COLLABORATIVE ATTACKS AND DEFENSE

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Trusted Router and Protection Against Collaborative Attacks

- Characterizing collaborative/coordinated attacks
- Types of collaborative attacks
- Identifying Malicious activity
- Identifying Collaborative Attack

Collaborative Attacks

Informal definition:

"Collaborative attacks (CA) occur when more than one attacker or running process synchronize their actions to disturb a target network"

Collaborative Attacks (cont'd)

- Forms of collaborative attacks
  - Multiple attacks occur when a system is disturbed by more than one attacker
  - Attacks in quick sequences is another way to perpetrate CA by launching sequential disruptions in short intervals
  - Attacks may concentrate on a group of nodes or spread to different group of nodes just for confusing the detection/prevention system in place
  - Attacks may be long-lived or short-lived
  - Collaborative attacks can be launched intentionally or accidentally
  - Attacks on routing

Collaborative Attacks (cont'd)

- Open issues
  - Comprehensive understanding of the coordination among attacks and/or the collaboration among various attackers
  - Characterization and Modeling of CAs
  - Intrusion Detection Systems (IDS) capable of correlating CAs
  - Coordinated prevention/defense mechanisms

Collaborative Attacks (cont'd)

- From a low-level technical point of view, attacks can be categorized into:
  - Attacks that may overshadow (cover) each other
  - Attacks that may diminish the effects of others
  - Attacks that interfere with each other
  - Attacks that may expose other attacks
  - Attacks that may be launched in sequence
  - Attacks that may target different areas of the network
  - Attacks that are just below the threshold of detection but persist in large numbers

Examples of Attacks that can Collaborate

- Denial-of-Messages (DoM) attacks
- Blackhole attacks
- Wormhole attacks
- Replication attacks
- Sybil attacks
- Rushing attacks
- Malicious flooding

We are investigating the interactions among these forms of attacks

Example of probably **incompatible** attacks:

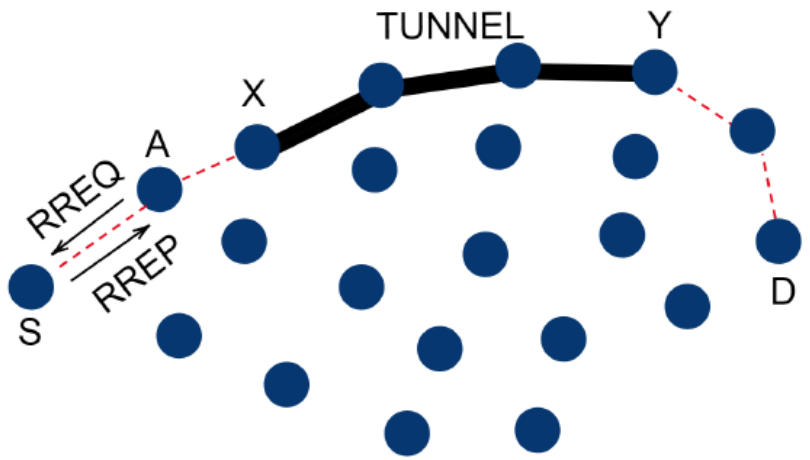
Wormhole attacks need fast connections, but **DoM** attacks reduce bandwidth!

Current Proposed Solutions

- Blackhole attack detection
  - Reverse Labeling Restriction (RLR)
- Wormhole Attacks: defense mechanism
  - E2E detector and Cell-based Open Tunnel Avoidance (COTA)
- Sybil Attack detection
  - Light-weight method based on hierarchical architecture
- Modeling Collaborative Attacks using Causal Model
- Detecting Collaboration using Machine Learning

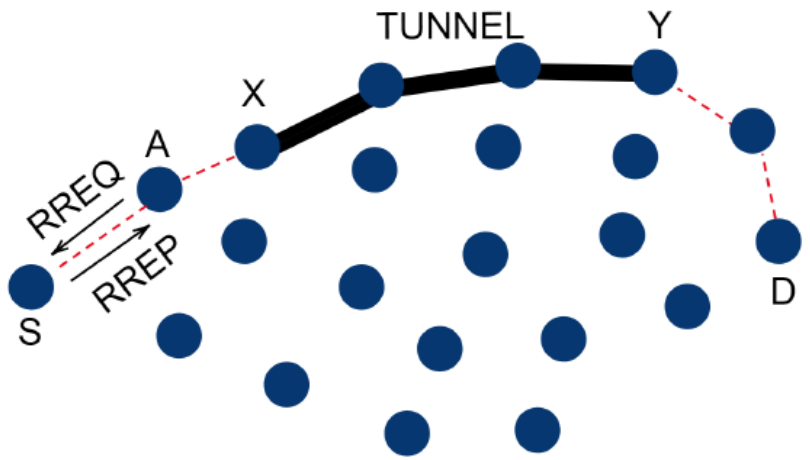
An example: blackhole attack and wormhole attack collaboration

- The attacker aims to attract as many packets as possible
  - to extract information about the system by packet inspection
  - or, to selectively drop the packets
- The goal is achieved by blackhole attack - wormhole attack collaboration

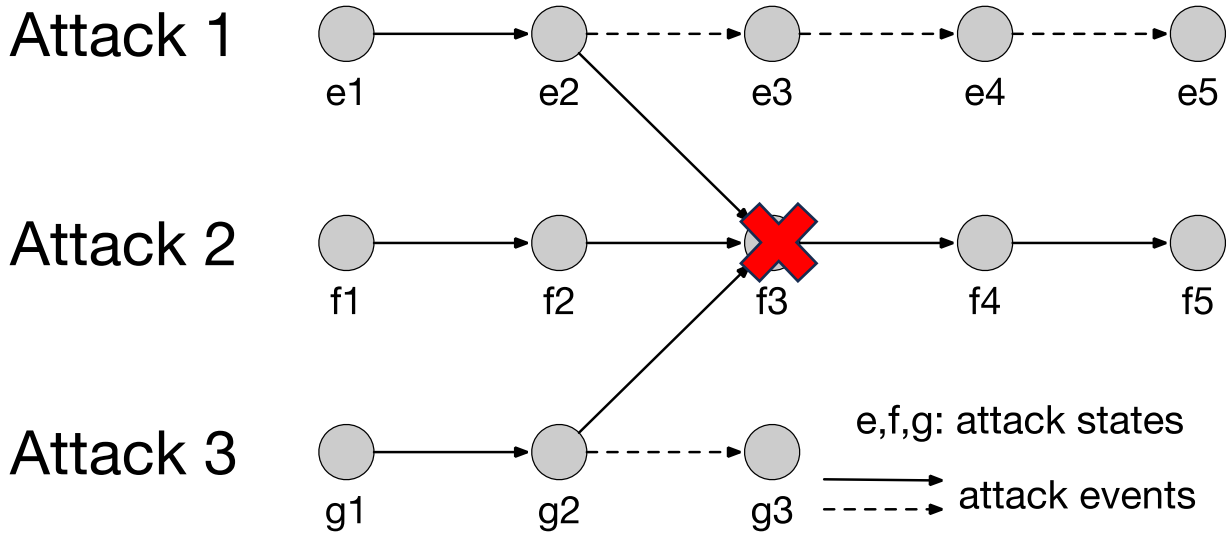


An example: blackhole attack and wormhole attack collaboration (cont'd)

- A is a blackhole attacker that attracts packets by sending fake RREP.
- X and Y are two ends of a wormhole that attract packets by advertising the one-hop route between them, namely, the wormhole.
- If A forward packets it attracted to X instead of dropping them like a normal blackhole, X will have more packets collected compared with not launching an attack or launching a wormhole attack only. The attack goal is achieved.



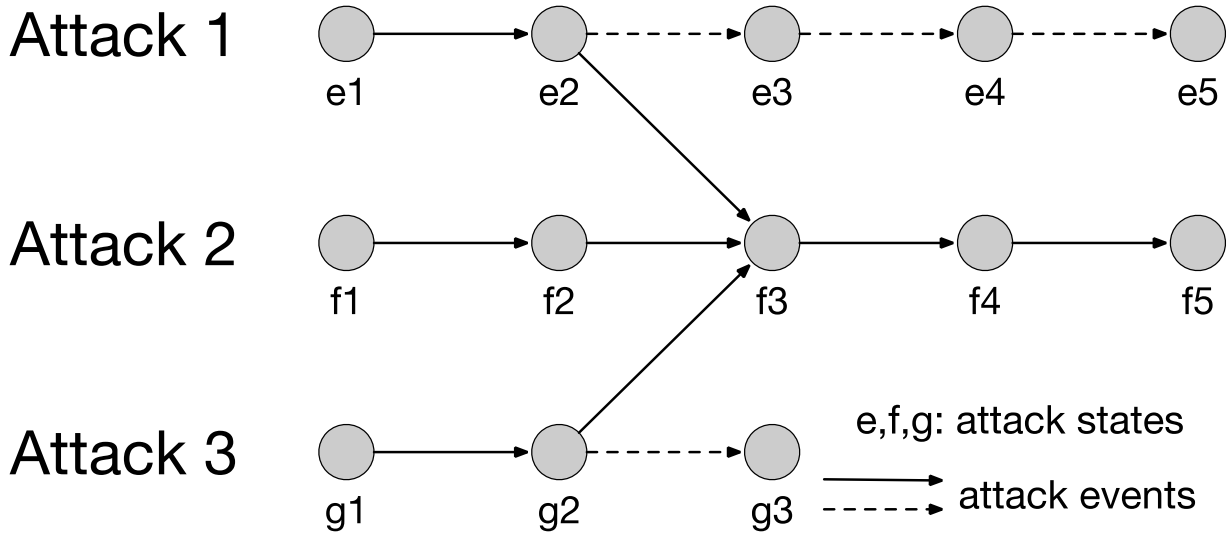
Modeling collaborative attacks with causal graph model



A collaborative attack can be modeled as a causal graph model <*S*, *E*, *M*, *L*>, where

- *S* is the set of attack states
- *E* is the set of events triggering state transition, which can be further defined by
  - Message exchange between attackers where messages are from set *E*, and
  - Local attack operations from operation set *L*
- The goal is to identify the malicious event sequences of collaborative attacks and stop it from reaching the key state (f3 in the above example)

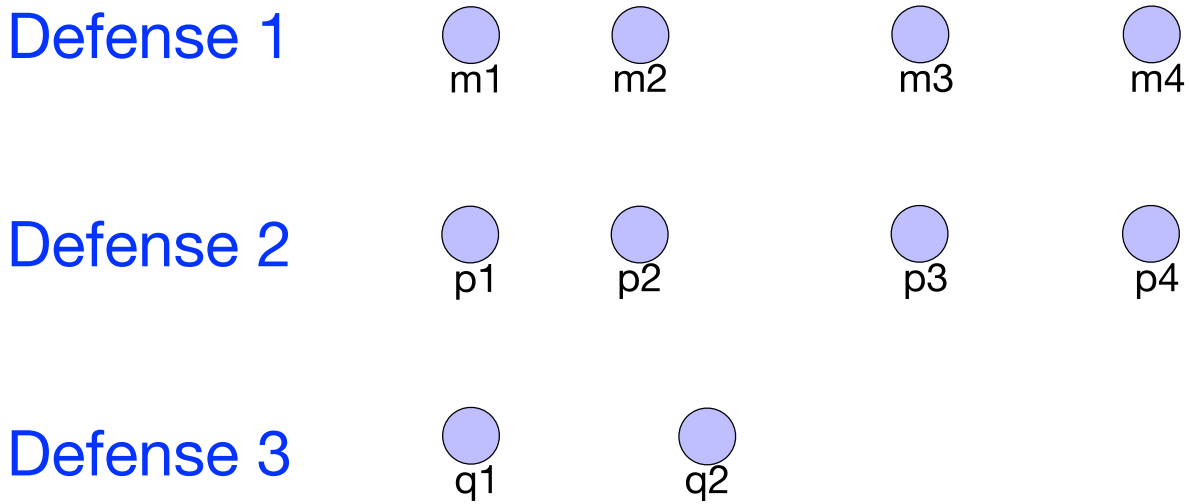
Modeling collaborative attacks with causal graph model



To prevent the attack model from reaching f3, the defender should collaborate to

1. stop Attacks 1, 2 and 3 from reaching e2, f2 and g2, respectively, or
2. stop the communication between attackers.

