Improving Resilience through Analysis and Synthesis of Adaptation Strategies

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The Problem

- Resilience is an important requirement for modern software-based systems

Maintain high-availability and optimal performance even in the presence of

- system faults
- changes in environment
- attacks
- changes in user needs and context

- Current resiliency mechanisms in systems are error prone, hard to maintain, difficult to verify

How is resilience addressed today?

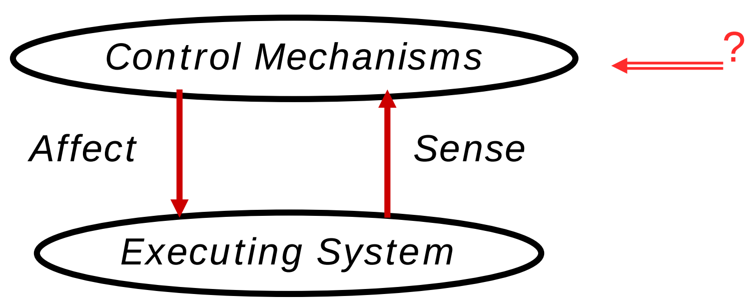
- Low-level, embedded mechanisms
  - Effective and timely
  - Local view of problem state makes it hard to diagnose and correct
  - Brittle to changes in needs/usage
  - Costly to modify after deployment
- High-level, human management
  - Global perspective on problem state
  - Flexible w/res/to changes in policy
  - Costly
  - Error-prone and slow

The Adaptive Systems Approach

- Goal: systems automatically and optimally adapt to handle
  - changes in user needs
  - variable resources
  - faults and attacks

But how?

Answer: Move from open-loop to closed-loop systems



Model-based Adaptation

Example: Google File System

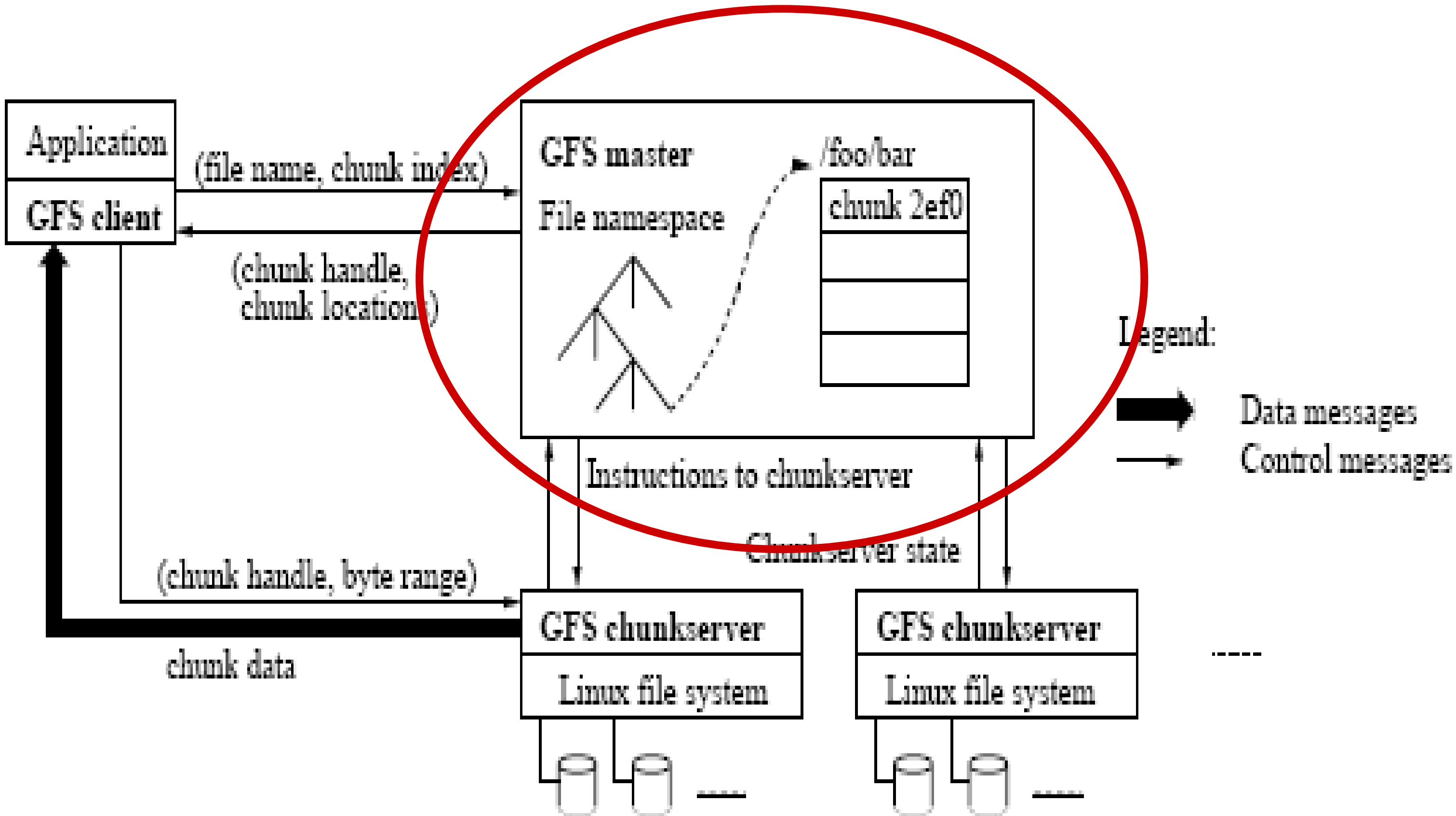


Figure 1: GFS Architecture

Source: "The Google File System" Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung. SOSP 2003.

