

**Self-defending software:  
Automatically patching  
errors in deployed software**

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**Joint work with:**

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# Problem: Your code has bugs and vulnerabilities

- Attack detectors exist
  - Code injection, memory errors (buffer overrun)
- Reaction:
  - Crash the application
    - Loss of data
    - Overhead of restart
    - Attack recurs
    - Denial of service
  - Automatically patch the application

# ClearView: Security for legacy software

Requirements:

1. Protect against **unknown** vulnerabilities
2. Preserve **functionality**
3. Commercial & **legacy** software

# 1. Unknown vulnerabilities

- Proactively prevent attacks via **unknown vulnerabilities**
  - “Zero-day exploits”
  - No pre-generated signatures
  - No hard-coded fixes
  - No time for human reaction
  - Works for bugs as well as attacks

## 2. Preserve functionality

- Maintain continuity: application **continues to operate** despite attacks
- For applications that require **high availability**
  - Important for mission-critical applications
  - Web servers, air traffic control, communications
- Technique: create a patch (**repair** the application)
  - Patching is a valuable option for your toolbox

## 3. Commercial/legacy software

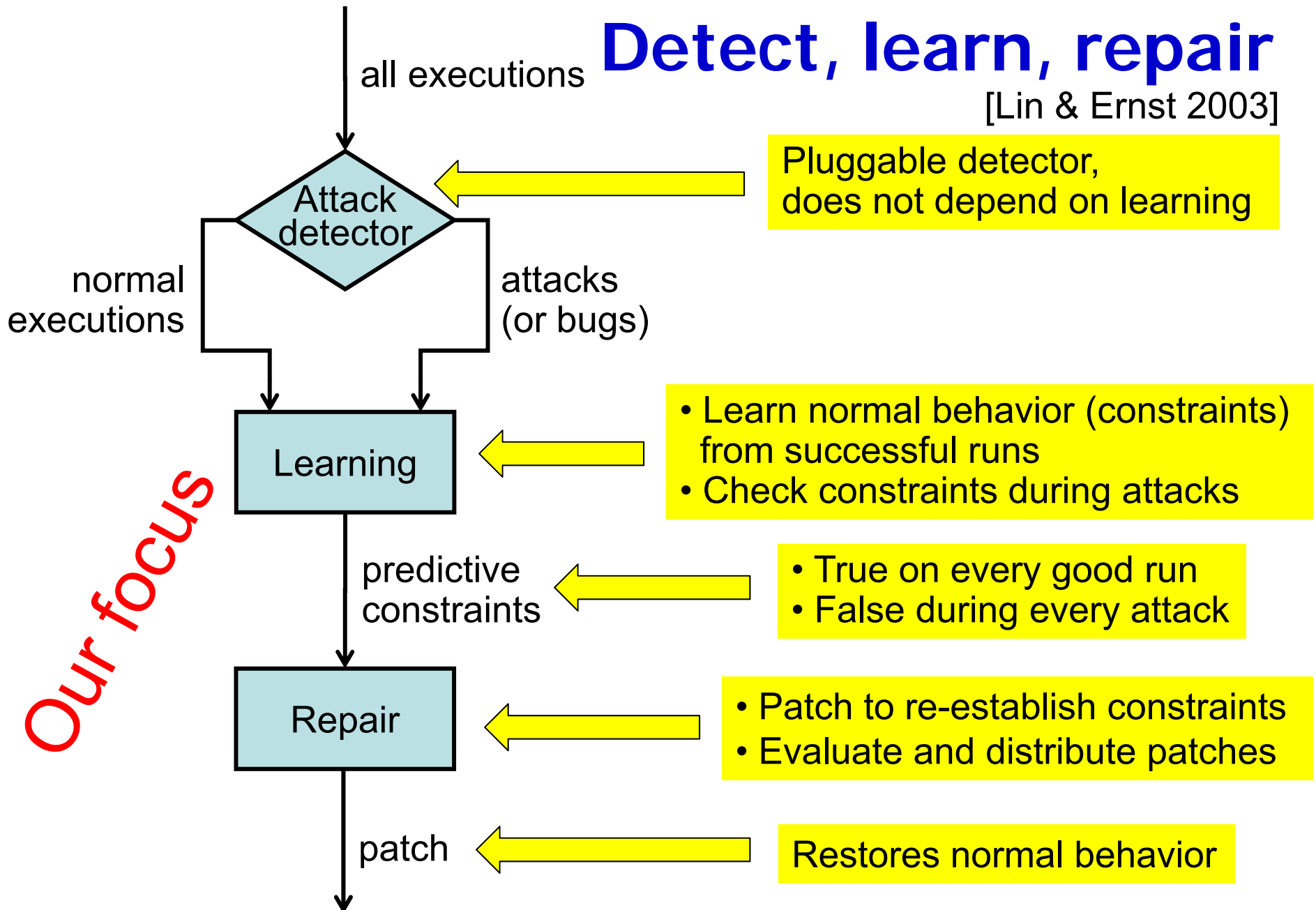
- No modification to source or executables
- No cooperation required from developers
  - Cannot assume built-in survivability features
  - No source information (no debug symbols)
- x86 Windows binaries

# Learn from success and failure

- **Normal executions** show what the application is supposed to do
- Each **attack** (or failure) provides **information** about the underlying vulnerability
- **Repairs** improve over time
  - Eventually, the attack is rendered harmless
  - Similar to an immune system
- **Detect all attacks (of given types)**
  - Prevent negative consequences
  - First few attacks may crash the application