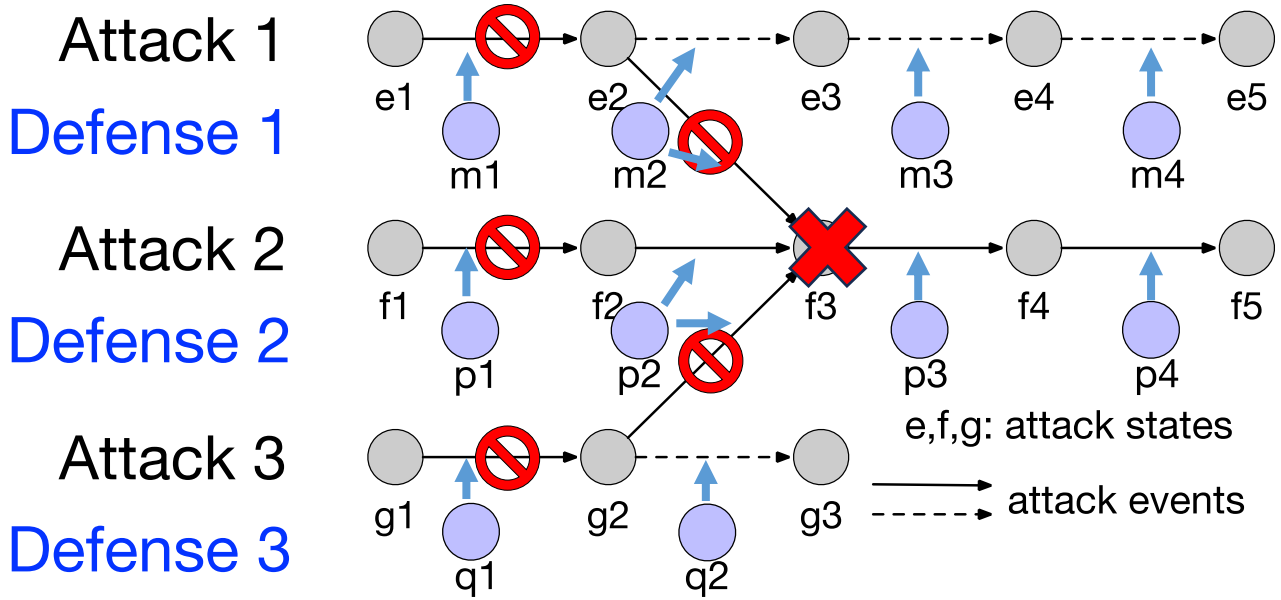
A defense strategy consists of multiple defensive events



A defense strategy consists of a set of defensive events, in the above example

- Defense 1 = $\{m_1, m_2, m_3, m_4\}$
- Defense 2 = $\{p_1, p_2, p_3, p_4\}$
- Defense 3 = $\{q_1, q_2\}$

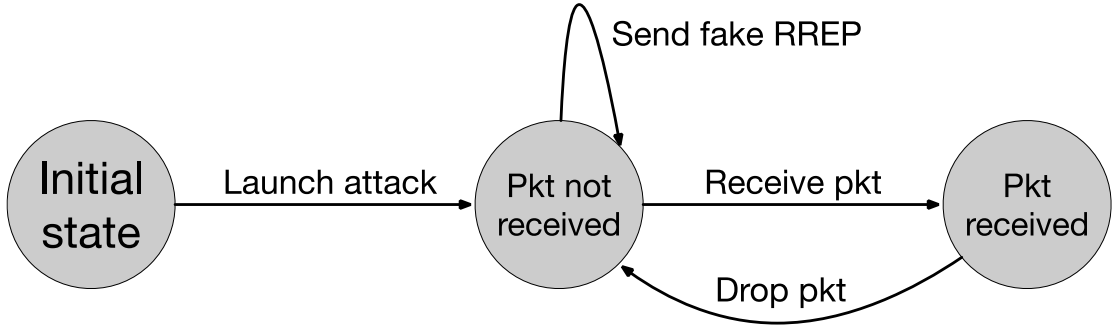
Defensive events collaborating to interfere with Attack events



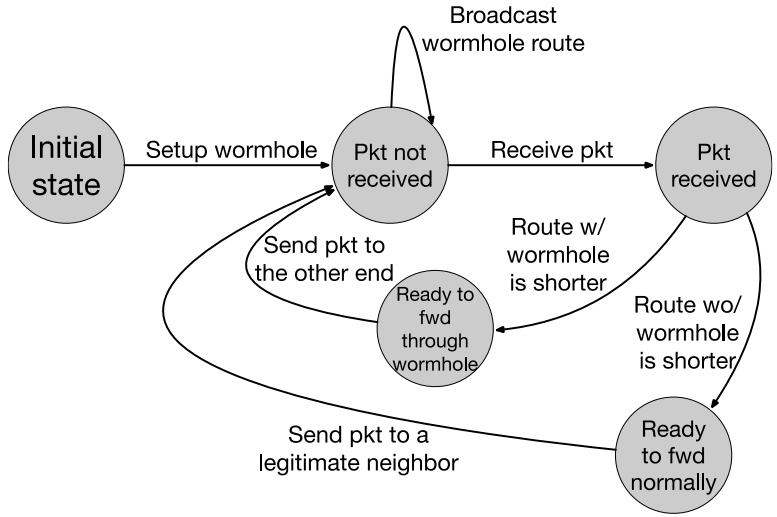
The defensive events collaborate to interfere with attack events or inter-attack communications to stop collaborative attack state transitions.

Graphs for blackhole attacks and wormhole attacks

- For blackhole attacker A:

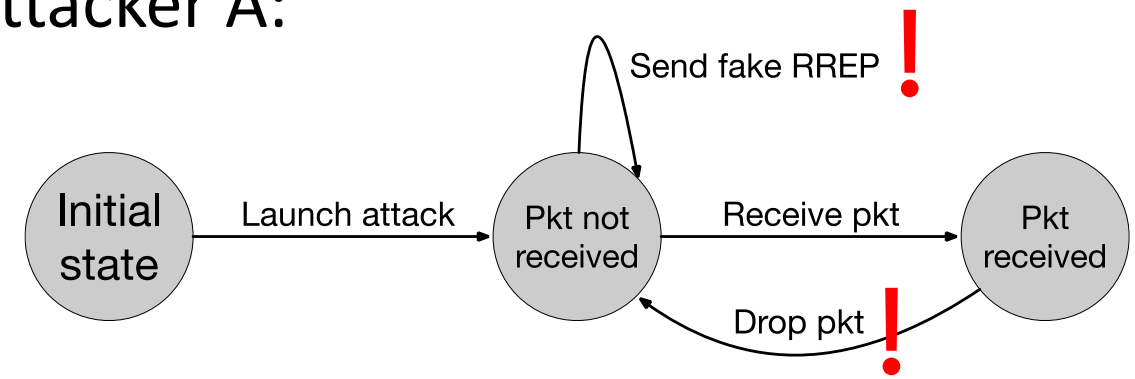


- For each of two ends of the wormhole, X and Y:



Defend against single attacks by detecting abnormal events

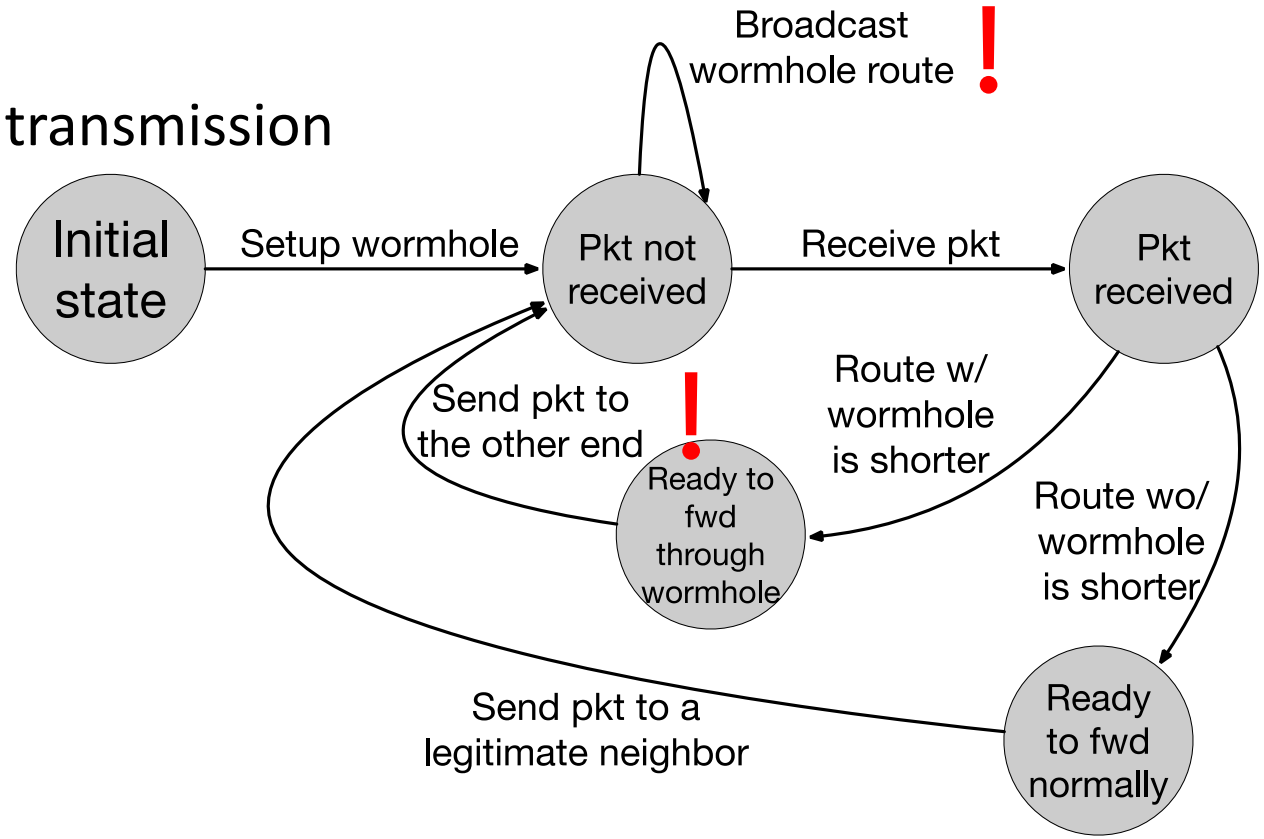
- For blackhole attacker A:



- Detector $D_A = \{d_{A1}, d_{A2}\}$
  - d_{A1}: monitors fake RREP
  - d_{A2}: monitors packet drop