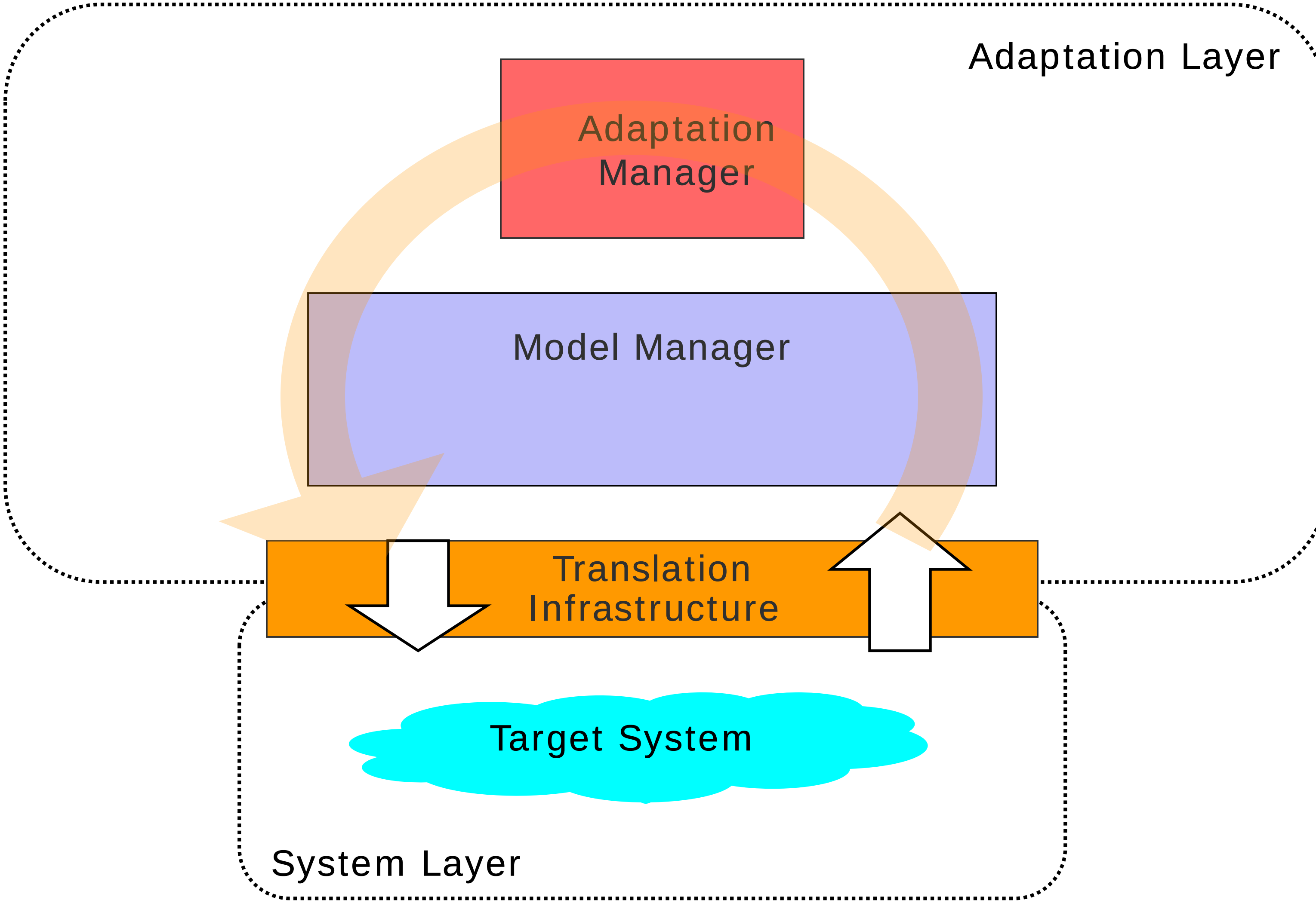
The Self-Adaptation Challenge

- Engineer self-adaptation to support
  - Cost-effectiveness
  - Legacy systems
  - Domain-specific adaptations
  - Multiple quality dimensions
  - Ease of changing adaptation policies
  - Assurance about the effects of self-adaptation actions and strategies

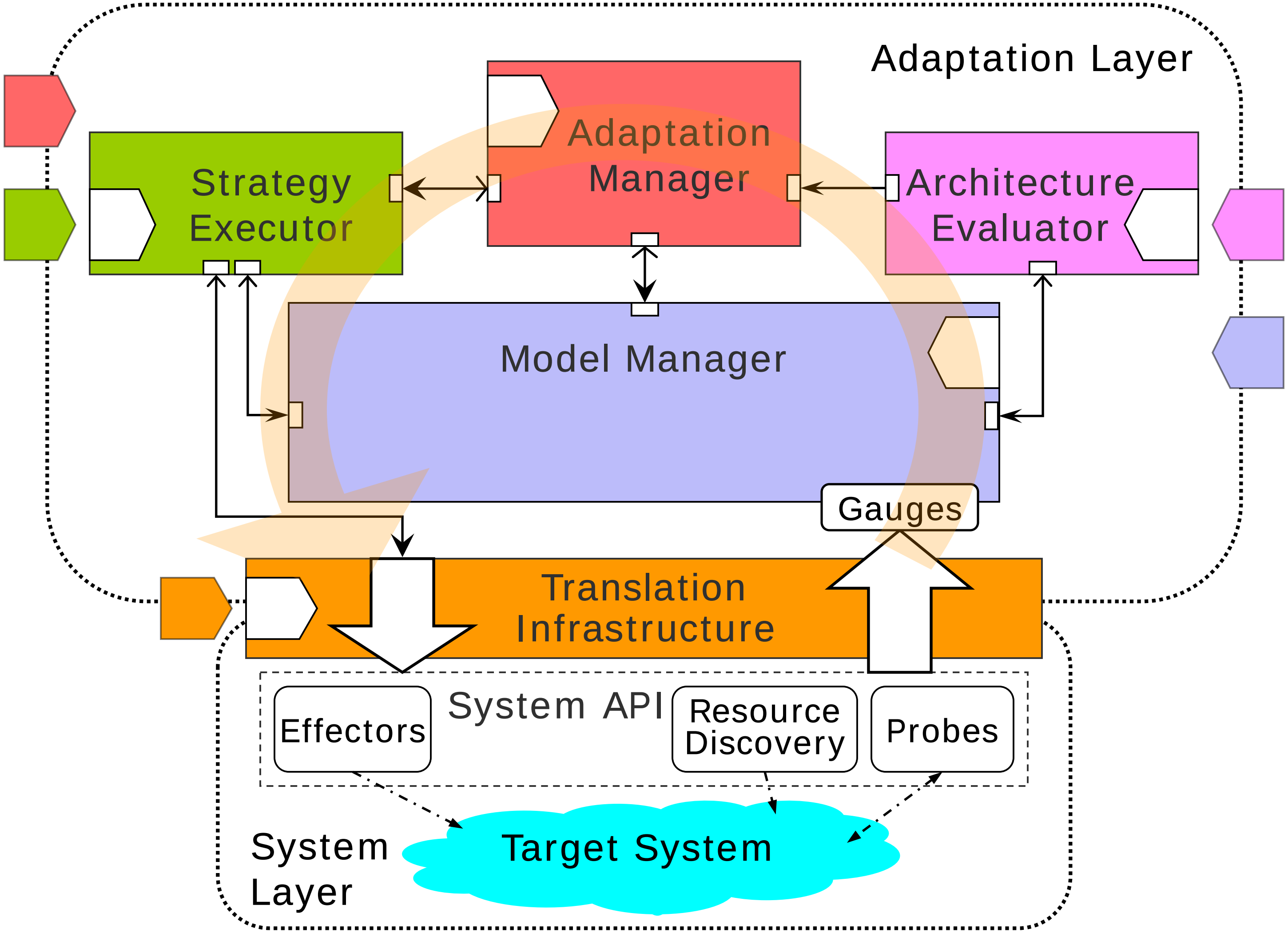
Rainbow

- A framework that
  - Allows one to add a control layer to existing systems
  - Uses dynamically updated architecture models to detect problems and reason about repair
  - Can be tailored to specific domains
  - Separates concerns through multiple extension points: sensors, actuators, models, conditions for adaptation, repair policies
- A language (Stitch) for specifying and reasoning about repair strategies