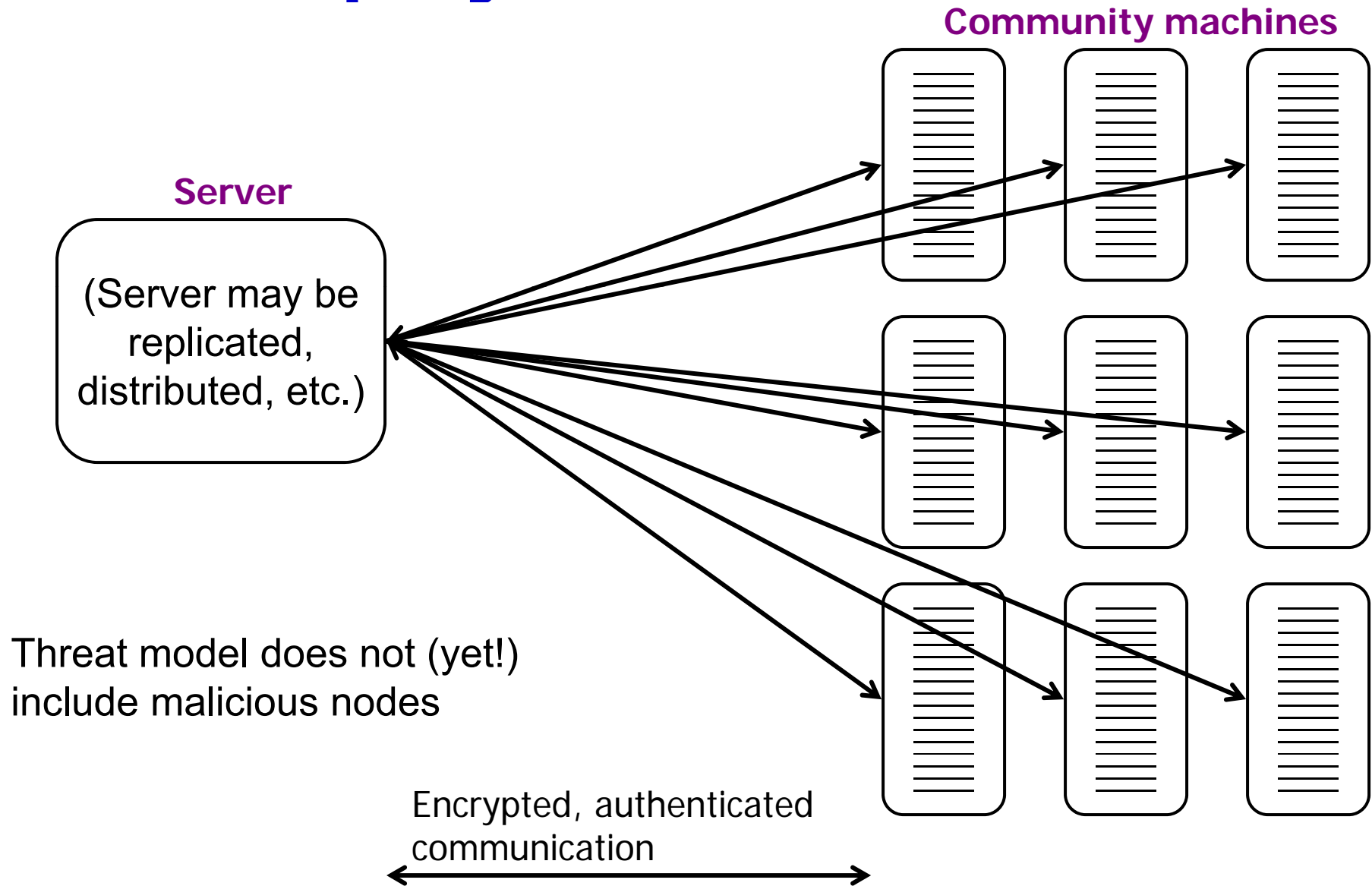
# Detect, learn, repair

[Lin & Ernst 2003]





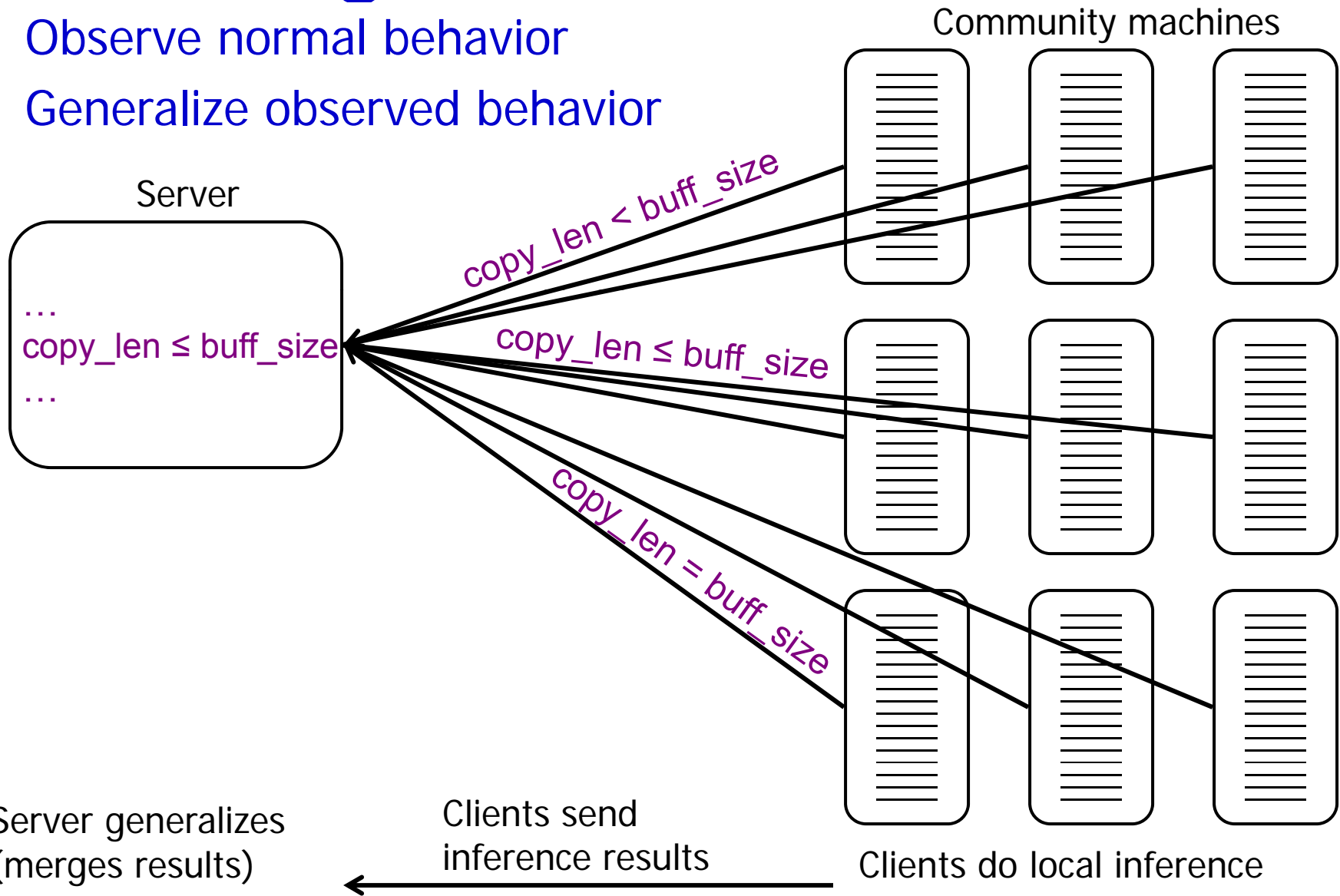
# A deployment of ClearView



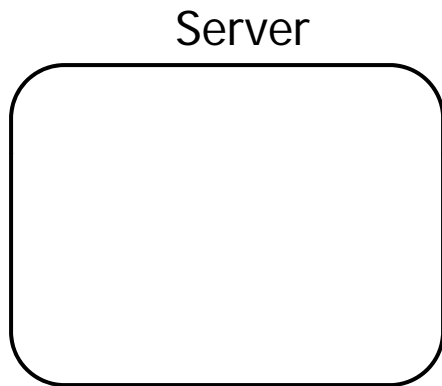
# Learning normal behavior

Observe normal behavior

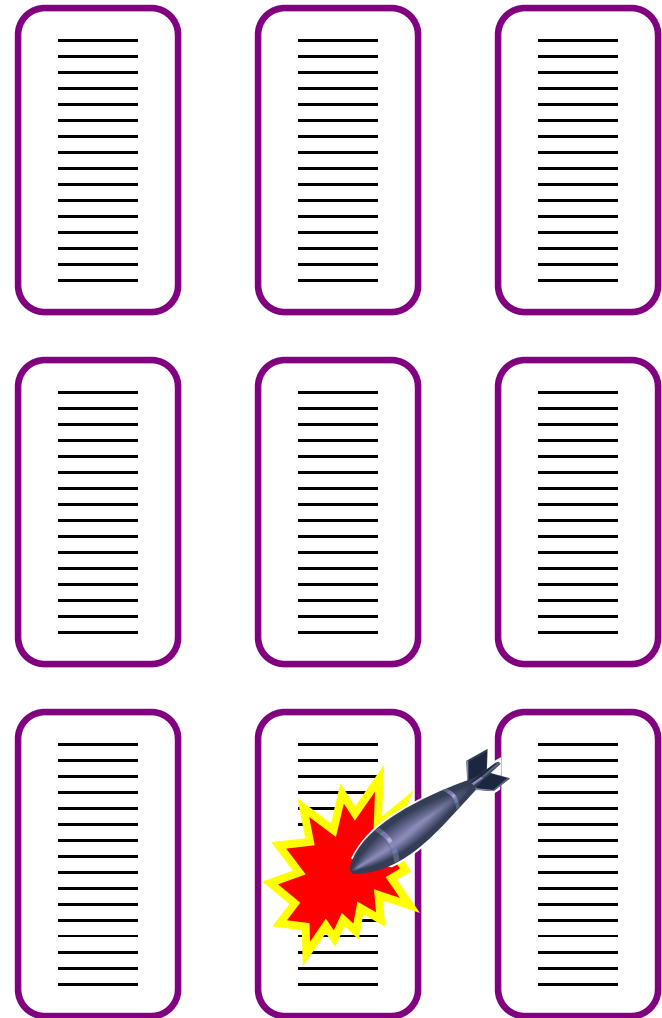
Generalize observed behavior



# Attack detection & suppression



Community machines



Detectors used in our research:

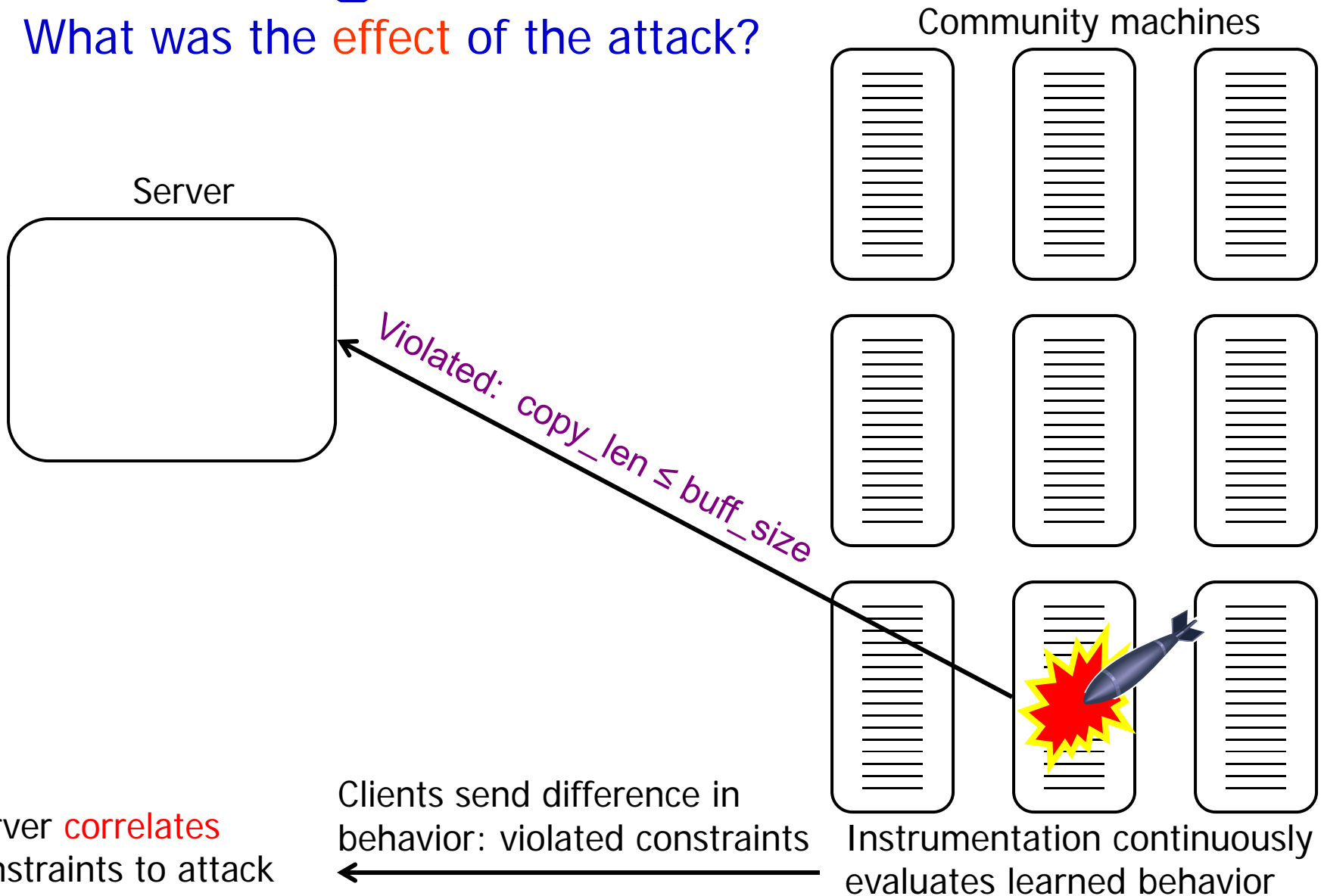
- Code injection (Memory Firewall)
- Memory corruption (Heap Guard)

Many other possibilities exist

Detector collects information and terminates application

# Learning attack behavior

What was the **effect** of the attack?



# Repair

Propose a set of patches for each behavior that predicts the attack

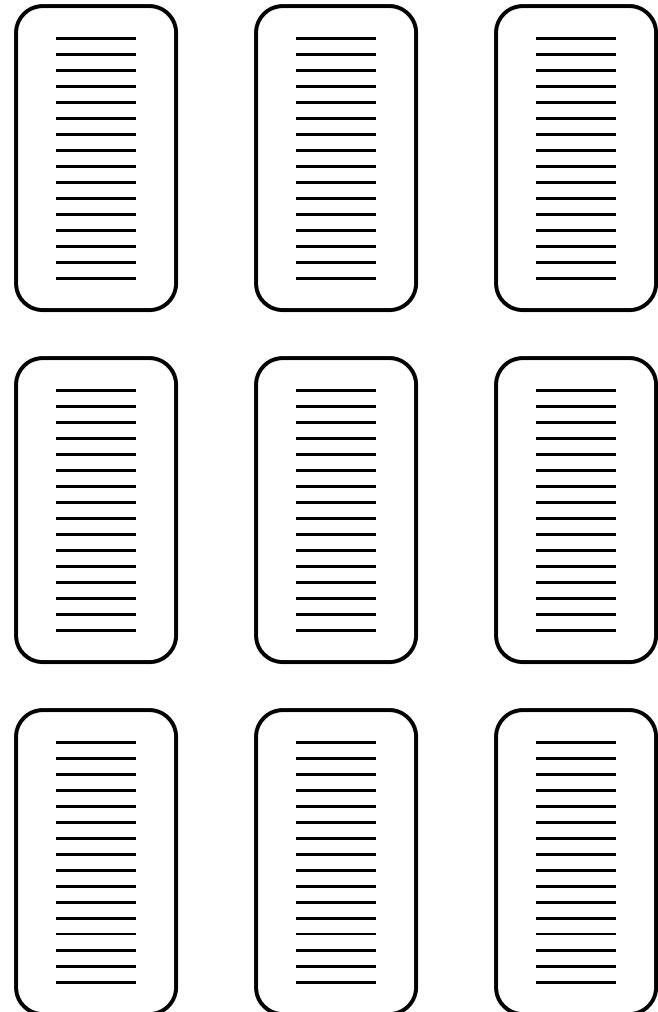
Server

Predictive:  $\text{copy\_len} \leq \text{buff\_size}$

Candidate patches:

1. Set  $\text{copy\_len} = \text{buff\_size}$
2. Set  $\text{copy\_len} = 0$
3. Set  $\text{buff\_size} = \text{copy\_len}$
4. Return from procedure