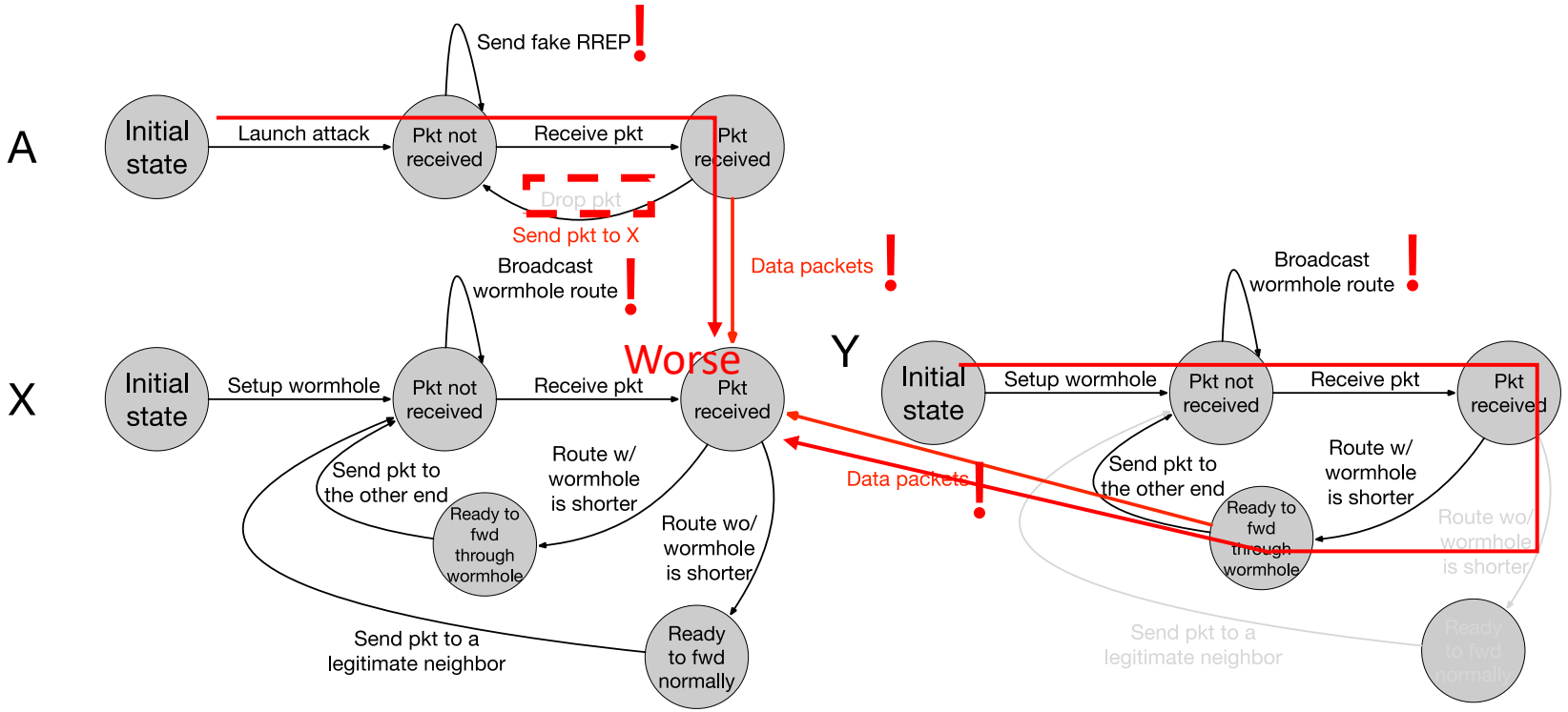
Defend against single attacks by detecting abnormal events (cont'd)

- For two ends of the wormhole X and Y:
- Detector $D_B = \{d_{B1}, d_{B2}\}$
  - d_{B1}: monitors abnormal RREP
  - d_{B2}: monitors abnormal packet transmission



Modeling and detecting collaborative attacks

- The ‘bad’ state (`X receives pkt`) becomes ‘worse’.
- Detection d_{A2} becomes ineffective since A no longer drops packets.
- The bad state can be reached through more paths due to collaboration.
- Thus, the detectors DA and DB have to collaborate to defend. $D_{collab} = \{d_{A1}, d_{B1}, d_{B2}\}$

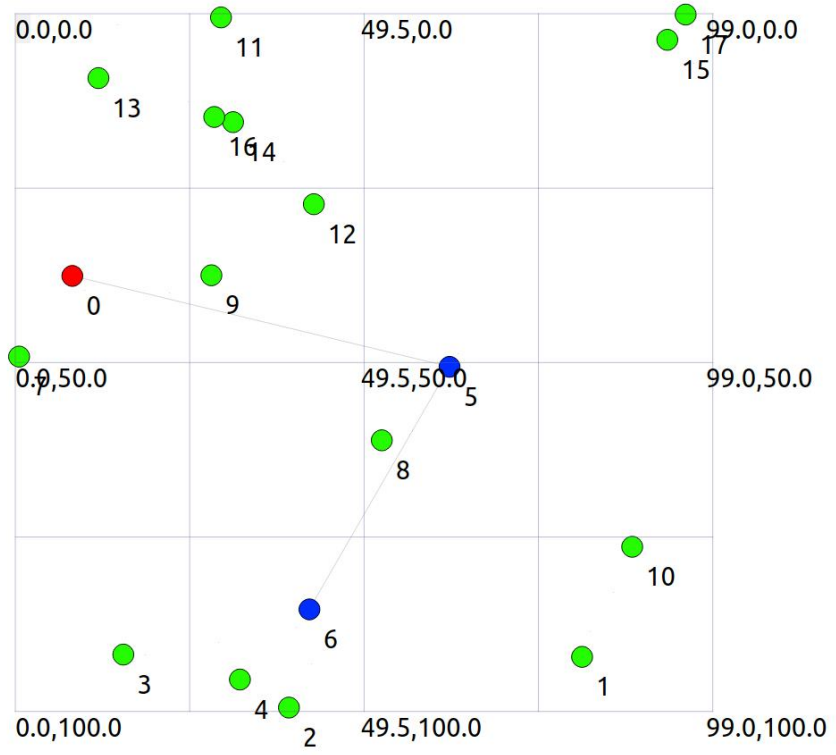


Evaluate the detection and defend mechanisms with ns3

We have implemented the above example with ns3

- Red node is the blackhole attacker A
- Blue nodes are wormhole attackers X and Y
- Gray lines are tunnel and wormhole

We will evaluate our solution mechanism with ns3



Follow-up research questions

- Given more single attack patterns (e.g., replication attacks, rushing attacks), we need to define causal rules to automatically judge whether and how those attacks can collaborate.
- As the number of attackers increases, the collaborative attack graph becomes more complex, we need more advanced techniques to exhaust the paths from initial states to bad states.
- In a system, how do we know that abnormal events are happening which may lead the system to a bad state?
  - We plan to use machine learning approaches (next slides)

Why to use Machine Learning

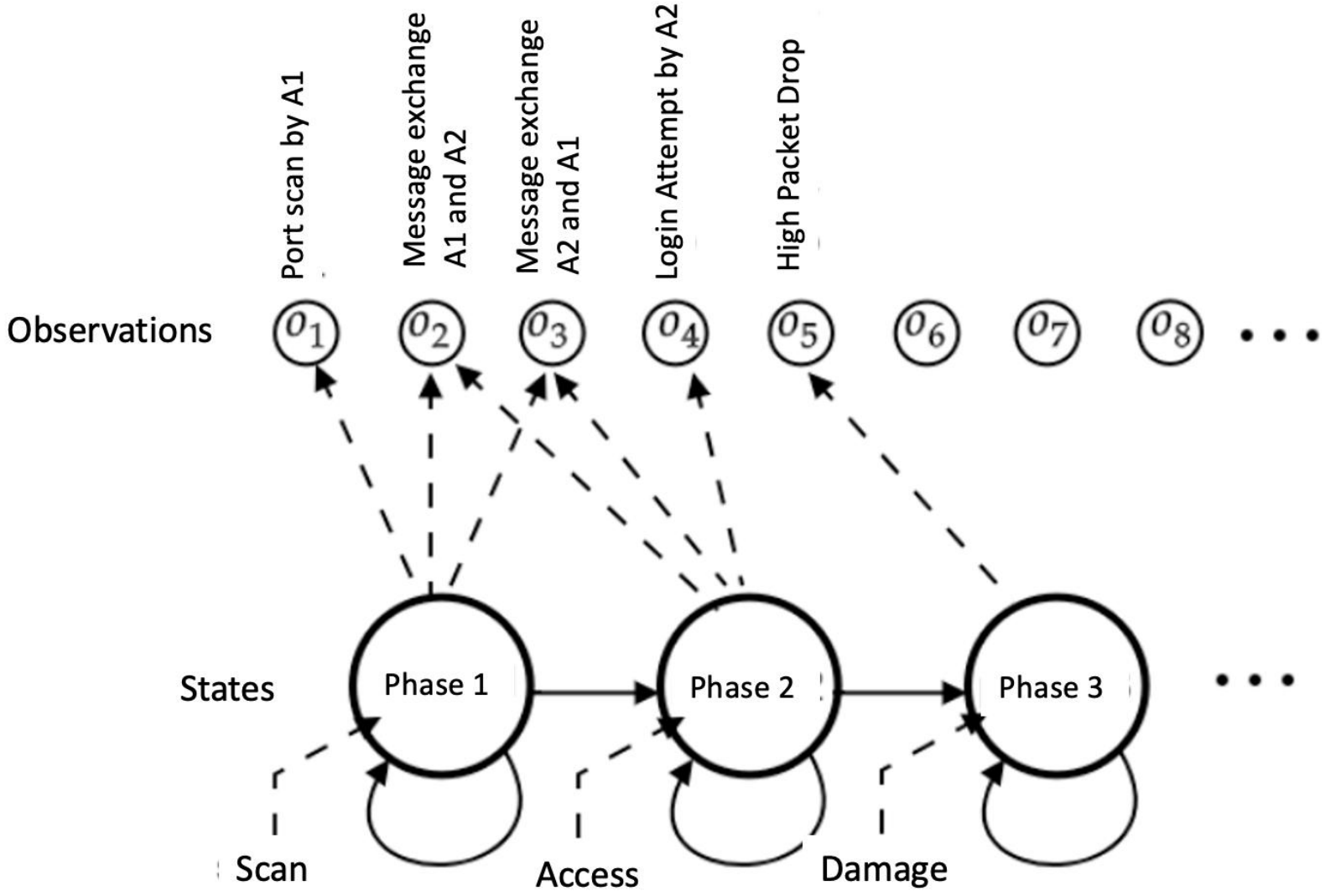
- The ML algorithm can continuously learn and adapt to new attack patterns.
- It can analyze large amounts of data to detect advanced threats and reduce false positives/negatives.
- It is initially resource-intensive but more economical in the long term.
- It reduces manual updates.

Hidden Markov Model

- A sudden spike in port scans on critical servers, coupled with a surge in message traffic and repeated login failures, potentially indicates a collaborative attack.

- HMM leverages temporal relationships and probabilistic state transitions to dynamically monitor and identify potential network attacks.

Hidden Markov Model



How Hidden Markov Model works?

- System States can be Normal, Port Scan, Access, Damage
- The system observes events called observations.
- The algorithm can be trained on data including port activities, message logs, etc.
- Baum-Welch (BW) and Viterbi algorithms can be used for training.
- HMM can be applied to real-time data for state sequence analysis.
- If there are suspicious activities, the IP address of the attacker can be blocked, and notifications can be provided

Utilizing LSTM (Long Short-Term Memory) Network

- LSTM's strength lies in its ability to process sequential data and capture long-term patterns, making it highly effective for real-time network security monitoring.

For instance, LSTMs can detect irregular patterns, such as identifying a mild port scan followed by spikes in messages and unusual login attempts (both could happen days later “mild port scan”). This capability allows LSTM to flag such sequences as potential collaborative attacks.

How can LSTM work

- Dataset:
  - Timestep 1: event 1 [Normal Traffic]
  - Timestep 2: event 2 [Port Scan]
  - Timestep 3: event 3 [Increased Messaging]
  - Timestep 4: event 4 [Failed Logins]

- LSTM Processing: LSTM can process all previous states to predict collaboration
  - input: event 1 => output: No Attack
  - input: event 1, event 2 => output: Port Scan
  - input: event 1, event 2, event 3 => output: Access
  - input: event 1, event 2, event, event 4 => output: Potential collaborative attack

Contrastive Learning

- Contrastive Learning's strength lies in its ability to learn nuanced differences between normal and malicious behaviors.

- A model trained with Contrastive Learning could recognize irregular message exchanges and login attempts, distinguishing them from normal behavior and flagging them as potential attacks.

- Not every login attempt failure is malicious; contrastive learning can help distinguish between normal login attempt failure and malicious login attempt failure.

How does Contrastive Learning work?

- The algorithm is provided an event that is an Anchor (without anomaly) during training.
- All other events are positive (P) or negative (N). The positive (P) event is an anomaly. The negative (N) is a legitimate data point.
- The algorithm maximizes the distance between A and P while minimizing the distance between A and N.
- In real-time, the algorithms compute the distance between the event and anchor to predict whether the event is an anomaly or legitimate.

Problem Statement

Packet drop attacks put severe threats to Ad Hoc network performance and safety

- Directly impact the parameters such as packet delivery ratio
- Will impact security mechanisms such as distributed node behavior monitoring
- Different approaches have been proposed
  - Vulnerable to collaborative attacks
  - Have strong assumptions of the nodes

Problem Statement

Many research efforts focus on individual attackers

- The effectiveness of detection methods will be weakened under collaborative attacks
  - E.g., in “watchdog”, multiple malicious nodes can provide fake evidences to support each other’s innocence
  - In wormhole and Sybil attacks, malicious nodes may share keys to hide their real identities

Problem Statement

We focus on collaborative packet drop attacks. Why?