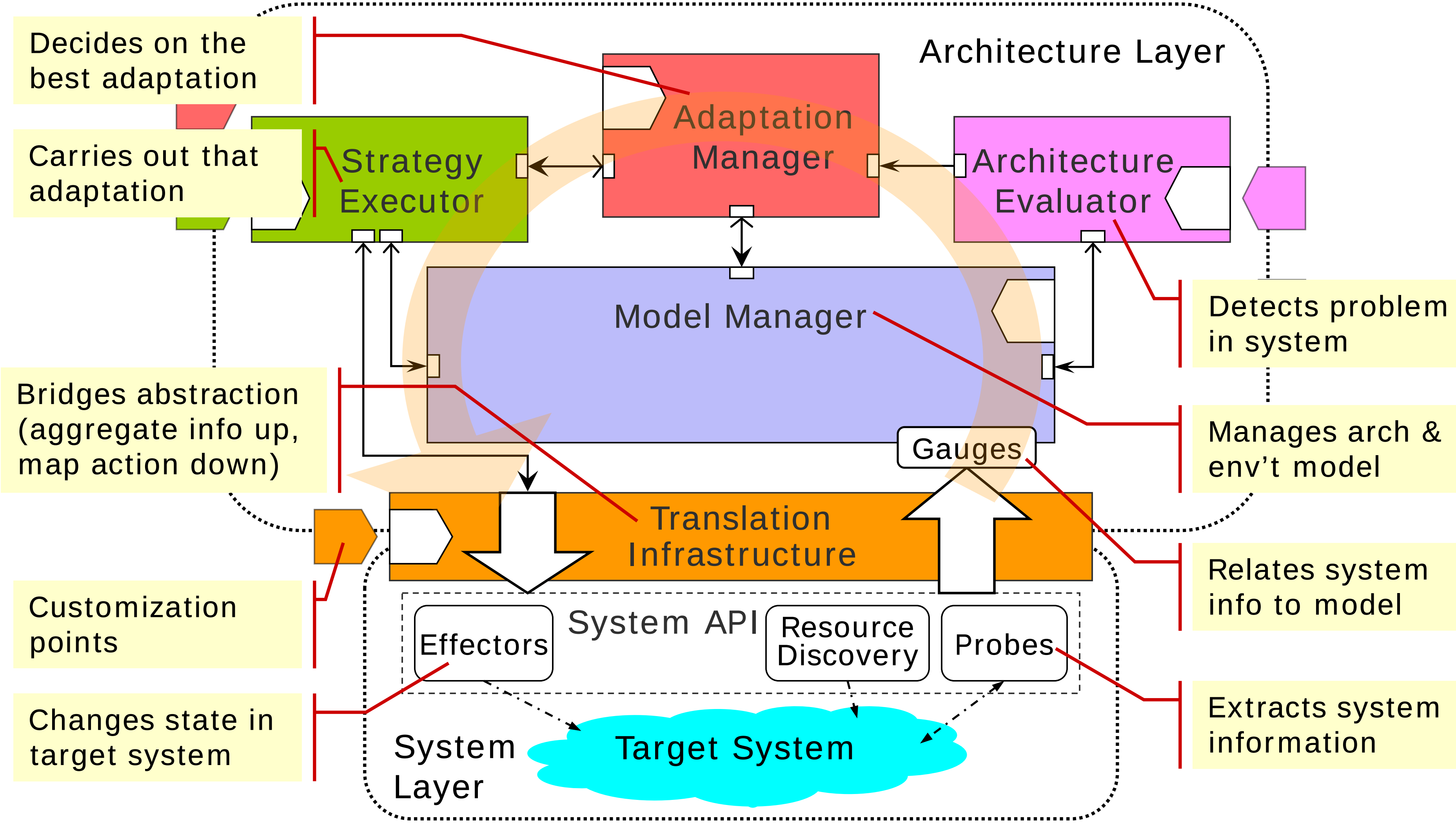
The Rainbow Framework



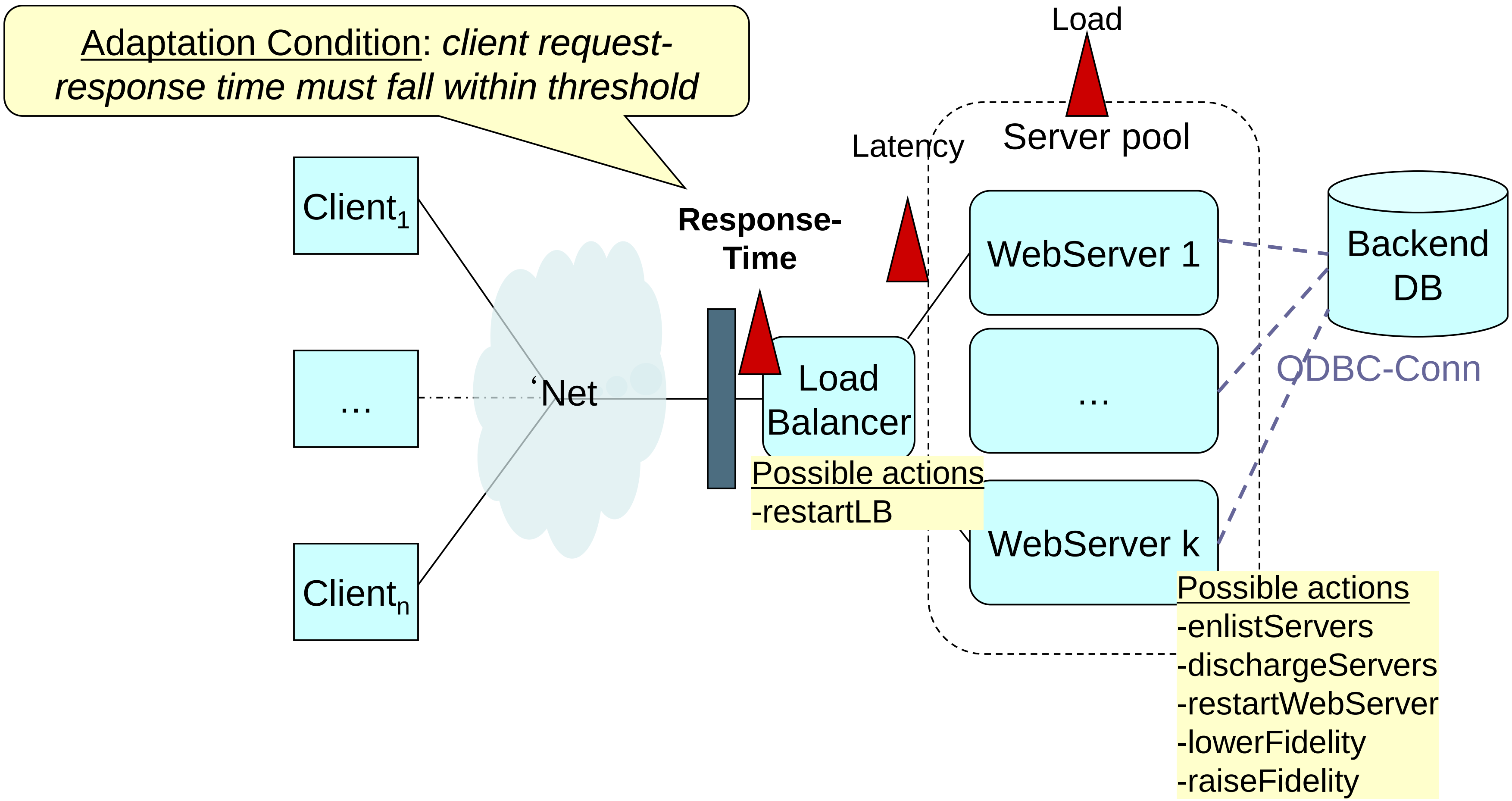
Rainbow Framework Overview



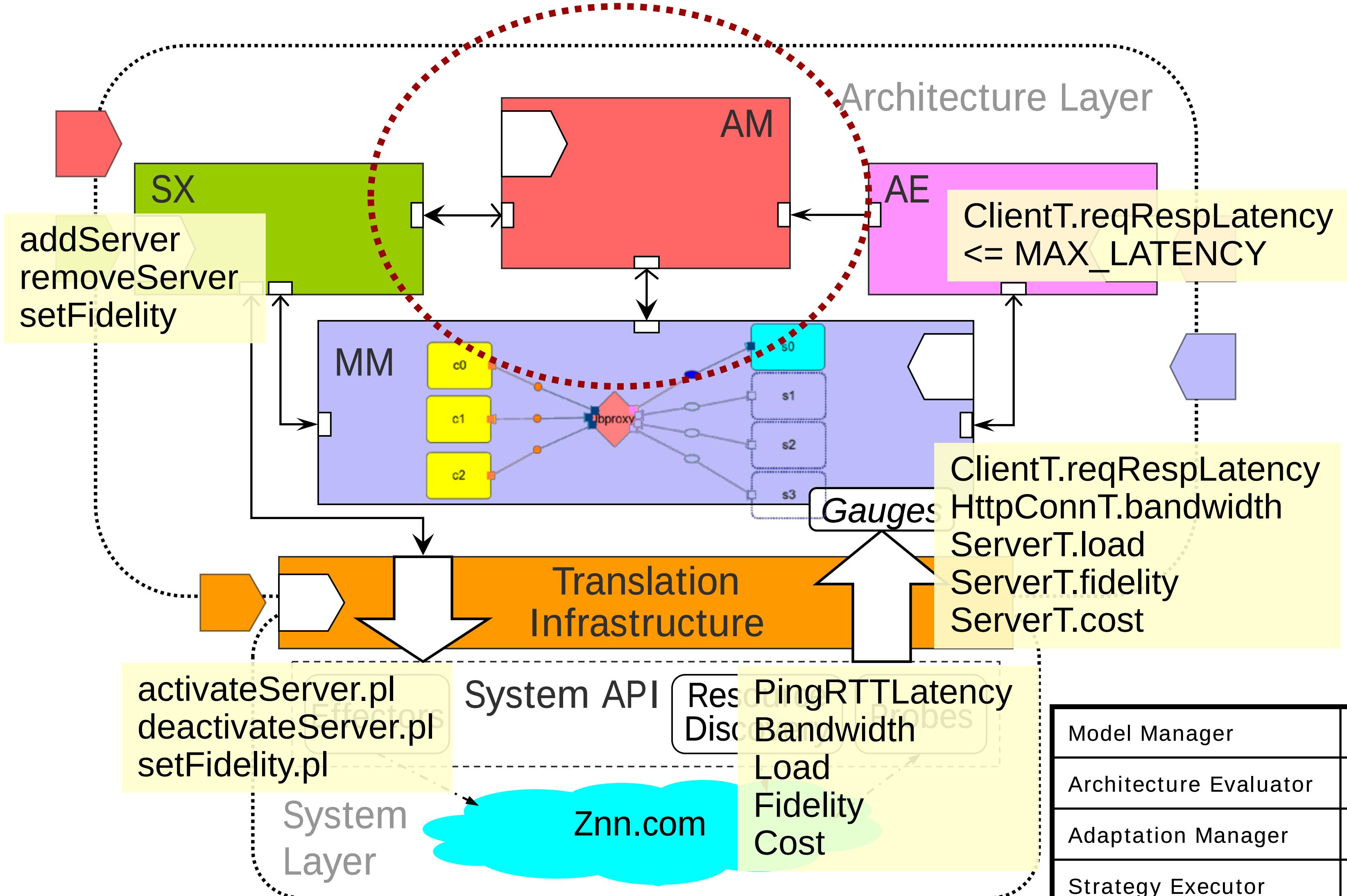
Rainbow Framework Overview



Self-Adaptation Example: *Znn.com*



Znn.com: Rainbow Customizations (Part 1)