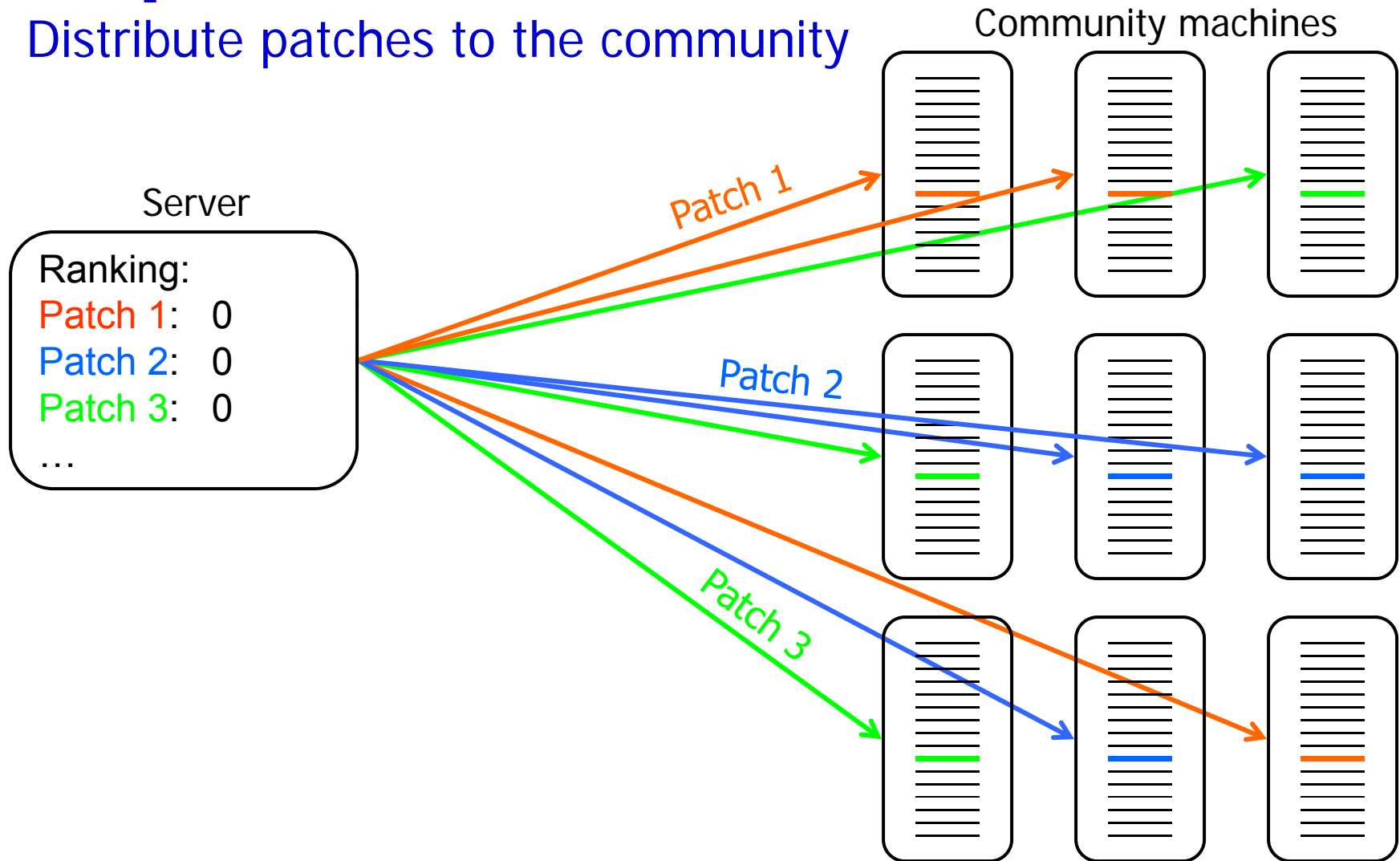
Community machines



Server generates  
a **set** of patches

# Repair

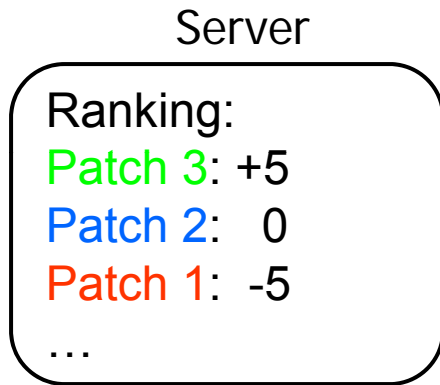
Distribute patches to the community



# Repair

Evaluate patches

Success = no detector is triggered



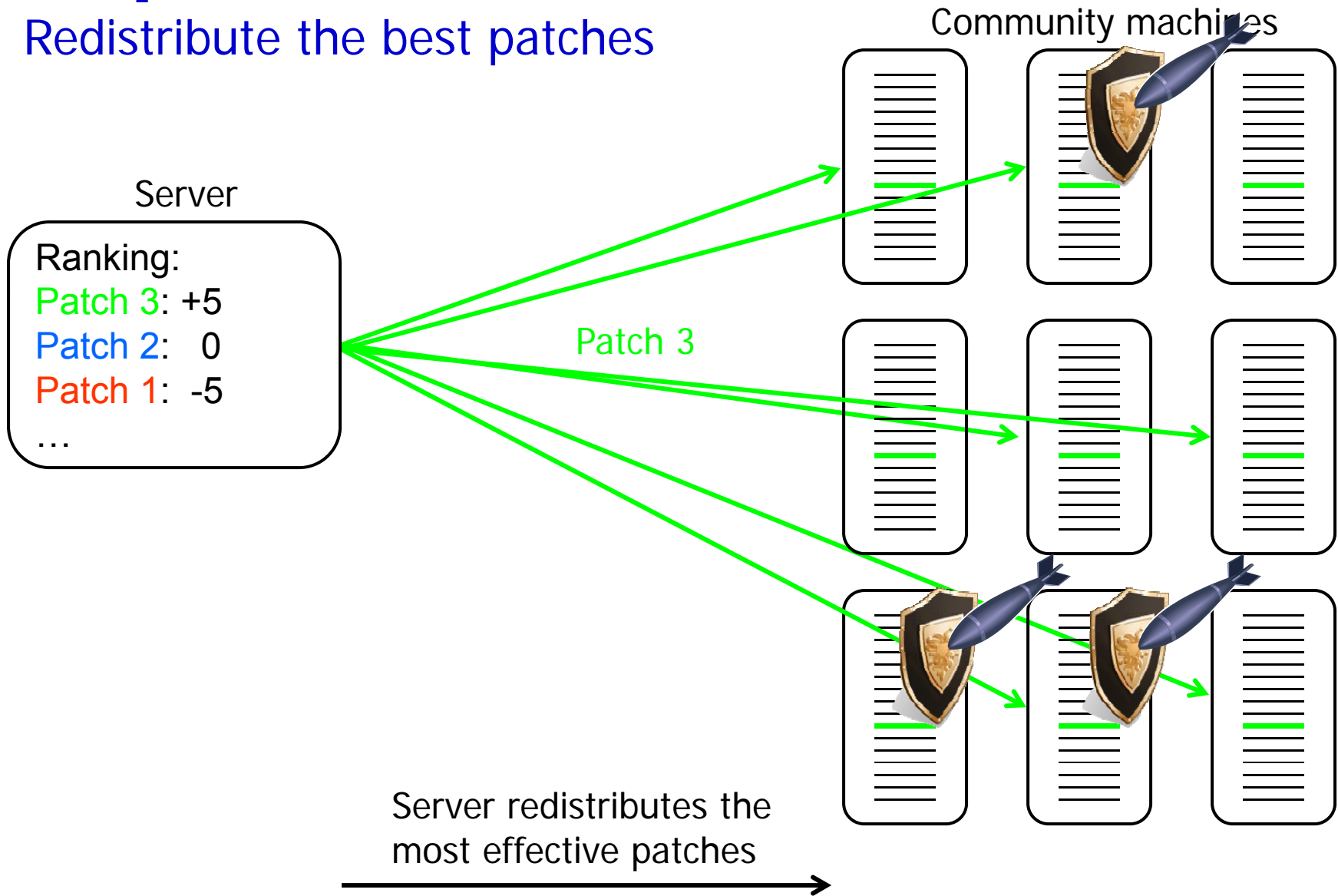
When attacked, clients send outcome to server

