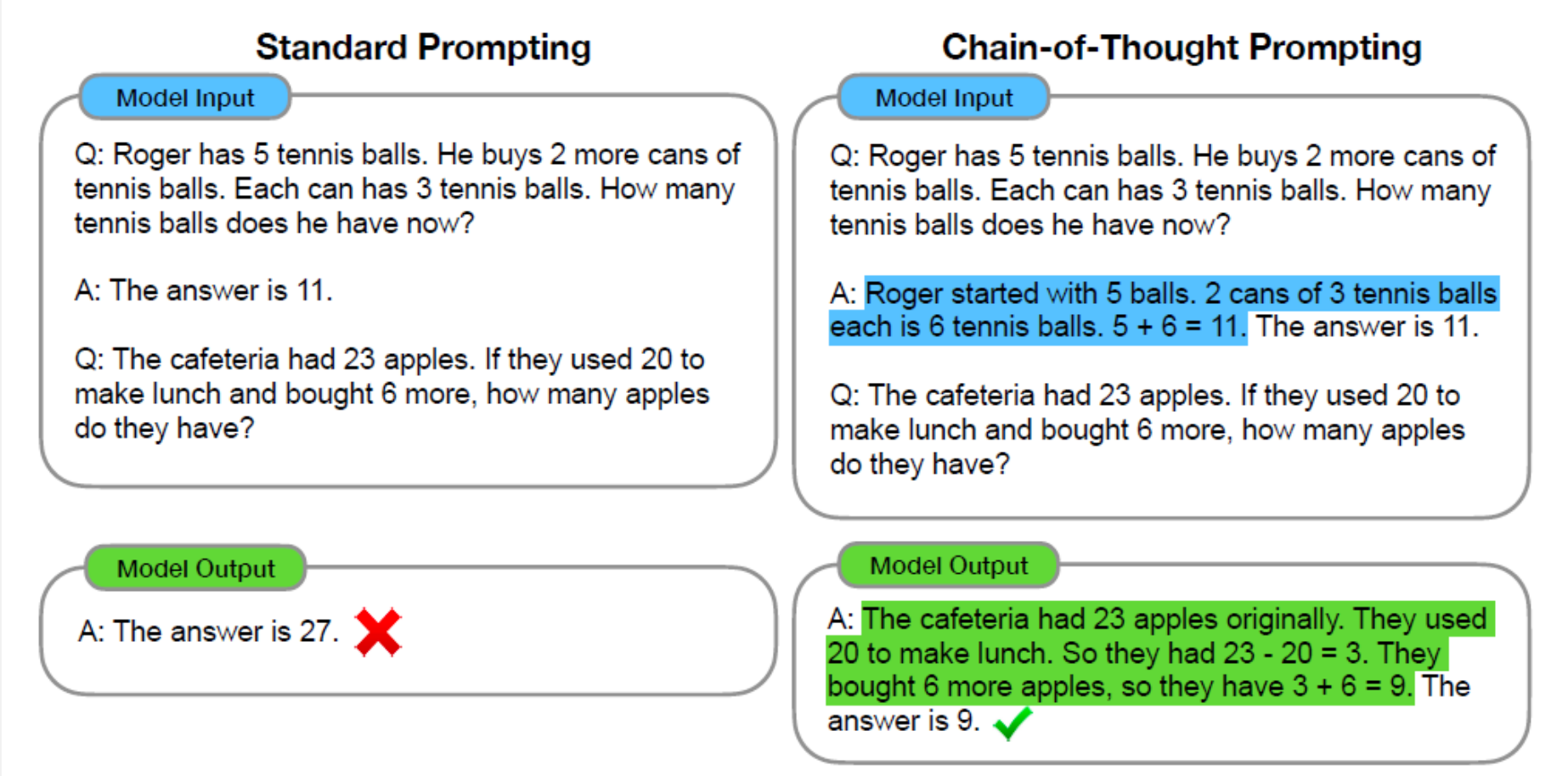
Domain-specific AI models (and problem-solving workflows)