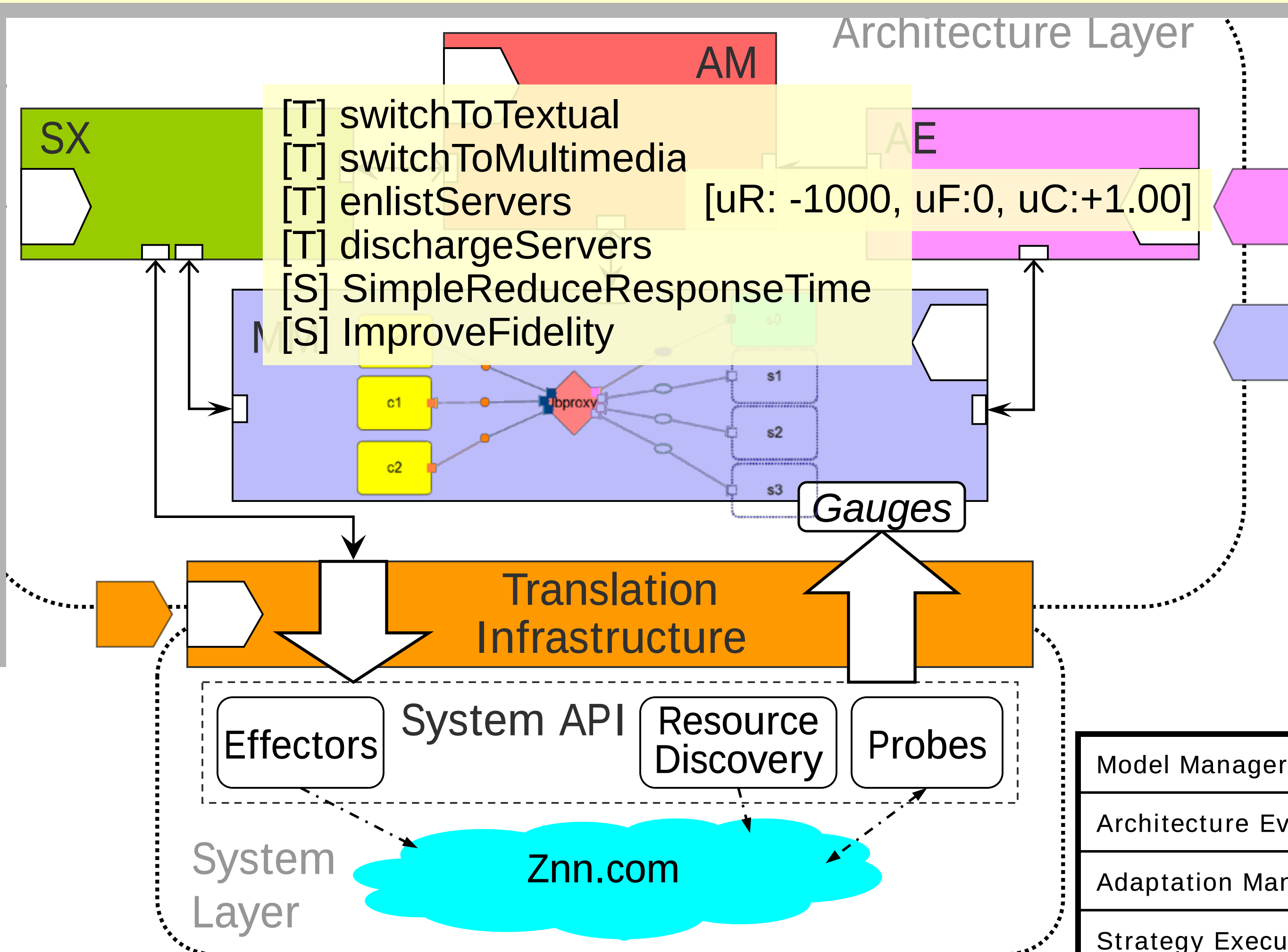
Model Manager	MM
Architecture Evaluator	AE
Adaptation Manager	AM
Strategy Executor	SX

Znn.com: Rainbow Customizations (Part 2)

Objectives: timely response (uR), high-quality content (uF), low-provision cost (uC)