Server ranks patches ←

Detector is still running on clients

# Repair

Redistribute the best patches





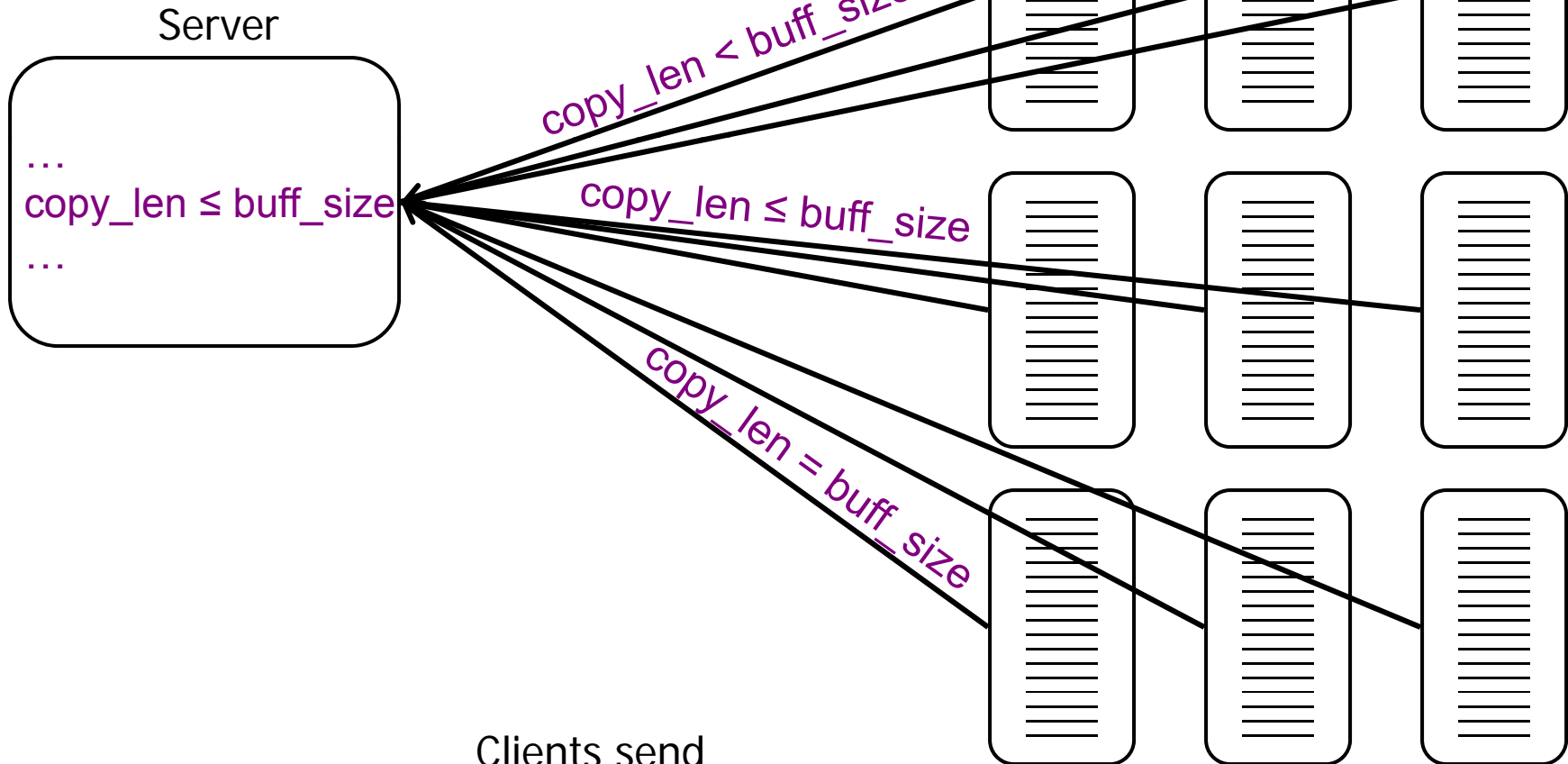
# Outline

- Overview
- Learning normal behavior
- Learning attack behavior
- Repair: propose and evaluate patches
- Evaluation: adversarial Red Team exercise
- Conclusion

# Learning normal behavior

Generalize observed behavior

Community machines



Server generalizes  
(merges results)

Clients send  
inference results

Clients do local inference

# Dynamic invariant detection

- Daikon generalizes observed program executions

Candidate constraints:

```
copy_len < buff_size
copy_len ≤ buff_size
copy_len = buff_size
copy_len ≥ buff_size
copy_len > buff_size
copy_len ≠ buff_size
```

Observation:

```
copy_len: 22
buff_size: 42
```



Remaining candidates:

```
copy_len < buff_size
copy_len ≤ buff_size
copy_len = buff_size
copy_len ≥ buff_size
copy_len > buff_size
copy_len ≠ buff_size
```

- Many optimizations for accuracy and speed
  - Data structures, code analysis, statistical tests, ...
- We further enhanced the technique

# Quality of inference results

- Not **sound**
  - Overfitting if observed executions are not representative
- Not **complete**
  - Templates are not exhaustive
- **Useful!**
- Unsoundness is not a hindrance
  - Does not affect attack detection
  - For repair, mitigated by the correlation step
  - Continued learning improves results

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# Detecting attacks (or bugs)

Goal: detect problems close to their source

Code injection (Determina Memory Firewall)

- Triggers if control jumps to code that was not in the original executable

Memory corruption (Heap Guard)