GPT-4 security problem-solving workflows

Hybrid problem-solving workflows: GPT-4 + domain-specific models + traditional security tools (e.g., LLCM, AFL, Angr)

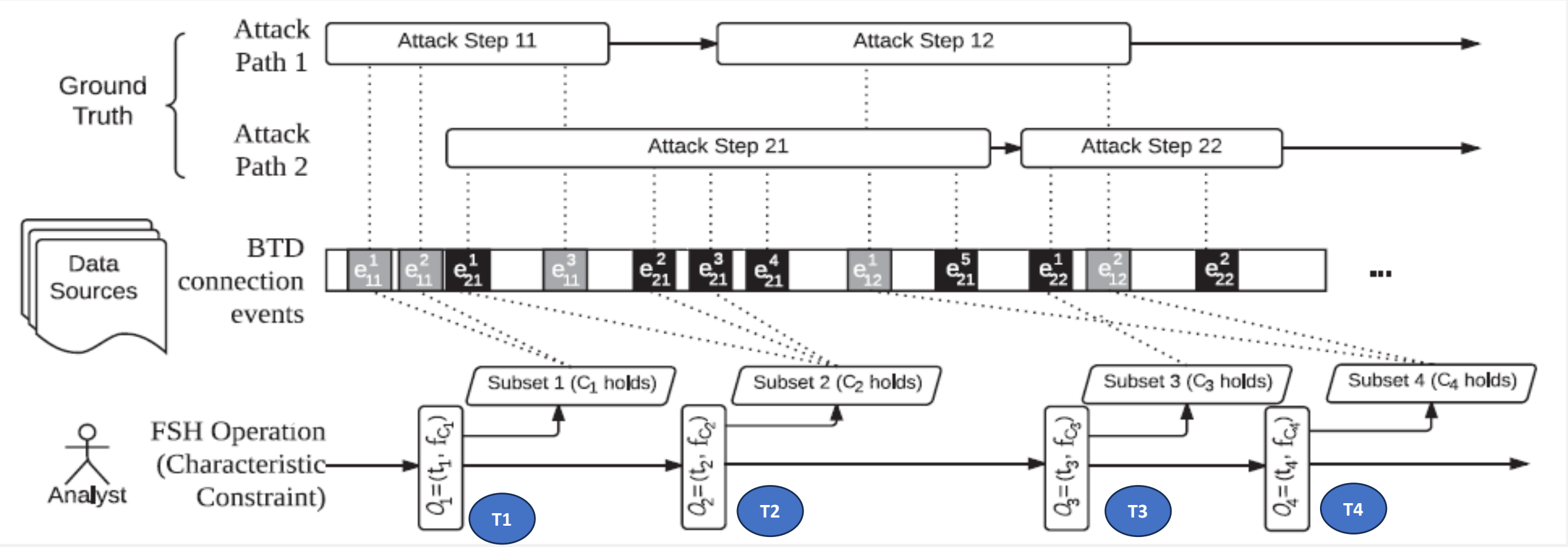
ChatGPT Chain-of-Thoughts (CoT)[1]

"… decompose multi-step problems into intermediate steps"



[1] J. Wei, et al., Chain-of-Thought Prompting Elicits Reasoning in Large Language Models, arXiv 2023

Problem-solving in security operations also involves chains of thoughts!



CoT-1: Thought 1 (T1) → find the relevant events → Thought 4 (t4) → find events

CoT-2: Thought 2 (T2) → find events → Thought 3 (T3) → find events

-- T1: Constraint C1 may correspond to the events involved in Attack Path 1

Conclusion

- A lot of progress has been made during the past 30 years; however, a few "broken heart" findings are there
- The “broken heart” findings motivate a pragmatic view of cybersecurity
- AI/ML introduce disruptive technologies in cybersecurity
- GPT-4 (and other LLMs) seems the biggest X factor

Questions?

Thank you!