uR:
  …
  utility:
    0: 1.00
    500: 0.90
    1500: 0.50
    4000: 0.00

weights:
  uR: 0.3
  uF: 0.4
  uC: 0.2
  uSF: 0.1



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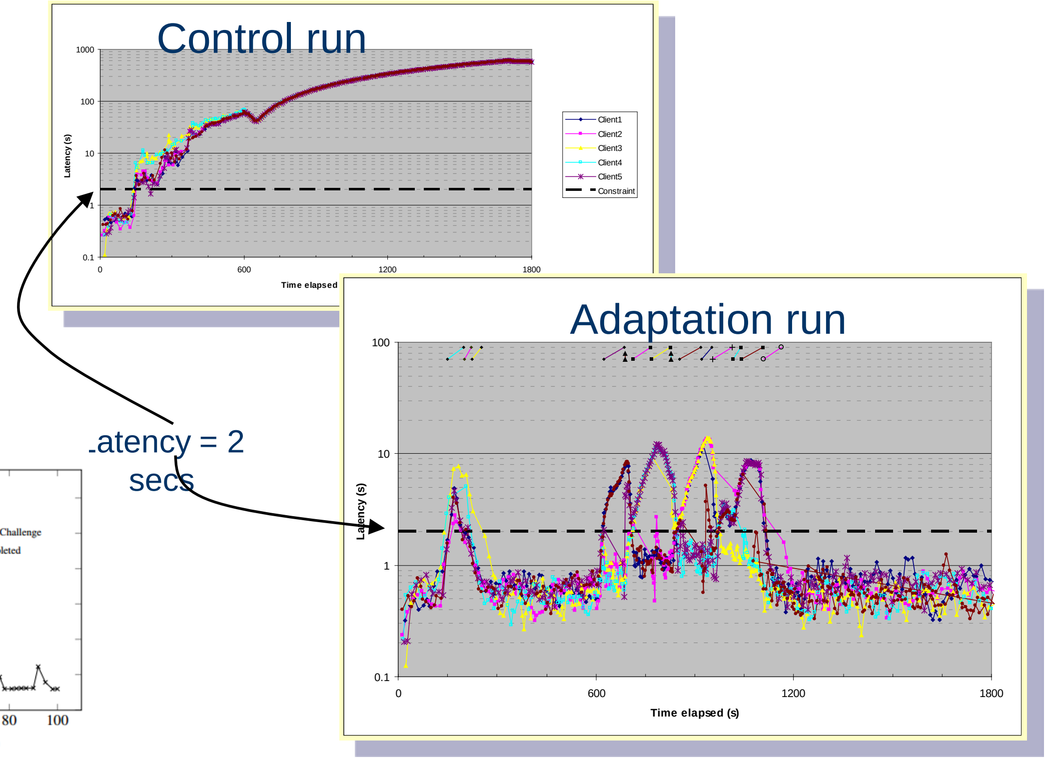
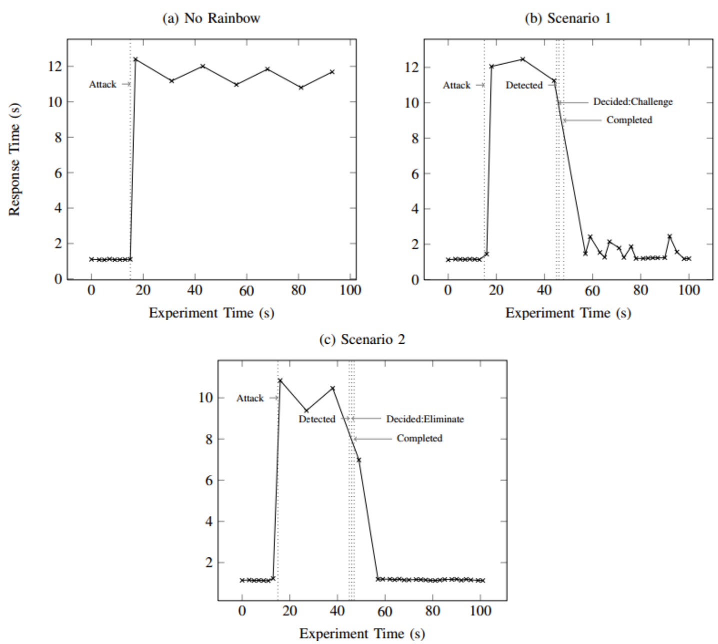
Prior Results

- Manage adaptation balancing cost, performance
- Respond to DoS attacks



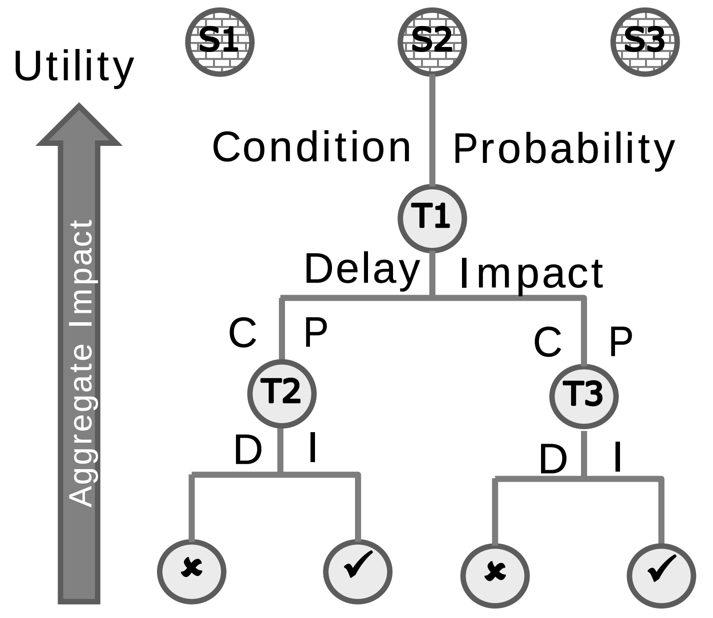


Rainbow Adaptation Decision Overview

- Selection from a set of adaptation strategies
  - Multiple strategies may be applicable at a given time
- Language for expressing strategies as a tree
  - Conditions: when are branches applicable
  - Actions: tactics that will modify the system
- Tree is annotated with properties that permit selection of strategy with highest utility
  - Delays: expected time for effects to be observed
  - Impacts: tactic impacts specified as expected effect of actions on quality dimensions
  - Utility: preferences over the quality dimensions determine utility of impact
  - Uncertainty: Nodes represent probabilistic choices

Stitch: A Language for Specifying Self-Adaptation Strategies

- Control-system model: Selection of next action in a strategy depends on observed effects of previous action
- Uncertainty: Probability of taking branch captures non-determinism in choice of action
- Asynchrony: Explicit timing delays to see impact
- Value system: Utility-based selection of best strategy allows context-sensitive adaptation



Strategy Selection: Example

- Given:
  - Quality dimensions and weights (e.g., 4)
  - A strategy with
    - N nodes
    - Branch probabilities as shown
    - Tactic cost-benefit attributes

$u_{latency}()$, $u_{quality}()$, $u_{cost}()$, $u_{disruption}()$
$(w_{latency}, w_{quality}, w_{cost}, w_{disruption})$
$= (0.5, 0.3, 0.1, 0.1)$ **[= 1]**

Algorithm

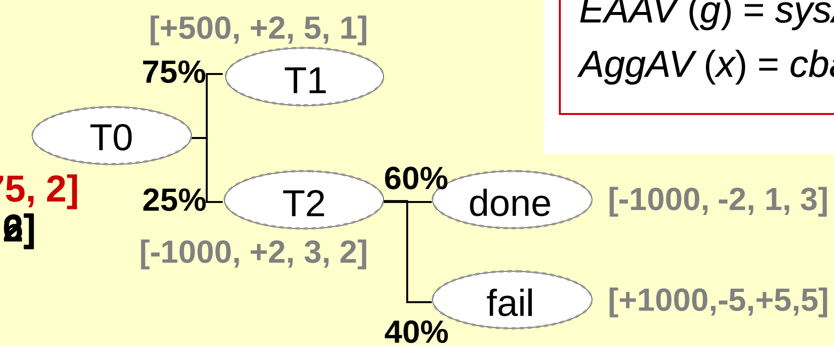
Given tree g with node x and its children c:

$EAAV(g) = sysAV + AggAV(root(g))$

$AggAV(x) = cbav(x) + \Sigma_c\, prob(x,c)\, AggAV(c)$

Score = 0.58

[-125, 1.5, 4.75, 2]



- Propagate cost-benefit vectors up the tree, reduced by branch probabilities
- Merge expected vector with current conditions (assume: [1025, 3.5, 0, 0])
- Evaluate quality attributes against utility functions
- Compute weighted sum to get utility **score**