- Secure and robust data delivery is a top priority for many applications
- The proposed approach can be achieved as a reactive method: reduce overhead during normal operations
- Can be applied in parallel to secure routing

Related Work

Detecting packet drop attacks

- Audit based approaches
  - Whether or not the next hop forward the packets
  - Use both first hand and second hand evidences
  - Problems:
    - Energy consumption of eavesdropping
    - Can be cheated by directional antenna
    - Authenticity of the evidence
- Incentive based approaches
  - Nuggets and credits
- Multi-hop acknowledgement

Related Work

Collaborative attacks and detection

- Classification of the collaborative attacks
- Collusion attack model on secure routing protocols
- Collaborative attacks on key management in MANET
- Detection mechanisms:
    - Collaborative IDS systems
    - Ideas from immune systems
    - Byzantine behavior based detection

REAct system and Vulnerability

REAct system:

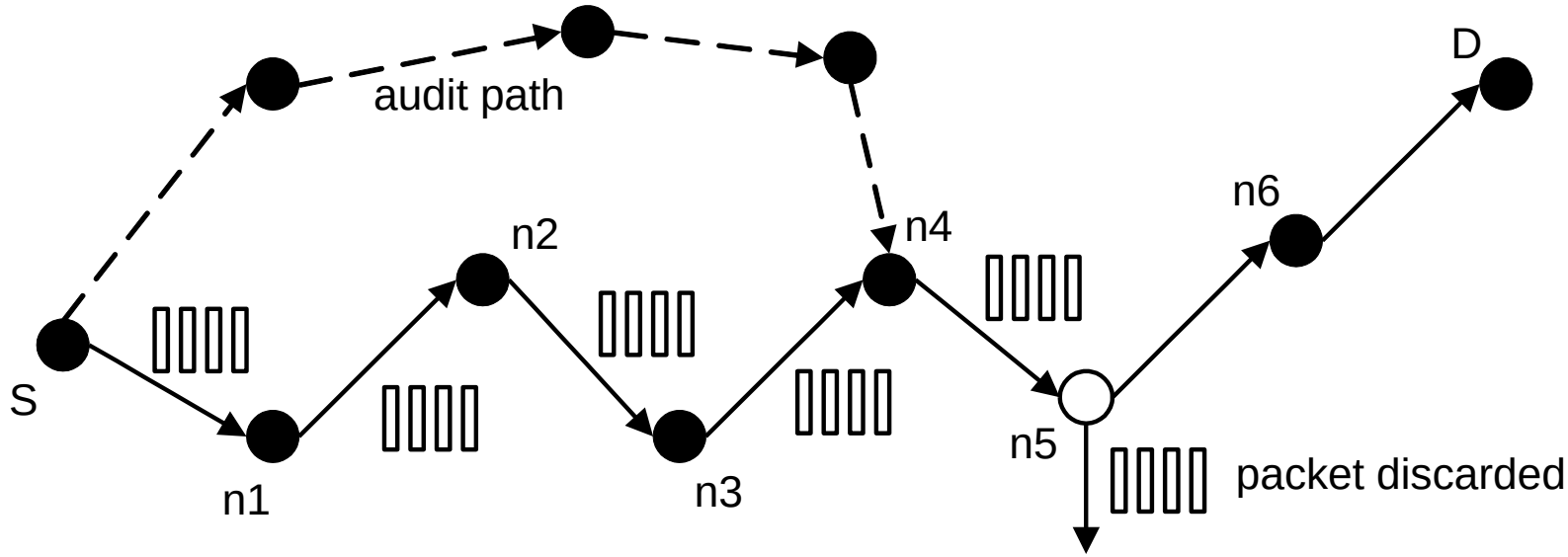
- Proposed by researchers in Arizona, ACM WiSec 2009
- Random audit based detector of packet drop
- A reactive approach: will be activated only when something bad happens
- Assumptions:
  - At least two node disjoint paths b/w any pair of nodes
  - Know the identity of the intermediate nodes
  - Pair-wise keys b/w the source and the intermediate nodes

REAct system and Vulnerability

Working procedure of REAct

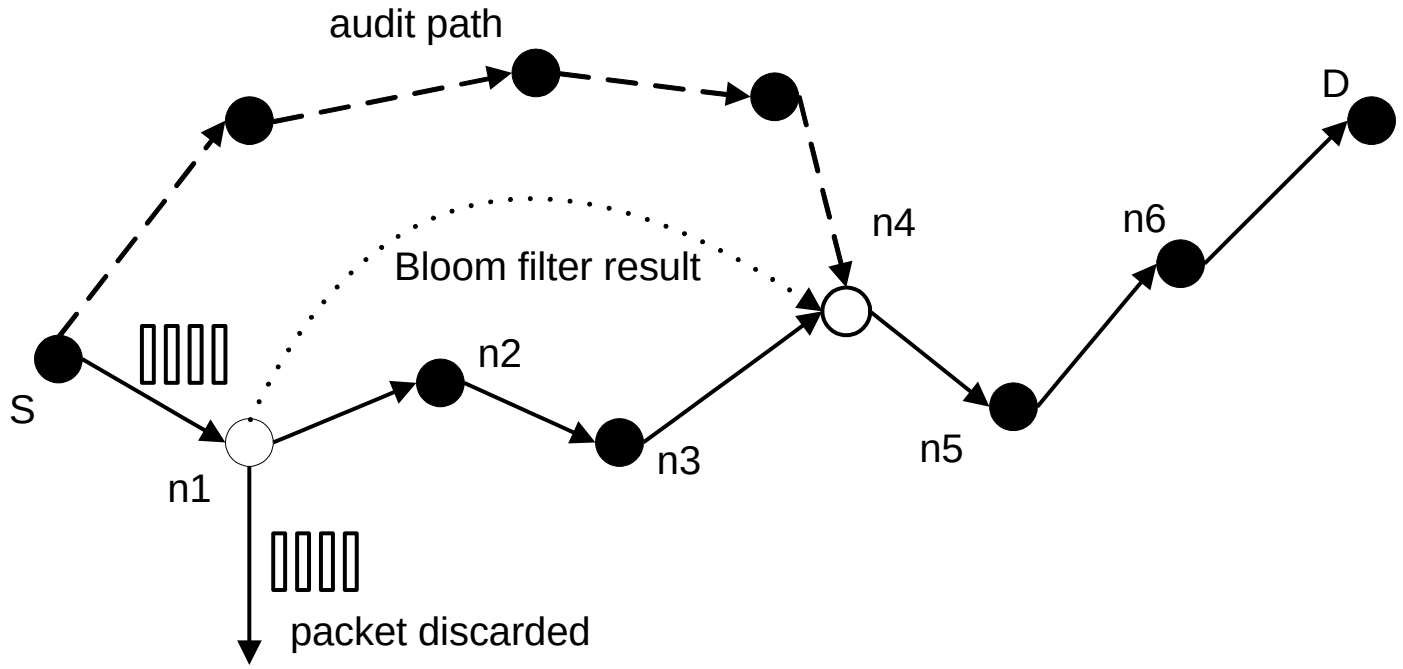
- Destination detects the drop in packet arriving rate and notifies the source
- Source randomly selects an intermediate node and asks it to generate a behavioral proof of the received packets
- Intermediate node constructs a bloom filter using these packets
- Source compares the bloom filter to its own value
  - If match: the attacker is after the intermediate node
  - Otherwise, it is before the intermediate node
- Repeat the procedure until the bad link is located

REAct system and vulnerability



Example of REAct: the source selects n4 to be the first audited node. n4 generates the correct bloom filter, so the attacker is between n4 and D.

Collaborative attacks on REAct



n1 and n4 are collusive attackers. n1 discards the packets but delivers the bloom filter to n4. Now the source will think that the attacker is between n4 and D.

Why REAct is vulnerable to this attack: the source can verify the bloom filter, but not the generator of the filter.

Proposed approach

Assumptions:

- Source shares a different secret key and a different random number with every intermediate node
- All nodes in the network agree on a hash function *h()*
- There are multiple attackers in the network
  - They share their secret keys and random numbers
  - Attackers have their own communication channel
  - An attacker can impersonate other attackers

Proposed approach

Hash based approach:

- Every node will add a fingerprint into the packet

  S1 sends out the packet to n1:

  $S \rightarrow n1$: (S, D, data packet, random number $t0$)

  Node *n1* will combine the received packet and its random number *r1* to calculate the new fingerprint:

  $t1 = h(r1 \,||\, S \,||\, D \,||$ data packet $||\, t0 \,||\, r1)$

  $n1 \rightarrow n2$: (S, D, data packet, $t1$)

  The audited node will generate the bloom filter based on the data packets and the fingerprints

  The source will generate its own bloom filter and compare it to the value of the audited node

Proposed approach

Why our approach is safe

- The node behavioral proofs in our proposed approach contain information from both the data packets and the intermediate nodes.
- Theorem 1. If node *ni* correctly generates the value *ti*, then all innocent nodes in the path before *ni* (including *ni*) must have correctly received the data packet selected by *S*.

Proposed approach

Why this approach is safe

- The ordered hash calculations guarantee that any update, insertion, and deletion operations to the sequence of forwarding nodes will be detected.
- Therefore, we have:
  - if the behavioral proof passes the test of S, the suspicious set will be reduced to {*ni, ni+1, ---, D*}
  - if the behavioral proof fails the test of S, the suspicious set will be reduced to {S, n1, ---, ni}

Discussion

- Indistinguishable audit packets
  - The malicious node should not tell the difference between the data packets and audited packets
  - The source will attach a random number to every data packet
- Reducing computation overhead
  - A hash function needs 20 machine cycles to process one byte
  - We can choose a part of the bytes in the packet to generate the fingerprint. In this way, we can balance the overhead and the detection capability.

Discussion

- Security of the proposed approach
  - The hash function is easy to compute: very hard to conduct DoS attacks on our approach
  - It is hard for attackers to generate fake fingerprint: they have to have a non-negligible advantage in breaking the hash function
- The attackers will adjust their behavior to avoid detection
  - The source may choose multiple nodes to be audited at the same time
  - The source should adopt a random pattern to determine the audited nodes

Dealing with Collaborative Attacks

- Earlier approach is vulnerable to collaborative attacks
- Propose a new mechanism for nodes to generate behavioral proofs
  - Hash based packet commitment
  - Contain both contents of the packets and information of the forwarding paths
  - Introduce limited computation and communication overhead
- Extensions:
  - Investigate other collaborative attacks
  - Integrate our detection method with secure routing protocols

Reasoning and Detecting Collaborative Attacks in Autonomous UAV Networks

Growing Autonomous UAV Network Market

- Autonomous UAV networks are gaining increasing prevalence.
  - The UAV market will reach 100 billion USD by 2030. [1]
- Their growing prevalence demands robust security, especially against collaborative attacks.

Autonomous UAV Network Security

- Inherit fundamental security vulnerabilities from traditional autonomous networks, while facing unique challenges
  - Wireless nature
  - Highly dynamic topology
  - Rapid node mobility
  - Communication disruptions and packet losses
- Thus, it is important to develop robust security mechanisms for autonomous UAV networks.
- These characteristics make them more vulnerable to collaborative attacks.

Collaborative Attack Definition

- Multiple adversaries coordinate and synchronize their actions to achieve disruption, deception, or usurpation of the target network.
- It is a threat that will be exacerbated by the increasing availability of commercial off-the-shelf (COTS) UAV platforms.
- Implications
  - Attackers can simultaneously compromise multiple UAVs within a network to wage attacks that exceed the capabilities of individual adversaries, such as co-ordinated jamming combined with false data injection.
  - Multiple attackers may employ different attack vectors concurrently, forcing the network to defend against diverse threats simultaneously.

Collaborative Attacks

- What are Collaborative Attacks?
  - DDoS Attacks [2]
  - Coordinated Eavesdropping [3]
- Why are they Important?
  - They are more harmful to the network
    - Amplifying Effect
    - Shortcut Effect
  - They are harder to detect and defend
    - Hiding Effect
  - The above effects are dubbed *synergy effects (SEs)*

Proposed Tasks

- Task 1: Defining Collaborative Attacks against Autonomous UAV Networks
  - Develops formal system and threat models for collaborative attacks against autonomous UAV networks, while establishing experimental validation approaches.
  - Three subtasks include:
    - characterizing system models that capture the features and resource constraints of autonomous UAV networks,
    - formulating threat models that define the capabilities and coordination patterns of collaborative attackers, and
    - developing comprehensive approaches for experimental validation of both attacks and defenses.