- Triggers if sentinel values are overwritten

These have **low overhead** and **no false positives**

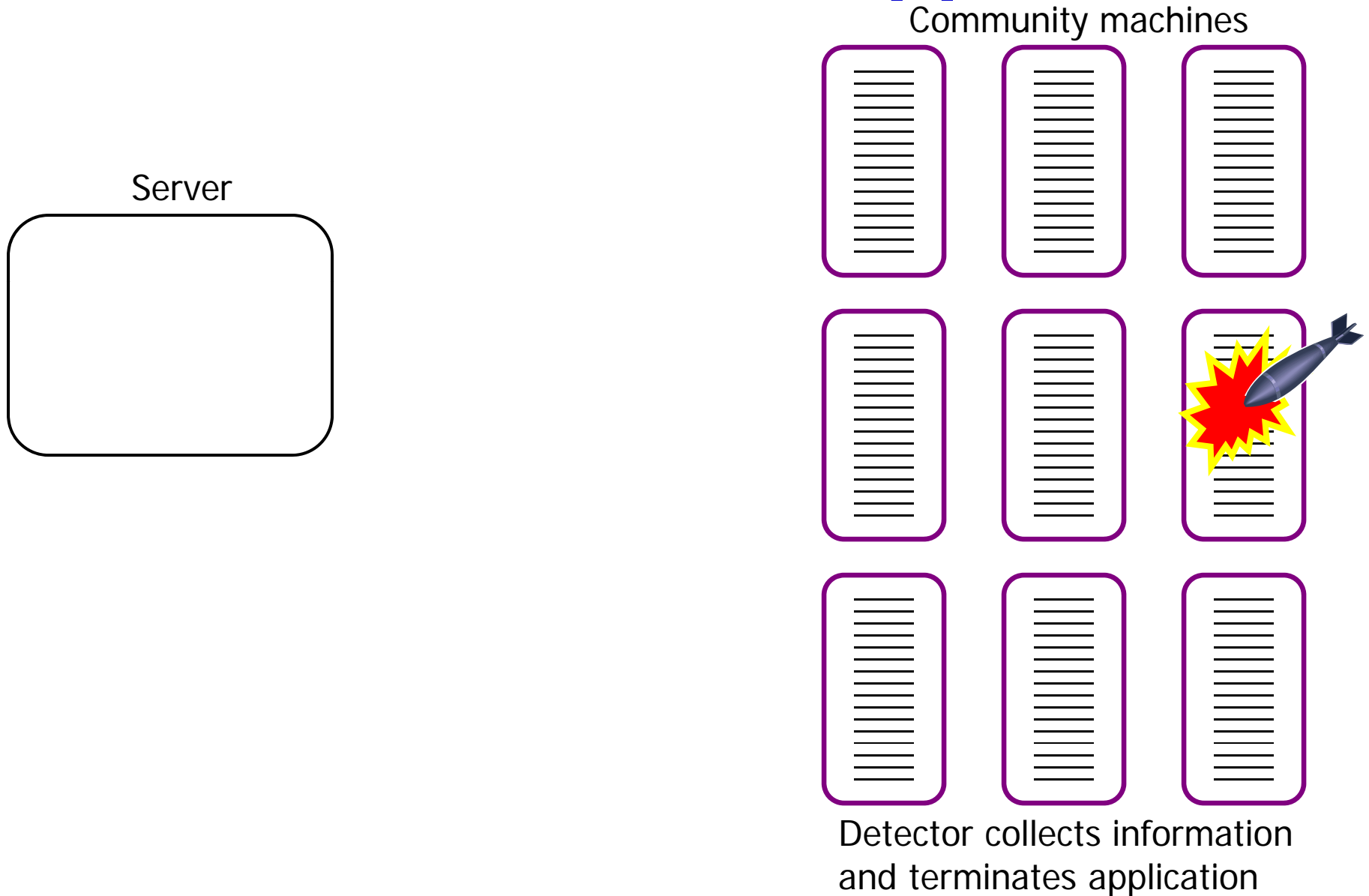
Other detectors are possible

# Learning from failures

Each **attack** provides **information** about the underlying vulnerability

- That it exists
- Where it can be exploited
- How the exploit operates
- What repairs are successful