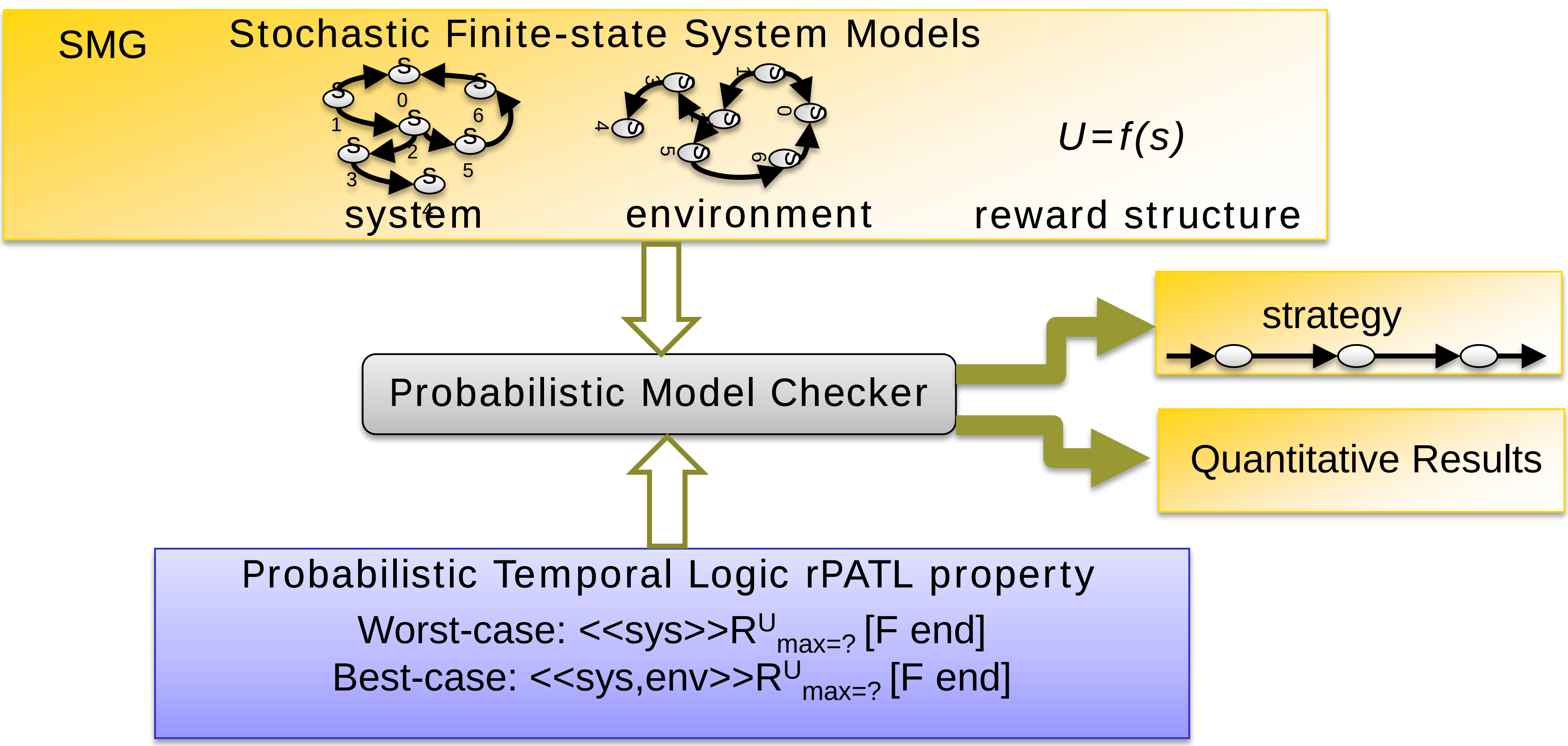
Beyond specification and selection

- Ability to accurately predict outcomes of strategy execution under various environment assumptions (e.g., best-case, worst-case)
- Ability to determine conditions under which different strategies are best suited
- Ability to quantify the value of adding new tactics to the adaptation repertoire
- Ability to synthesize strategies
  - Off-line
  - On-line
- Ability to know when humans should be brought in to the process

Probabilistic Model Checking

- Probabilistic Model Checking: formal verification technique that enables the modeling and (quantitative) analysis of systems that exhibit probabilistic behavior
  - Used in communication protocols, security, biological systems, ...
  - Can capture different sources of uncertainty (e.g., environment changes, outcome of adaptation tactics)
- Stochastic Multiplayer Games (SMGs)
  - Enable modeling and analysis of competitive behavior
  - SMG models include a set of player coalitions that compete against each other to achieve their own goals
  - Each player controls a set of stochastic processes
  - Can be extended with rewards/costs (e.g. time, battery consumption)
  - Can naturally model the interplay between an adaptive system and an adversarial environment
  - Can be used to synthesize optimal strategies

Analysis via Probabilistic Model Checking of SMGs



Strategy Analysis

Goal

Determine the behavioral envelope of the system under adaptation

- Model system and environment as players in a SMG
  - System tries to maximize objective function *f* (e.g., utility, probability of satisfying a property expressed in TL, etc.)
  - Environment can be considered as
    - Adversarial: tries to minimize the value of *f* -> worst-case analysis
    - Cooperative: tries to maximize the value of *f* -> best-case analysis
- Use probabilistic model checking to analyze adaptation performance with respect to *f*
  - Compute the maximum and minimum values of *f* that system player can achieve by following an optimal strategy

Example: Znn.com SMG Model

- Environment player
  - Every period places an arbitrary but bounded amount of request arrivals
- System player
  - Computes average response time using queuing model
  - Selects adaptation tactic non-deterministically
    - Enlist server (latency)
    - Discharge server (no latency)
    - Do nothing

Key idea

No decision algorithm is encoded in the model.

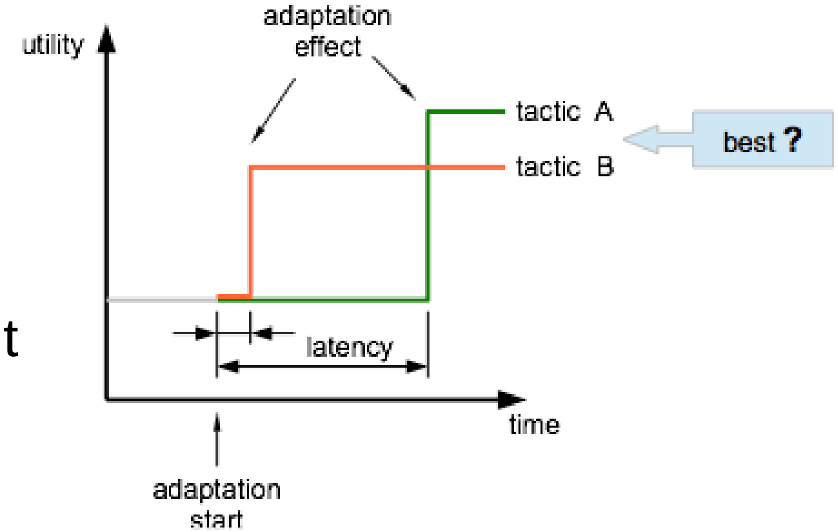
Adaptation strategy based on

• what the system can do (tactics)

• the expected utility of the adaptation

Example: Assessing the Potential Benefit of Proactive, Latency-Aware Adaptation

- Different tactics take different time to produce the intended effect
  - Changing content fidelity: <1s
  - Adding a new Cassandra node: ~3min [Gambi 2013]
- How does the latency of different tactics affect the decision?



Goal

Compare latency-aware (LA) adaptation with non-latency-aware (NLA) adaptation to assess its potential benefit. Synthesize an optimal strategy.