Proposed Tasks

- Task 2: Designing Mechanisms to Secure Autonomous UAV Networks against Collaborative Attacks
  - Resource-constrained UAVs require a lightweight, onboard filtering mechanism to handle high-volume traffic loads, for which we employ lightweight machine learning (ML) models as the initial detection layer.
  - The filtered alerts are then processed with two complementary tracks: an instant analysis track and a long-term analysis track.
    - Instant track: alerts trigger security verification against defined attack models using model checking technology to identify immediate threats.
    - Long-term track: employs sequential and attention-based ML techniques to uncover complex temporal dependencies between alerts that may indicate coordinated adversarial behavior.

Proposed Tasks

- Task 2: Designing Mechanisms to Secure Autonomous UAV Networks against Collaborative Attacks (continued)
  - The discovered long-term attack patterns are then fed back into the model checker for pattern analysis.
    - This creates a closed-loop system where model checking discovers attack patterns that guide the refinement of ML models

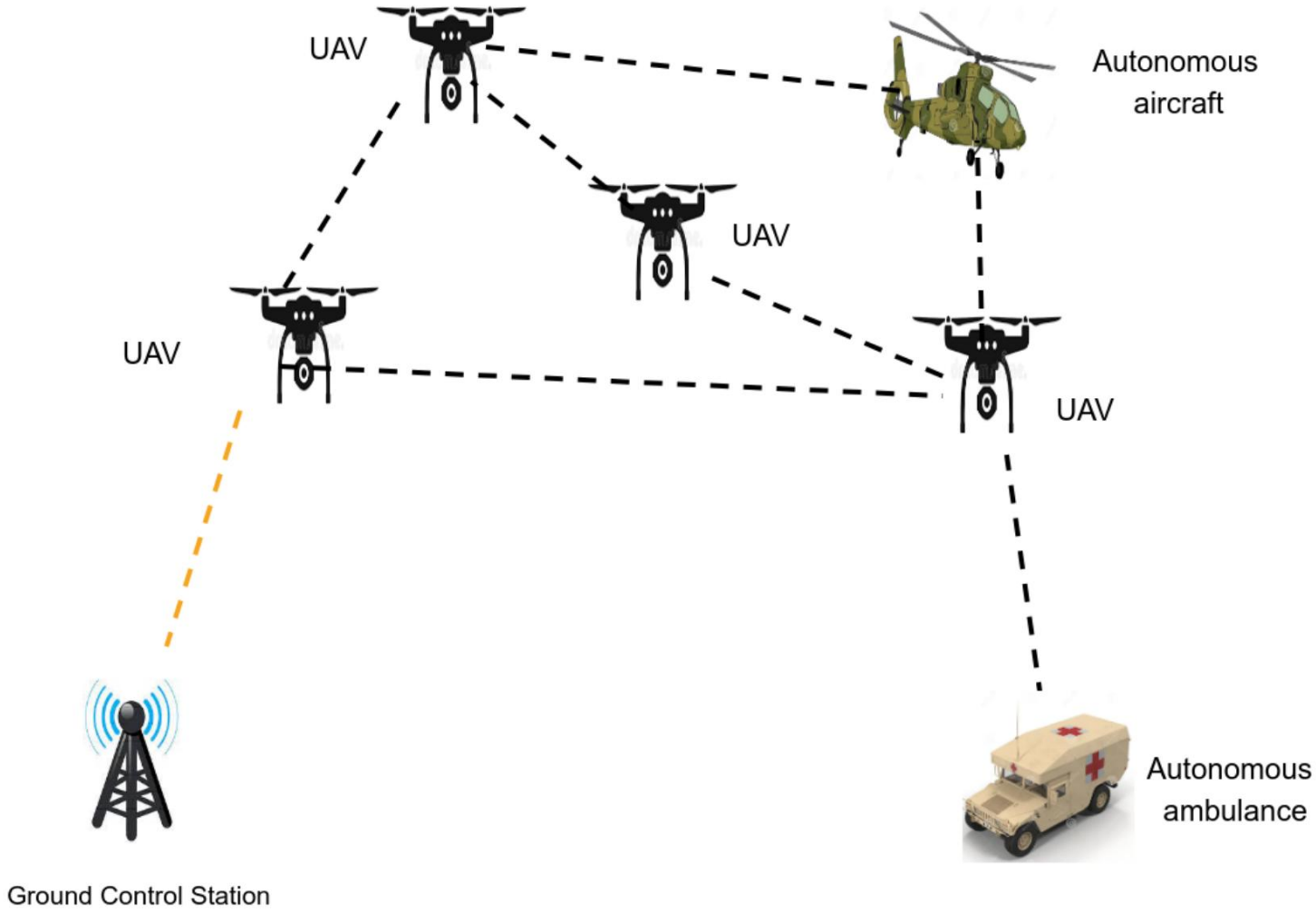
Proposed Tasks

- Task 3: Designing Defense Framework to Counter Collaborative Attacks
  - We exemplify the approach through a framework designed for a centralized autonomous UAV network topology.
  - It serves as a baseline example — through this project, the research will explore framework variations including decentralized architectures, hybrid networks with ground vehicles, and other topological configurations.
  - The modular design ensures the research not only validates the core detection mechanisms but also establishes foundations for adapting the framework to diverse autonomous UAV network deployments.

Task 1: Developing System Model of Autonomous UAV Networks

- Autonomous UAV networks also include ground vehicles and other autonomous aircraft (see figure in next slide).
- The network can operate in various configurations:
  - networks with and without ground vehicle nodes,
  - fully autonomous versus human-supervised operations, and
  - centralized versus decentralized control structures.
- Each configuration presents distinct security implications and requires tailored defensive approaches.
- Furthermore, we should consider dynamic network membership, where nodes can join or leave during task.

An Autonomous UAV Networks with Ground Vehicles and Other Autonomous Aircrafts



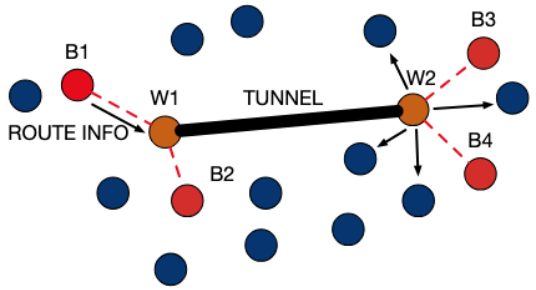
Limitations of Prior Works

- Traditional defense mechanisms are inadequate because they focus on detecting and mitigating *individual* attack patterns rather than identifying the *subtle interplay between multiple coordinated adversaries*.
  - For example, attackers deliberately distribute their malicious activities across multiple nodes to stay below detection thresholds or employ complementary attack methods that mask each other's signatures.
- Prior research on collaborative attacks
  - focused primarily on developing detection and defense strategies for traditional networks,
  - failing to address the resource limitations inherent to UAV platforms, their limited energy capacity and limited onboard computational capabilities.
- These constraints affect the feasibility and effectiveness of security solutions, as resource-intensive defense mechanisms can potentially compromise the network's operational lifetime and mission capabilities.

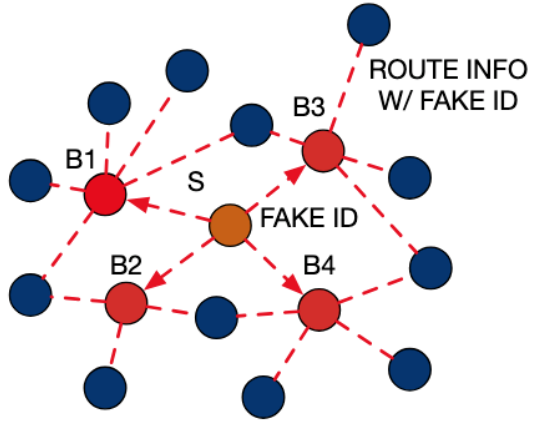
Understanding Threat Models against Autonomous UAV Networks

- Real world implications
  - In search and rescue operations, coordinated attacks can disrupt communications while injecting false data to mislead rescue efforts.
  - In precision agriculture, attackers can manipulate UAV routing while depleting ground sensor resources in critical areas.
  - In military applications, physical sabotage may be synchronized with cyber attacks to maximize fleet vulnerability.
- A collaborative attack is composed of individual, atomic attacks
  - Sybil attacks, where attackers create multiple fake identities to manipulate system-wide collaborative decisions;
  - Wormhole attacks, where adversaries record and retransmit packets between different network locations to disrupt routing;
  - Black hole attacks, where malicious nodes advertise false shortest paths to intercept network traffic.

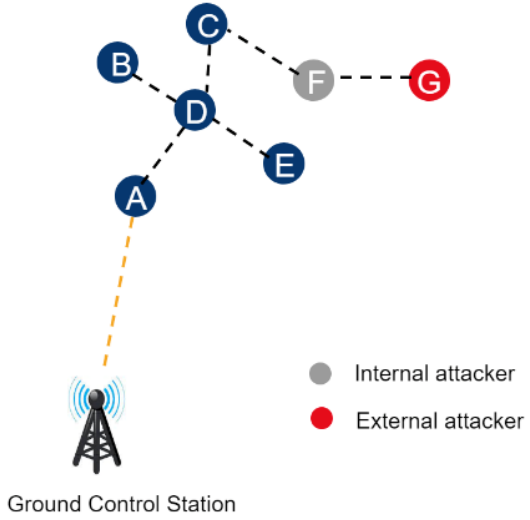
Examples of Collaborative Attacks



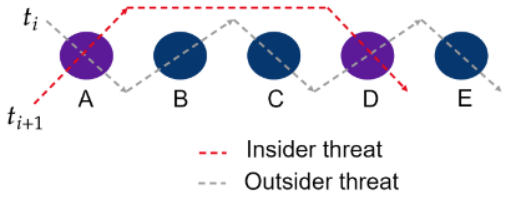
(a) Wormhole and black hole attack.



(b) Sybil attack combined with Black hole attack.



(c) Insider and outsider attack.



(d) Sequential and coordinated actions of insider and outsider attackers.

(a): Wormhole nodes (W1, W2) collaborating with blackhole nodes (B1-B4) for amplified routing disruption;
(b): Sybil node (S) providing fake IDs to blackhole nodes for detection evasion;
(c) and (d): Sequential insider (F) and outsider (G) attack coordination across time steps.

The Hiding Effect: A Blackhole-Sybil example

- Blackhole-Sybil Collaborative Attack
  - The Sybil adversary secretly transfers valid IDs to blackhole adversaries instead of abusing them.
    - SE1: It does not trigger abnormal events and, thus, is hidden from detection.
  - Blackhole adversaries broadcast false routing information with distinct IDs received from the Sybil adversary.
    - SE2: Making blacklisting-based blackhole attack defense mechanisms[4~6] invalid.

Task 2: Designing Mechanisms to Secure Autonomous UAV Networks against Collab- orative Attacks

- Defense against Multi-Stage Attacks (MSAs) vs. Defense against Collaborative Attacks:
  - Defenses against MSAs are concerned with finding patterns in sequential actions that are typically conducted by a single attacker.
  - By contrast, collaborative attacks are more general because they involve multiple attackers, who can execute their actions in an interleaved fashion which is more sophisticated than sequential events.
- Nevertheless, the research will use sequential data analysis as some building-blocks in the defenses.
- Moreover, the MSAs launched by a single attacker cannot achieve synergy effects as discussed above.

Task 2: Designing Mechanisms to Secure Autonomous UAV Networks against Collab- orative Attacks

- Current multi-stage attack defenses fail to address three challenges in UAV environments:
  - (1) coordinated actions by multiple attackers,
  - (2) rapidly changing attack surfaces due to UAV mobility, and
  - (3) resource constraints that limit computational defense mechanisms.

Using Formal Methods to Detect Collaborative Attacks

Traditional ML models struggle to detect multi-step, coordinated attack behavior. Collaborative attacks often span multiple nodes and evolve over time — difficult to capture via flow-based features alone.

Our Approach:

- Treat network events as **state transitions** in a system model.
- Use **formal verification techniques** (e.g., model checking) to:
  - Detect illegal state transitions or unexpected sequences.
  - Identify if multiple agents are collaborating across time to breach security.