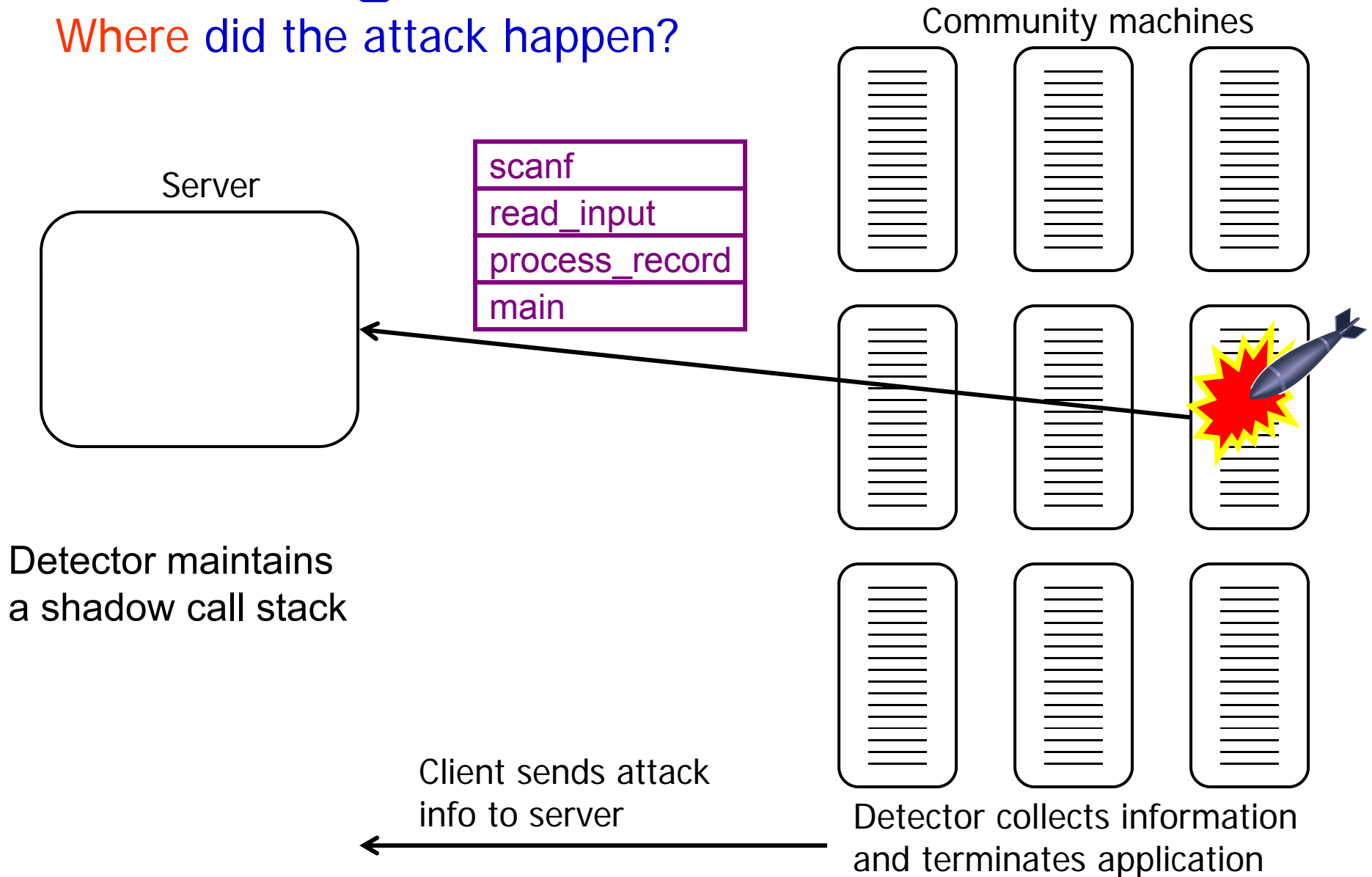
# Attack detection & suppression





# Learning attack behavior

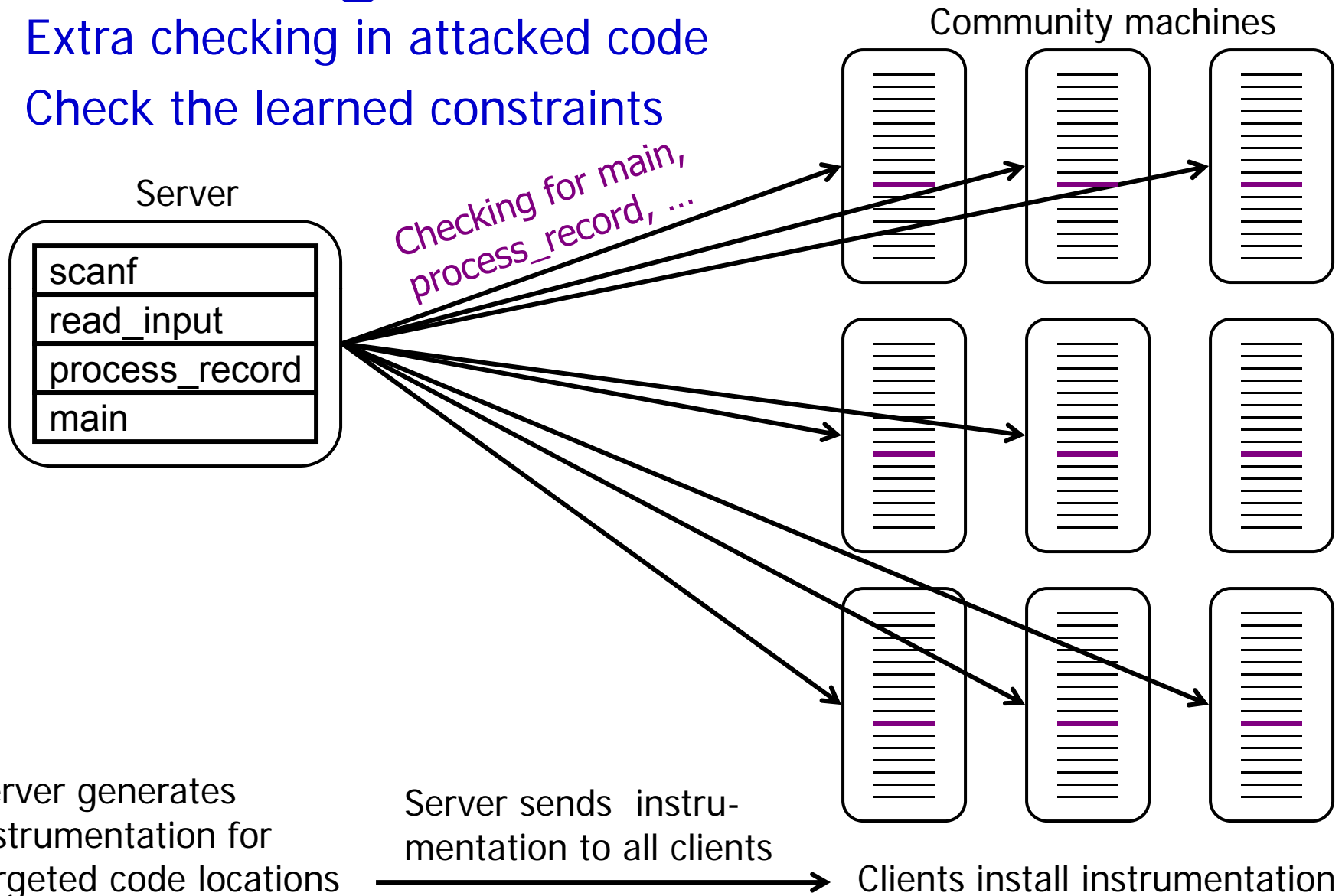
Where did the attack happen?



# Learning attack behavior

Extra checking in attacked code

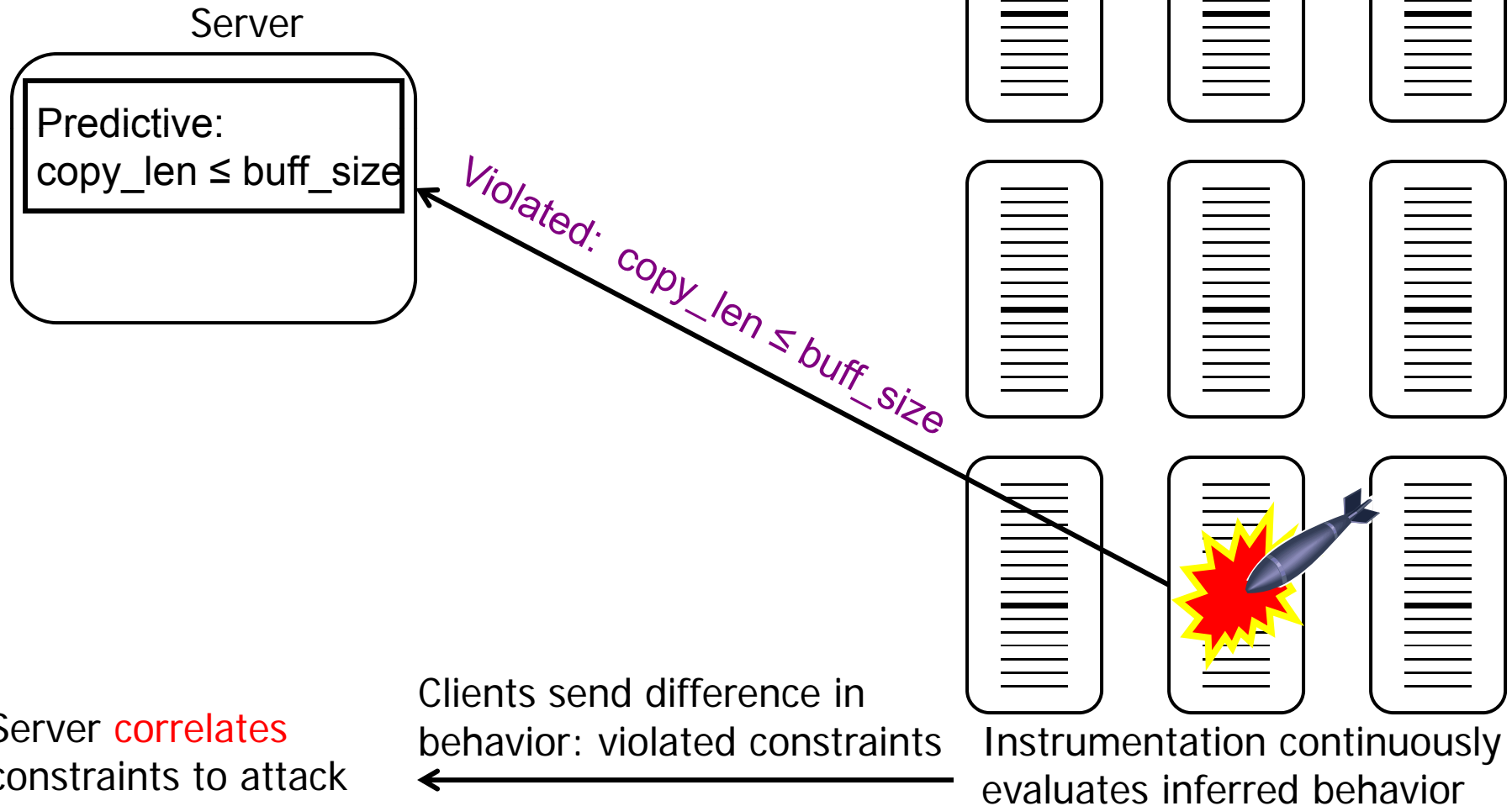
Check the learned constraints



# Learning attack behavior

What was the **effect** of the attack?

Community machines



# Correlating attacks & constraints

Check constraints only at attack sites

- Low overhead

A constraint is **predictive** of an attack if:

- The constraint is violated **iff** the attack occurs

Create repairs for each predictive constraint

- Re-establish normal behavior

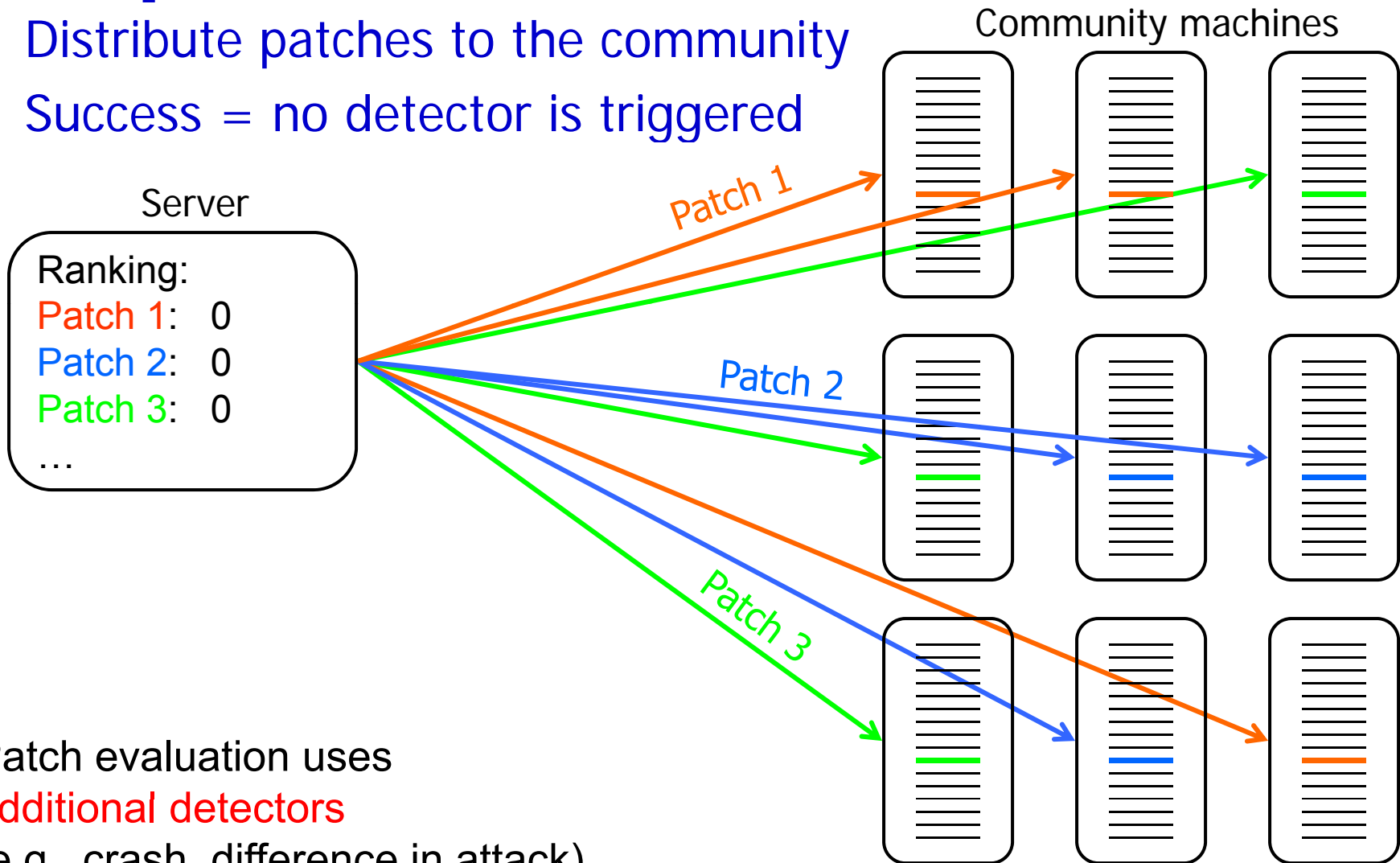
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# Repair

Distribute patches to the community

Success = no detector is triggered



Patch evaluation uses  
**additional detectors**  
(e.g., crash, difference in attack)

# Attack example

- Target: JavaScript system routine (written in C++)
  - Casts its argument to a C++ object, calls a virtual method
  - Does not check type of the argument
- Attack supplies an “object” whose virtual table points to attacker-supplied code
- Predictive constraint at the method call:
  - JSRI address target is one of a known set
- Possible repairs:
  - Call one of the known valid methods
  - Skip over the call
  - Return early

# Repair example

```
if (! (copy_len ≤ buff_size))  
    copy_len = buff_size;
```

- The repair **checks** the predictive constraint
  - If constraint is **not** violated, no need to repair
  - If constraint **is** violated, an attack is (probably) underway
- The patch does not depend on the detector
  - Should fix the problem before the detector is triggered
- Repair is not identical to what a human would write
  - Unacceptable to wait for human response



# Example constraints & repairs

$V_1 \leq V_2$

`if (! (v1 ≤ v2)) v1 = v2;`

$V \geq C$

`if (! (v ≥ c)) v = c;`

$V \in \{ C_1, C_2, C_3 \}$

`if (! (v == c1 || v == c2 || v == c3)) v = ci;`

Return from enclosing procedure

`if (! (...)) return;`

Modify a use: convert “call \*v” to

`if (...) call *v;`



Constraint on v (not negated)

# Evaluating a patch

- **In-field evaluation**
  - No attack detector is triggered
  - No other behavior deviations
    - E.g., crash, application invariants
- **Pre-validation**, before distributing the patch:
  - **Replay** the attack
    - + No need to wait for a second attack
    - + Exactly reproduce the problem
    - Expensive to record log; log terminates abruptly
    - Need to prevent irrevocable effects
    - Delays distribution of good patches
  - Run the program's **test suite**
    - May be too sensitive
    - Not available for commercial software

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# Red Team

- Red Team attempts to break our system
  - Hired by DARPA; 10 engineers
- Red Team created 10 Firefox exploits
  - Each exploit is a webpage
  - Firefox executes arbitrary code
  - Malicious JavaScript, GC errors, stack smashing, heap buffer overflow, uninitialized memory

# Rules of engagement

- Firefox 1.0
  - ClearView may not be tuned to known vulnerabilities
  - Focus on most security-critical components
    - No access to a community for learning
- Red Team has access to all ClearView materials
  - Source code, documents, learned invariants, ...

# ClearView was successful

- Detected all attacks, prevented all exploits
- For **7/10** vulnerabilities, generated a patch that **maintained functionality**
  - No observable deviation from desired behavior
  - After an average of 4.9 minutes and 5.4 attacks
- Handled polymorphic attack variants
- Handled simultaneous & intermixed attacks
- **No false positives**
- Low overhead for detection & repair

# 3 un-repaired vulnerabilities

Consequence: Application crashes when attacked. No exploit occurs.

1. ClearView was mis-configured: didn't try repairs in all procedures on the stack
2. Learning suite was too small: a needed constraint was not statistically significant
3. A needed constraint was not built into Daikon

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# Limitations

ClearView might **fail to repair** an error:

- Only fixes errors for which a detector exists
- Daikon might not learn a needed constraint
- Predictive constraint may be too far from error
- Built-in repairs may not be sufficient

ClearView might **degrade** the application:

- Patch may impair functionality
- Attacker may subvert patch
- Malicious nodes may induce bad patches

Bottom line: Red Team **tried** unsuccessfully

# Related work

- Attack detection: ours are mostly standard
  - Distributed: Vigilante [Costa], live monitoring [Kiciman], statistical bug isolation [Liblit]
- Learning
  - FSMs of system calls for anomaly detection
  - Invariants: [Lin], [Demsky], Gibraltar [Baliga]
  - System configuration: FFTV [Lorenzoli], Dimmunix [Jula]
- Repair & failure tolerance
  - Checkpoint and replay: Rx [Qin], microreboot [Candea]
  - Failure-oblivious [Rinard], ASSURE [Sidiroglou]

# Credits

- Saman Amarasinghe
- Jonathan Bachrach
- Michael Carbin
- Michael Ernst
- Sung Kim
- Samuel Larsen
- Carlos Pacheco
- Jeff Perkins
- Martin Rinard
- Frank Sherwood
- Stelios Sidiroglou
- Greg Sullivan
- Weng-Fai Wong
- Yoav Zibin

Subcontractor: Determina, Inc.

Funding: DARPA (PM: Lee Badger)

Red Team: SPARTA, Inc.

# Contributions

ClearView: framework for patch generation

- Pluggable detection, learning, repair

1. Protects against **unknown** vulnerabilities

- Learns from success

- Learns from failure: what, where, how

- Learning focuses effort where it is needed

2. Preserves **functionality**: repairs the vulnerability

3. **Commercial** software: Windows binaries

Evaluation via a Red Team exercise