SMG Analysis Results

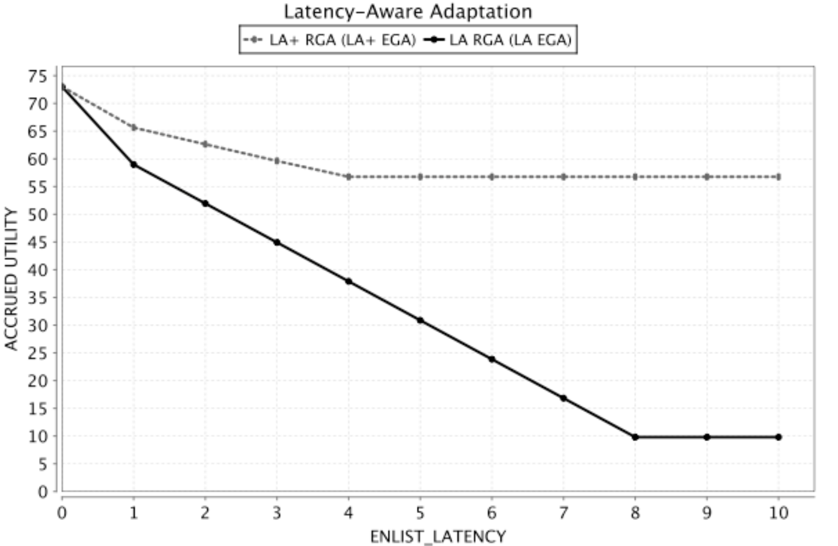
% improvement with latency-aware adaptation in worst- and best-case scenarios

Latency	$\Delta U(\%)$ worst-case	$\Delta U(\%)$ best-case
τ	12.83	21.44
2τ	27.46	22.24
3τ	34.61	23.05

τ : time between adaptation decisions = 10 sec

$\Delta U(\%)$: increase in utility with LA over NLA

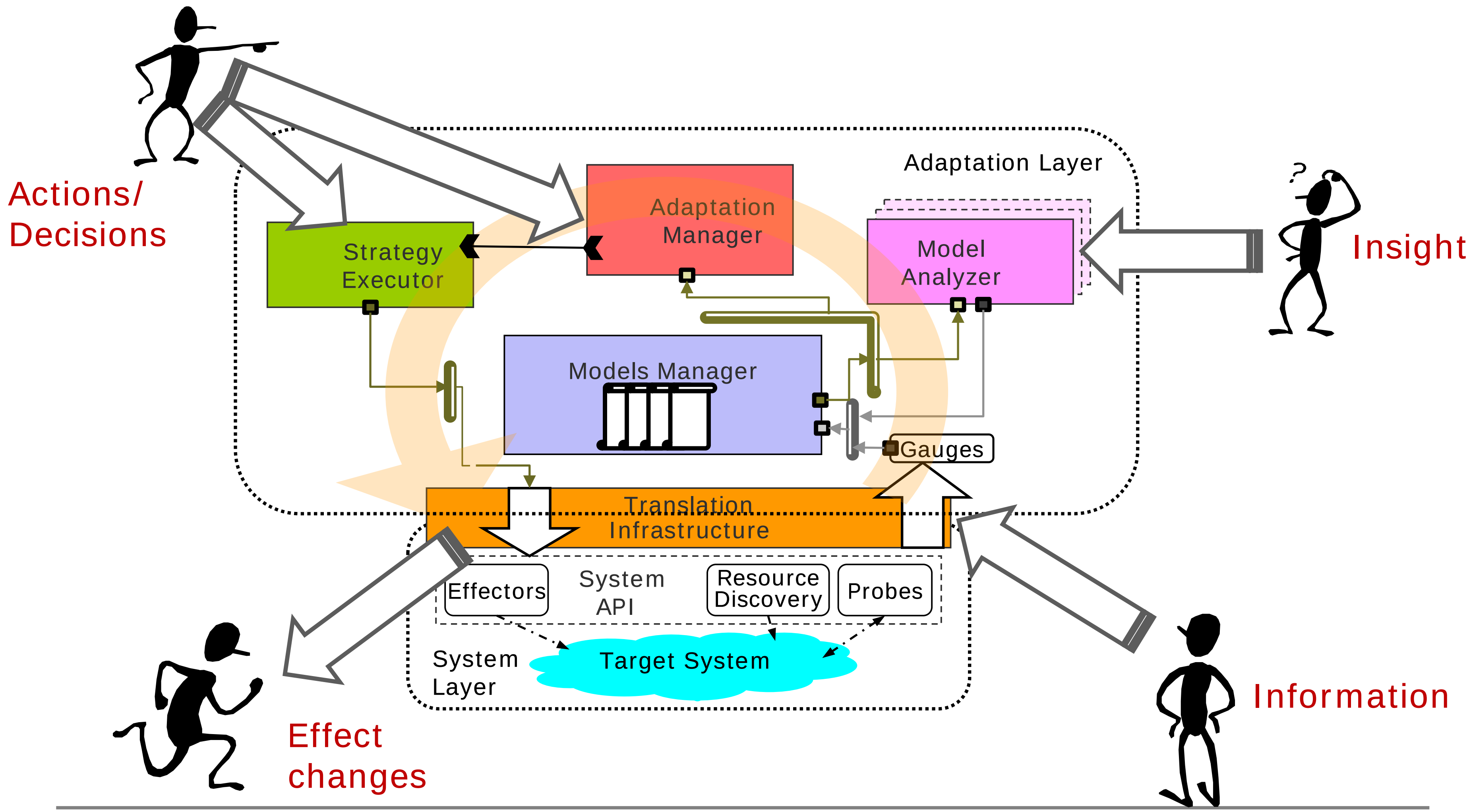
quantify impact of adding new tactics



Reasoning about Human Involvement in Adaptive Systems

- Eliminating human operators is a nice goal, but not always possible
- It is not always possible for a system to automatically adapt for all situations.
- Some actions may require human involvement
- Humans may understand context better than the system

Humans in the Loop

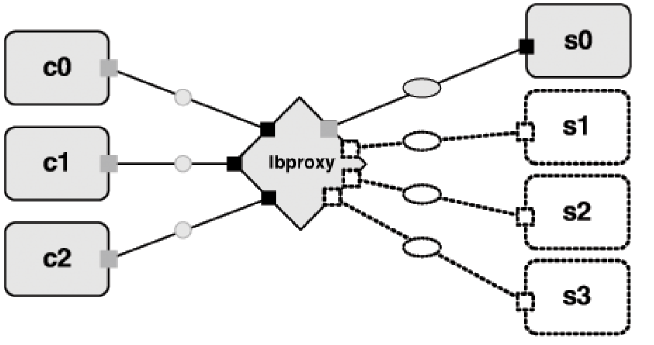


Reasoning about Humans in the Loop

- Human behavior influenced by
  - Changing load and attention
  - Different expertise
  - Physical attributes (access to physical locations, timing)
- Questions that we want to be able to answer
  - What is the likely outcome if a human is involved?
  - Should human participate in the adaptation?
- Framework to formally reason about human involvement in adaptation
  - Focus on **humans as actuators**
  - Extension of language to express adaptation models (Rainbow/Stitch) with human factors (OWC model)
  - Formalization to analyze human-system-environment interactions (Stochastic Multiplayer Games)

Example: Denial of Service in Znn.com

- **Typical news website infrastructure**
  - Pool of replicated servers connected to load balancer
    - Size can be dynamically adjusted
  - Servers can deliver contents with different fidelity levels (text, images, videos...)
    - Content fidelity can be dynamically changed



- **Application layer DoS** (e.g., Slowloris)
- **Quality objectives**
  - Performance: request-response time for legitimate clients
  - Cost: number of active servers
  - Maliciousness: percentage of malicious clients
  - Annoyance: disruptive side effects of tactics

Tactics and Strategies

- **DoS mitigation tactics/strategies selected to provide interesting analytical situations**
  - For example, Adding capacity is much less aggressive than Blackholing, but it is more costly

Tactic	Description
Add capacity	Activate additional servers to distribute the workload
Blackhole ☹	Blacklists clients, requests are dropped
Reduce service	Reduce content fidelity level (e.g., text vs. images)
Throttle ☹	Limits the rate of requests accepted

Strategy	Description
Outgun/Absorb	Combines Add capacity and Reduce service
Eliminate ☹	Combines Blackholing and Throttling

Strategies with Humans: Approach

- Tactics can be automated or manual
- Human actions as tactics
  - Will ask the human to do an action
  - Timing delay gives humans time to do operation
- Model of human sufficient for making the decision
  - Represent characteristics of humans that could affect the decisions
  - Understand how would those characteristics affect the decision about when to involve the human