Key Ideas:

- Model UAV network behavior using **finite state machines** or **temporal logic**.
- Encode known benign and malicious interaction patterns.
- Use runtime verification or offline checking to flag potential coordinated attacks.

Learning-Based Models for Sequential Detection

Hidden Markov Models (HMM):

- Probabilistic models capturing transitions between hidden system states.
- Suitable for lightweight onboard detection.
- Assumes limited memory (Markov property) and works best with relatively simple or periodic attack patterns.

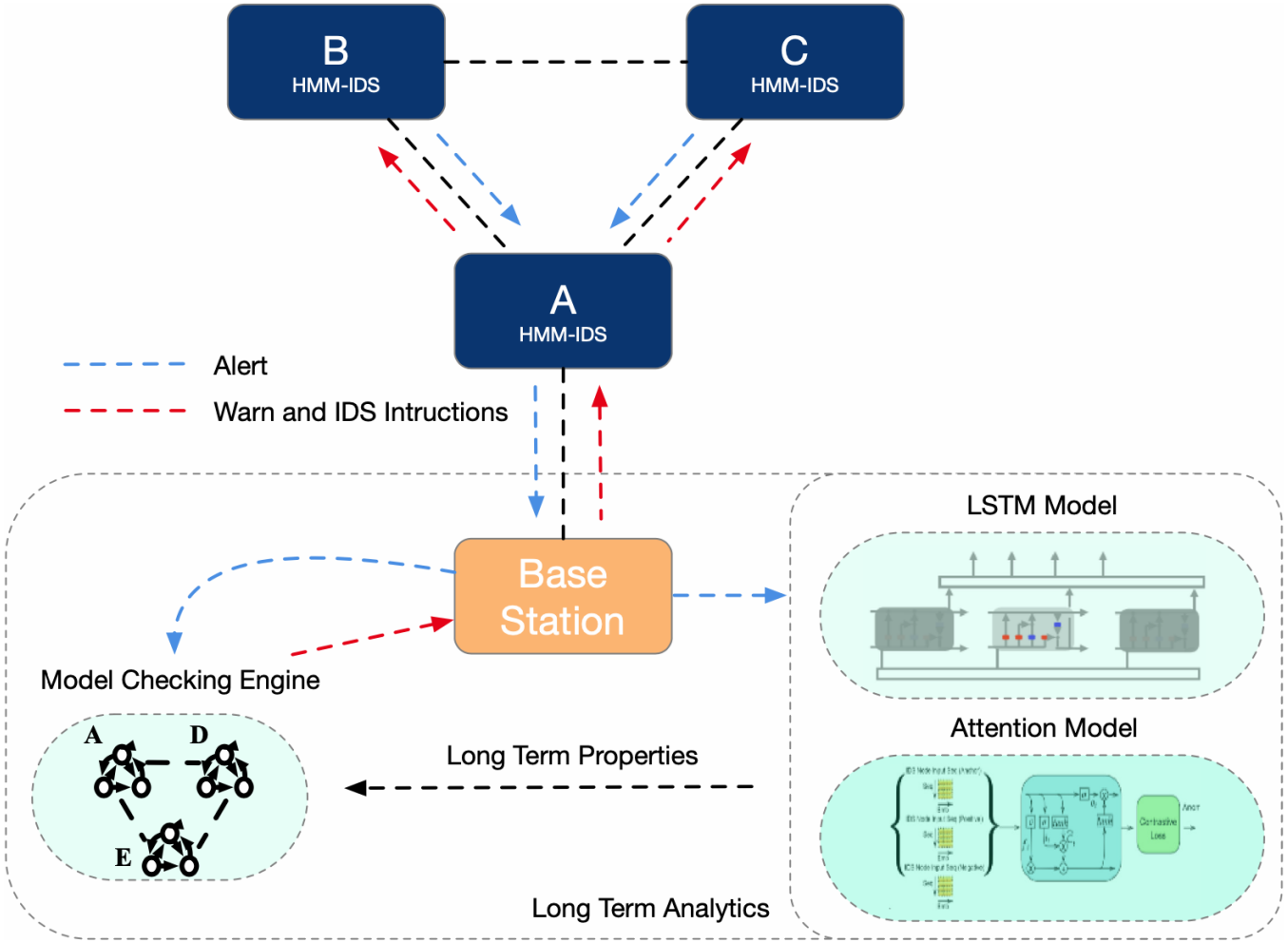
Long Short-Term Memory Networks (LSTM):

- A type of recurrent neural network designed to capture long-term dependencies.
- Effective in learning subtle, delayed, or multi-stage attack patterns.
- Requires extensive training data and higher computational resources.

Examples of events and actions associated with the four proposed mechanisms in the context of three examples of collaborative attacks.

Col. Attack	**HMM**	**LSTM**	**Attention**	**Model Checking**
Hidden Black-hole with Sybil	- Sudden routing changes - ID distribution events - Immediate routing manipulations	- Trust building period - Gradual increase in ID generation - Correlation between distributions and attacks	- ID transfer moments - Attack timing patterns - Network topology shifts	- FSM state transitions validation - ID distribution → attack sequencing - Temporal constraint verification
Insider-Outsider Coordi-nation	- Internal scanning activities - External connection attempts - Unusual data flows	- Insider's information gathering - Reconnaissance patterns - Behavioral shifts over time	- Insider-outsider communications - Behavior change points - Attack timing correlations	- Reconnaissance → attack sequencing - Temporal dependency validation - Collaboration pattern matching
Wormhole-Enhanced Black-hole	- Tunnel establishment attempts - Routing manipulations - Packet dropping events	- Position establishment patterns - Tunnel-blackhole correlations - Attack evolution across segments	- Tunnel establishment timing - Node synchronization points - Information duplication events	- Attack model conformance - Spatial-temporal constraint checks - Amplification effect verification

Task 3: Designing Defense Framework to Counter Collaborative Attacks



A Proposed Framework

- The figure highlights the preliminary framework
  - The framework implements a distributed detection architecture that balances detection capability with UAV resource constraints.
  - It leverages the Base Station (BS) for computationally intensive analysis while deploying efficient short-term detection on individual UAVs.
- Base Station Components
  - The Model Checking Engine forms the framework's foundation, providing three functions.
    1. Discovers and verifies possible attack collaboration patterns.
    2. Generates attack signatures to guide HMM deployment on UAVs.
    3. Identifies temporal dependencies and critical events for LSTM and attention analysis.

A Proposed Framework

- The architecture offers several key advantages.
  - Immediate threat detection occurs at network edges through lightweight HMMs while complex attack evolution analysis is centralized at the BS.
  - UAVs maintain minimal state information and computational overhead, yet the framework continuously adapts to new attack patterns.
  - Most importantly, all detection decisions can be verified through model checking.
- The preliminary experiments show this distributed approach provides a good tradeoff between effectiveness in detecting collaborative attacks and resource utilization.

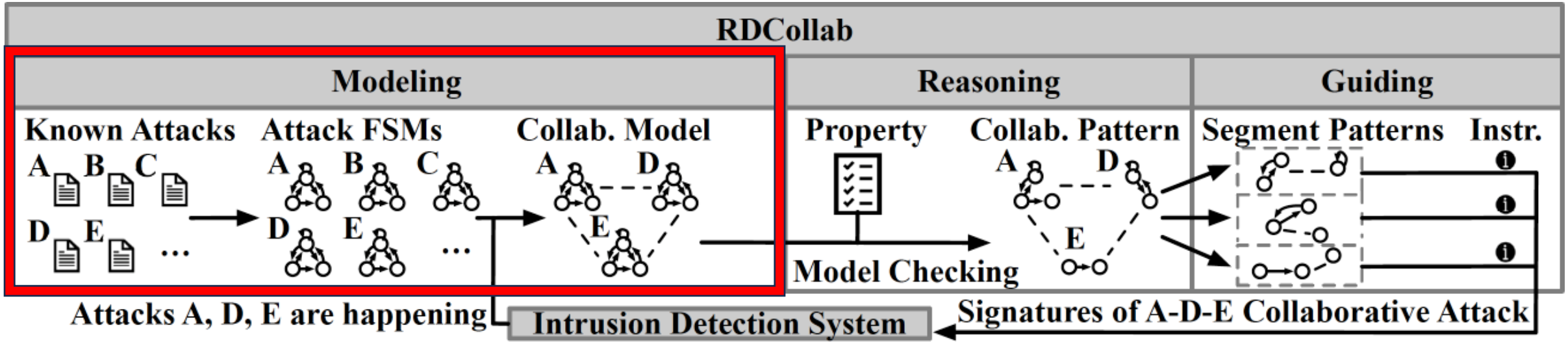
A Variant of the Proposed Framework

- RDCollab: **R**easoning and **D**etecting **Collab**orative Attacks
  - A framework to reason about and detect collaborative attacks in autonomous UAV networks that leverages model checking to explore attack patterns.
  - It models individual attacks as finite state machines (FSMs) that can be combined to represent collaboration.
  - The framework uses properties describing network safety to explore collaborative attacks and guide intrusion detection systems.
  - RDCollab improves IDSs' detection rates on non-hidden adversaries by up to 63% and can detect hidden adversaries within 6.1 seconds.

A Variant of the Proposed Framework

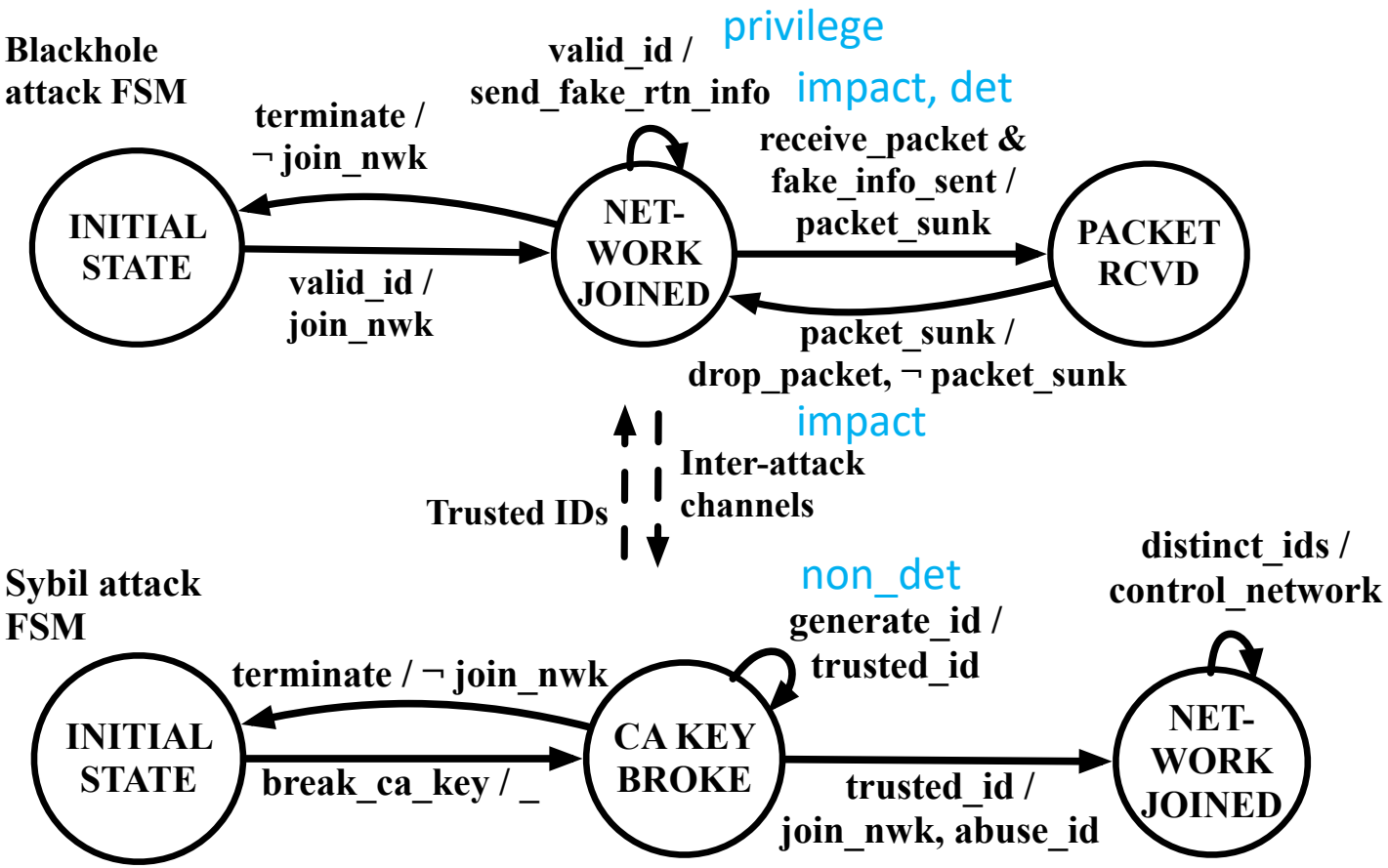
- RDCollab: **R**easoning and **D**etecting **Collab**orative Attacks
  - Three major synergy effects are identified: Hiding Effect, Amplifying Effect, and Shortcut Effect.
    - The Hiding Effect makes adversaries more difficult to detect or makes specific adversaries undetectable.
    - The Amplifying Effect occurs when coordinated attacks cause more damage than the sum of individual attacks.
    - The Shortcut Effect allows adversaries to launch attacks with fewer steps or achieve goals faster.
  - Seven novel collaborative attacks were discovered through model checking, including Hidden Blackhole Attack, Hidden Wormhole Attack, Duplicated Routing Disturbance Attack, Distributed Data Exfiltration Attack, and others.
  - The framework extracts segment patterns from collaborative attack counterexamples as signatures to guide IDSs.
  - Three baseline ML-based IDSs were used for evaluation: HMM-based, SVM-based, and RFC-based.

Our Solution: RDCollab (**R**easoning and **D**etecting **Collab**orative Attacks)



The collaborating attacks are formally modeled as finite states machines (FSMs) connected by channels for message exchange.

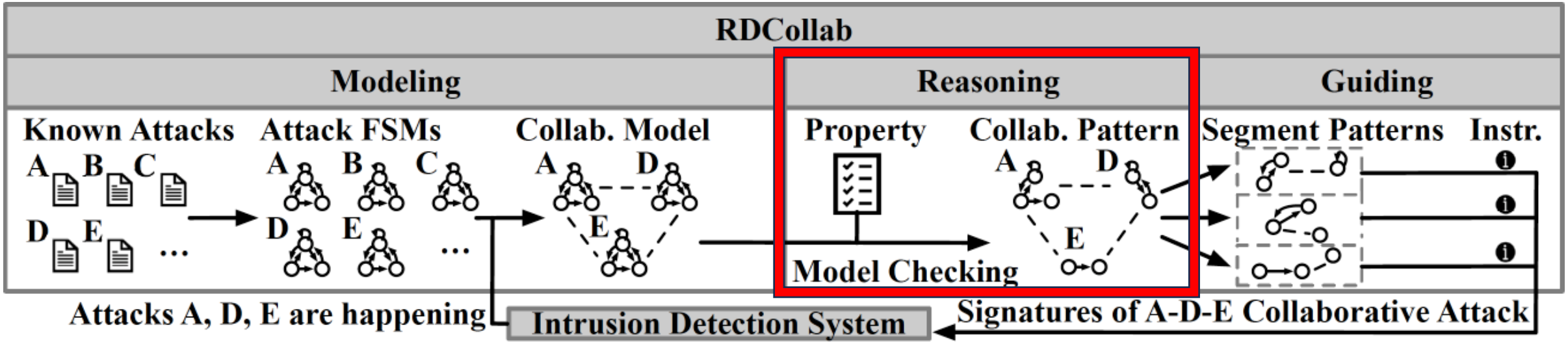
An Example of Collaborative Attack Model



More Details of the Modeling Phase

- We define impact labels that describe how an adversary's actions violate the confidentiality, integrity, or availability of the system. For example, we label "send_fake_rtn_info” (send fake routing information) with "int_viol" for integrity violation, and "drop_packet" with "avai_viol" for availability violation.
- Then we have detectability labels that indicate how observable an adversary's actions are. We use "det" for detectable actions, "part_det" for partially detectable actions, and "non_det" for actions that can't be observed externally. For instance, "send_fake_rtn_info" is labeled as "det" since it's observable, while "generate_id" in the Sybil FSM is labeled as "non_det" as it's done locally by the adversary.
- These labels help us bridge the gap between abstract security requirements and concrete system behaviors.

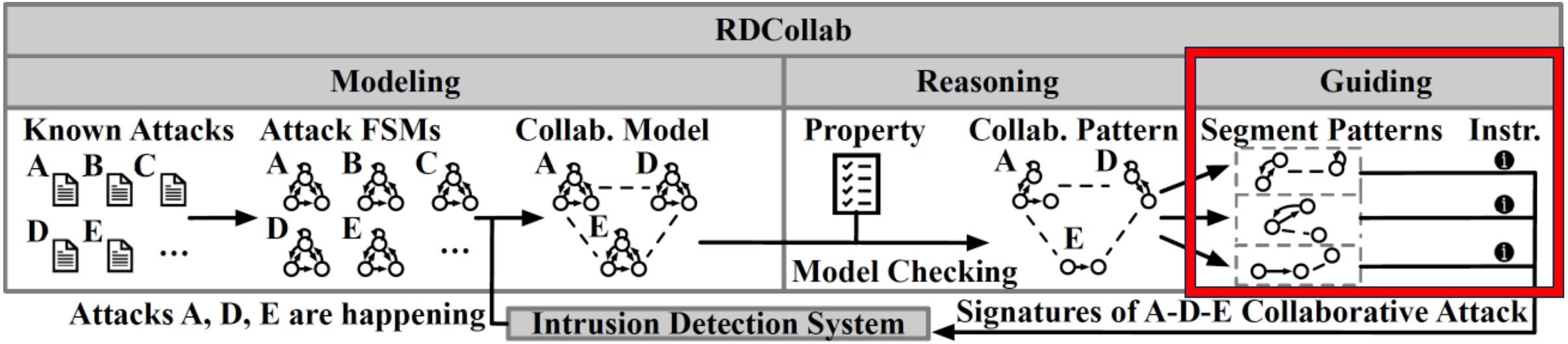
Our Solution: RDCollab (**R**easoning and **D**etecting **Collab**orative Attacks)



Synergy effects are encoded as security properties in linear temporal logic (LTL) formulas.

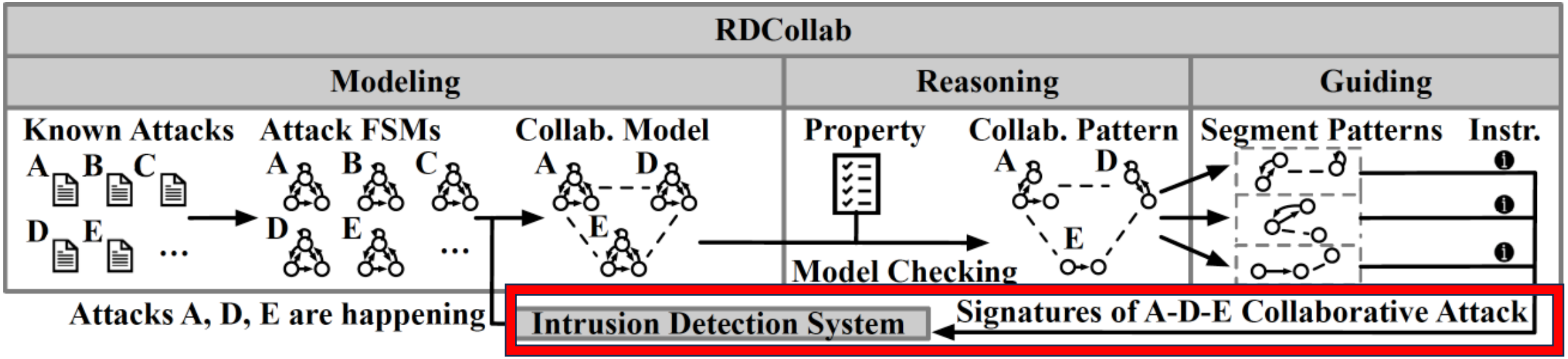
Model checking is used to check collaborating model consisting of attack FSMs against the LTL-form security properties indicating attack collaborations.

Our Solution: RDCollab (**R**easoning and **D**etecting **Collab**orative Attacks)



If the check fails, the model checker outputs a counterexample which can be referred to by IDS as oracles on how individual attacks collaborates.

Our Solution: RDCollab (**R**easoning and **D**etecting **Collab**orative Attacks)



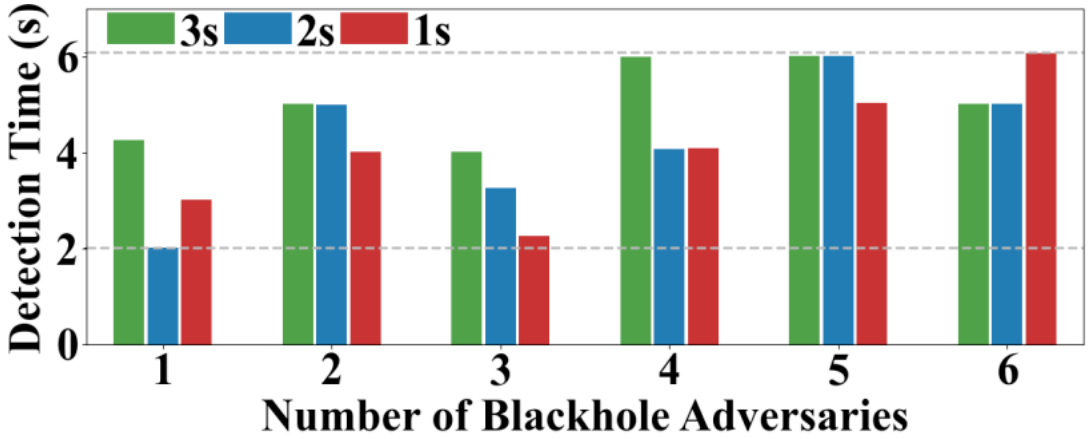
The IDS thus updates its detection and defense strategy accordingly.

More Details of the Reasoning and Guiding Phases

- RDCollab defines properties the model should satisfy in a synergy effects-free scenario (i.e., the scenario without the collaborative attacks that cause synergy effects).
- It then uses the model checking to verify the collaboration model against the properties. If the model violates a property, the model checker outputs a counterexample demonstrating a model execution that can be interpreted as a collaboration pattern with synergy effects.
- The segments of such a pattern are used in the guiding phase, as they can be used as signatures to detect collaborative attacks.
- RDCollab translates the segments into instructions to guide IDS in improving its detection effectiveness.

RDCollab Evaluation Results

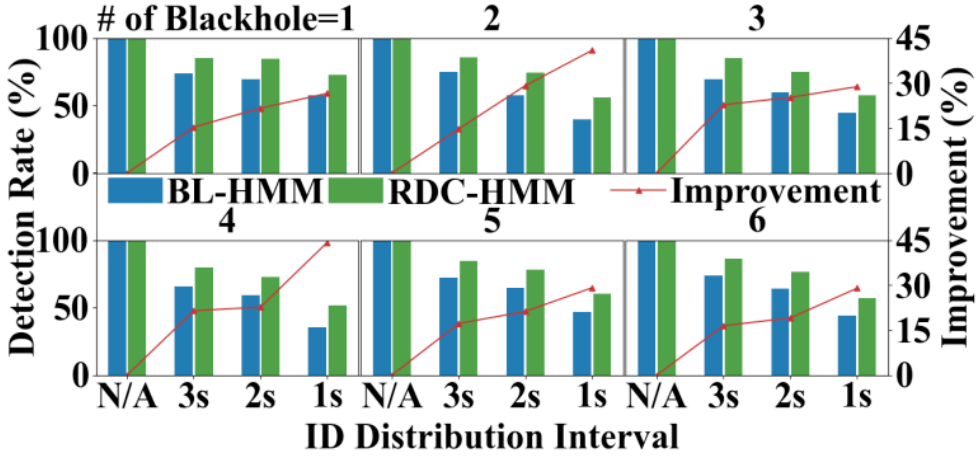
- Detecting the Hidden Sybil Adversary (SE1)



- With various numbers (1~6, x-axis) of blackhole adversaries, RDCollab can detect the Sybil adversary that transfer fake IDs to them every 3, 2 and 1 second(s) within 6 seconds (y-axis).

RDCollab Evaluation Results

- Improving the Detection of Blackhole Adversaries (SE2)



- With various numbers (1~6, subfigure titles) of blackhole adversaries, RDCollab-guided HMM-based IDS improves the detection rate of blackhole adversaries compared with baseline HMM-based IDS.
- The improvements are shown by the red lines.

Takeaways and Contributions

- Collaborative attacks pose a growing threat to UAV networks.
- RDCollab provides a comprehensive approach to tackling these challenges.
  - A solution to detect collaborative attacks against autonomous UAV networks.
  - Implementation of RDCollab instantiating the proposed solution.
  - Evaluation of RDCollab’s effectiveness of collaborative attack detection.
- The next steps are to enhance collaborative attack detection and response systems.

Another research effort
for Advancing Collaborative Attack Detection

- Existing IDS datasets lack UAV-specific attacks, aerial mobility, and real wireless traffic patterns.
- Due to High costs of collecting large network datasets, we use data augmentation using MLP function approximation method. This makes current IDS system robust against false positives caused by mobility in UAV networks.

Three-Phase Plan for Advancing Collaborative Attack Detection

Phase 1: Dataset Creation

- Develop a comprehensive dataset simulating collaborative attacks in UAV networks.
- Include realistic mobility models, packet-level logging, and diverse adversarial behaviors.
- Emphasize attack diversity (e.g., blackhole, wormhole, Sybil) and coordination mechanisms.
- Use Data Augmentation to increase diversity of dataset.

Phase 2: Transformer-Based Detection

•Leverage attention-based models (e.g., Transformers) to capture temporal dependencies and multi-agent coordination patterns.
•Fine-tune on domain-specific UAV datasets.
•Benchmark against baseline ML models and analyze detection accuracy under dynamic conditions.

Phase 3: Enhancing Detection Efficiency

•Optimize detection models for onboard deployment using techniques like knowledge distillation, pruning, and quantization.
•Explore hierarchical detection: light-weight edge models + cloud-based heavy analysis.
•Integrate detection with real-time response mechanisms.

Phase 1: Why Existing Datasets Fall Short for UAV Networks

Lack UAV-specific attacks

- Most datasets focus on generic IT or IoT threats, not aerial or coordinated UAV threats.

Static or limited mobility

- Many datasets assume fixed topologies, unsuitable for dynamic, mobile UAV environments.

No real UAV traffic

- Missing realistic communication patterns like video/image transmission or inter-UAV coordination.

Not designed for swarm behavior

- Fail to capture group dynamics, cooperation, or synchronized attacks.

Misaligned threat models

- Include irrelevant attack types (e.g., fuzzing, worms) not applicable to UAV use cases.

Partial relevance (e.g., IoT/WSN)

- Offer some overlap in resource constraints, but lack full UAV context.

Phase 1: Our UAV IDS Dataset: Key Features

Dynamic UAV Network & Mobility

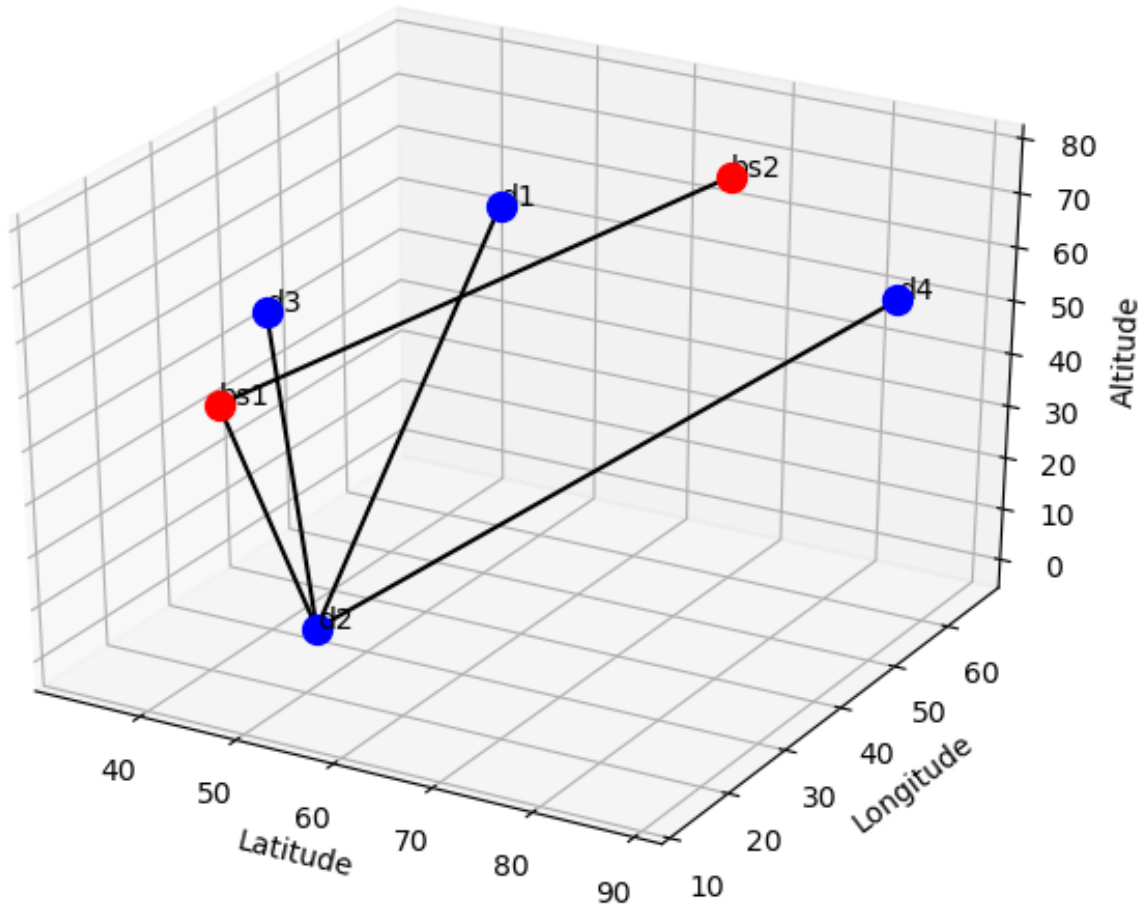
- UAVs (10-50) & Basestations (1-5) move using Gaussian-Markov model.
- Links dynamically change based on Euclidean distance, simulating WiFi characteristics (capacity, delay, loss).
- Packet loss modeled via BER, SNR, & FSPL, with retransmission-based correction.

Attacks Simulated

- DoS & DDoS – SYN floods (100 to 100K packets/sec), Black Hole, Wormhole, Replay Attack.

Realistic UAV Data Capture

- UAVs send images/videos, simulating reconnaissance transmission.
- Traffic captured at node & switch levels for IDS evaluation.
- Systematic variation: 100 runs per setup (60s each) with diverse UAV counts, attacks, & packet rates.



Phase 1: Our data augmentation: Using MLP as a function approximation

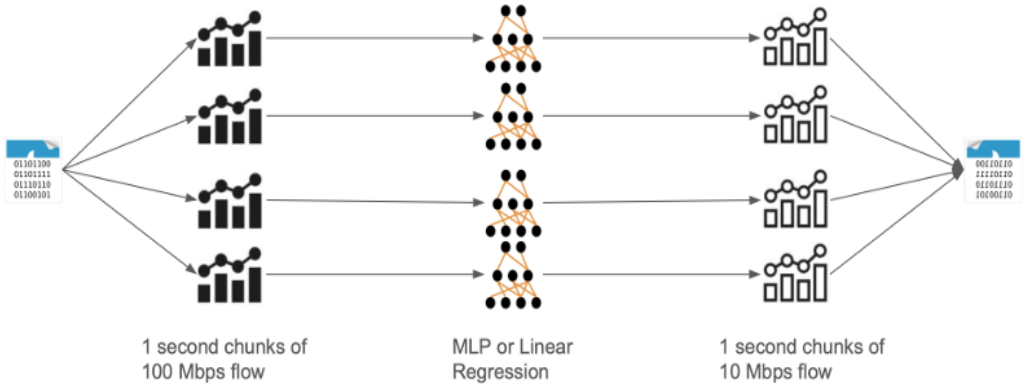
MLPs (Multi-Layer Perceptrons): are powerful function approximators that can learn nonlinear mappings between input and output feature distributions.

They capture complex relationships between flow statistics like inter-arrival times, packet sizes, and burstiness patterns across different bandwidths.

Unlike linear regression, MLPs can model diverse traffic behaviors more accurately, especially when the transformation is not linearly scalable.

Phase 1: Our data augmentation: Using MLP as a function approximation

- **Input**: Original network traffic is segmented into 1-second flow chunks from a 100 Mbps environment.
- **Feature Extraction**: We extract statistical features for each chunk (e.g., flow size, number of packets, arrival times).
- **MLP Transformation**: These features are passed through a trained MLP (or linear regression as baseline) to generate a mapped version mimicking how the same traffic would appear on a 10 Mbps link.
- **Output**: The resulting 10 Mbps-style flow chunks are recombined into an augmented dataset with realistic traffic for low-bandwidth settings.



F1- score of different ML techniques using Flow features.

- We use these vanilla models on three public datasets.
- We measure 65 different flow features based on packet size, packet time of arrival, and TCP flags.
- We measure F1-scores as these datasets are imbalanced.
- As dataset diversity and complexity increase, traditional models struggle to generalize—highlighting the need for more expressive, context-aware approaches.

Machine learning model	**CICIDS 2017[x]**	**CICIOT2023[x]**	**UNSW-NB15[x]**
1D – CNN	97.98	67.68	60.62
Long short-term memory	87.15	64.29	46.17
Random Forest	99.63	79.12	87.66
Stochastic gradient descent	95.98	50.41	39.03
Logistic Regression	93.16	48.24	37.82
Multilayer perceptron	95.87	61.55	48.45

Phase 2 – Transformer-Based Detection Ideas

Older detection methods often rely on shallow models or handcrafted features, which struggle to capture the complex temporal and multi-agent coordination patterns in collaborative attacks—necessitating more expressive architectures like Transformers.

Multi-Agent Attention Modeling

- Capture inter-node interactions by modeling UAV network as a sequence of events with node-level embeddings.

Graph-Transformer Hybrid

- Combine GNNs with Transformers to account for both network structure and temporal behavior.

Contrastive Learning

- Learn discriminative features by contrasting collaborative vs. non-collaborative attack traces.

Few-Shot Fine-Tuning

- Enable rapid adaptation to unseen coordinated attacks with minimal labeled data.

Phase 3 – Making Detection Efficient

Multi-Agent Attention Modeling

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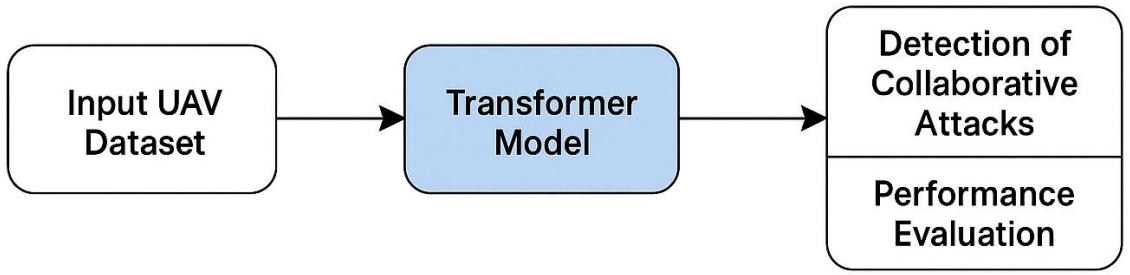

Phase 3 – Making Detection Efficient

Lightweight Transformer Variants

- Explore MobileBERT, TinyBERT, and Linformer for onboard inference with low overhead.

Hierarchical Deployment

- **On UAVs**: Quick screening via distilled models or rule-based alerts.
- **On Base Station**: Deep analysis using full models and historical context.

Dynamic Resource Adaptation

- Adjust model complexity based on available compute, energy, and threat severity.

On-the-Fly Model Updates

- Incorporate detected counterexamples from RDCollab to update the detection pipeline in real time.

Future Directions

- Apply RDCollab techniques to related domains like VANETs
- Apply federated learning across UAVs without raw data sharing

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