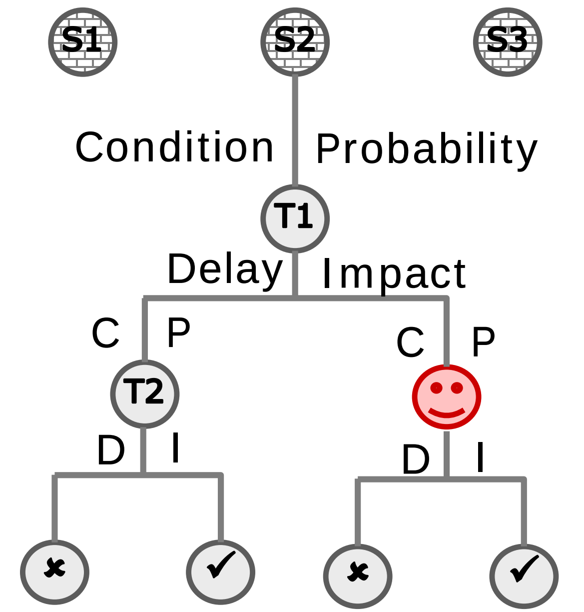
Candidate Model for Human Involvement

- Opportunity-Willingness-Capability model (OWC)*
  - Inspiration from human-cyber systems
- Opportunity:
  - Conditions of applicability for tactics to be done
  - E.g., is human physically located on site? Do they have access to room?
- Capability:
  - How likely the human is to succeed at the task
    - E.g., level of training, seniority, etc.
- Willingness:
  - How likely the human is to do the task
    - E.g., level of attention, stress

*Eskins, Sanders: The Multiple-Asymmetric-Utility System Model: A Framework for Modeling Cyber-Human Systems.

Integrating OWC in Stitch

- Some tactics enact humans
- Opportunity is captured in conditions
- Willingness and Capability affect probabilities
- (Human tactics will likely have longer delays)



OWC Model for blackHoleAttacker (bha)-1

- Opportunity
  - Elements OE={L,B}, where L represents the operator's location:
    - *L.state ∈ {on location (ONL), off location (OFFL)}*

  and B represents whether the operator is busy:
    - *B.state ∈ {busy (OB), not busy (ONB)}*
  - Function: $f_o^{bha}=(L.state==ONL)\ (B.state==ONB)$

Opportunity Elements

```
define boolean ONLNB=exists o:operatorT in M.participants | o.onLocation && !o.busy;
define boolean cHiRespTime=exists c:ClientT in M.components |
c.experRespTime>M.MAX_RESPTIME;

tactic blackHoleAttacker(){
  condition {ONLNB && cHiRespTime;}
  action {ao=Set.RandomSubSet({select o:operatorT in M.participants | o.onLocation && !o.busy},1);
            notify(op, "Blackhole potentially malicious clients");}
  effect {!cHiRespTime;}
}
```

Opportunity Function

OWC Model for blackHoleAttacker (bha)-2

- Willingness
  - Elements WE={S}, where S represents the operator's stress level:
  - Function: $f_w^{bha}=pr_w(S.state)$, *with* pr_w *->* *[0,1]* maps stress levels to probability of the tactic being carried out
- Capability
  - Elements CE={T}, where T represents the operator's level of training.
  - Function: $f_c^{bha}=pr_c(T.state)$, *with* pr_c *->* *[0,1]* where pr_c maps training levels to probabilities of successful tactic performance.

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Example: Strategies to Absorb/Eliminate excess traffic

Fully automated

```
strategy Outgun
[cHiRespTime] {
   t0 : (cHiRespTime) -> enlistServers(1)@[30000 /*ms*/] { // enlist server, wait 30s
      t1: (sucess) -> done;
      t2: (fail) -> lowerFidelity() @[2000 /*ms*/] {
            t2a: (success) -> done;
            t2b: (fail) -> TNULL;
      }
   }
}
```

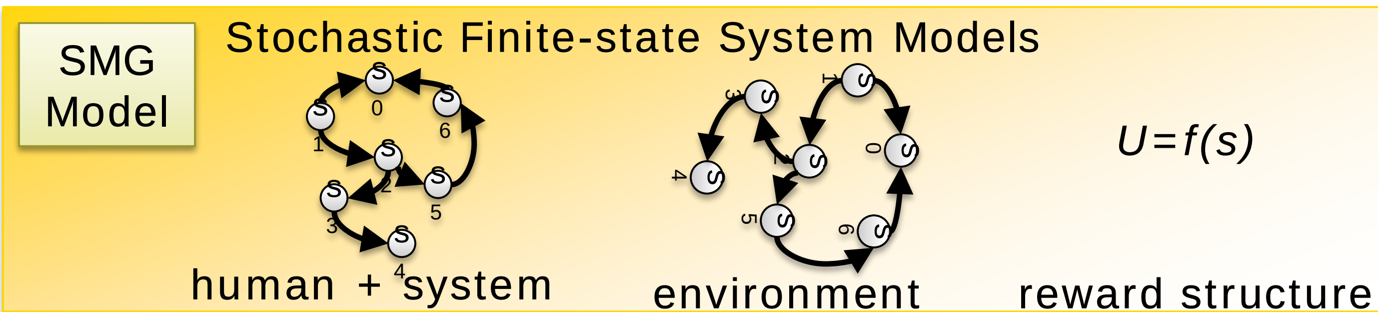
Relies on human effectors

```
strategy Eliminate
[ONLNB & (unhandledMalicious || unhandledSuspicious)] {
   t0: (unHandledMalicious) -> : blackHoleAttacker()@[300000 /*ms*/] { // blackhole, wait 5 min
      t0a: (success) -> done;
      t0ab: (unhandledSuspicious) -> throttleSuspicious()@[30000 /*ms*/] {
            t1a: (success) -> done;
             t1b: (fail) -> TNULL;
             }
      }
}
```

Under what conditions will one strategy be better than the other?

Probabilistic Modeling for HuIL

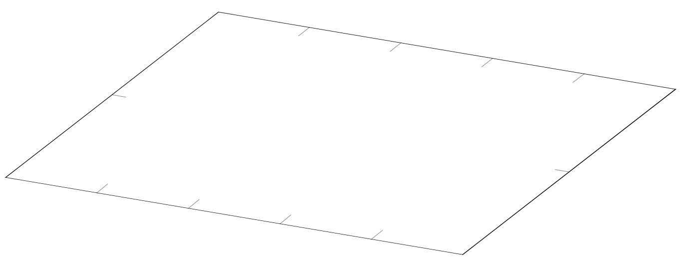
- Model system-human-environment interactions as a Stochastic Multiplayer Game*
  - System + human player tries to maximize utility
  - Environment player tries to minimize utility
    - Enables worst-case scenario analysis



- Quantification of maximum utility that system+human player can obtain
- Synthesis of optimal player strategies
  - Insight about best combined operator/automatic adaptations
  - Context-sensitive notion of optimality

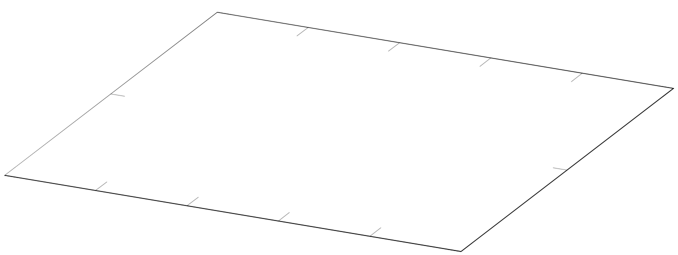
*J. Cámara, G.A. Moreno, D. Garlan: ***Reasoning about Human participation in Self-Adaptive Systems***. 10th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS 2015)

Analysis results: varying **C**apability elements (Scenario 1- eliminate malicious clients)



Outgun vs Eliminate accrued utility

Analysis results: varying **C**apability elements (Scenario 2 – optimize user experience)



Outgun vs Eliminate accrued utility

Analysis results: strategy selection (Scenario 1 – eliminate malicious clients)

Eliminate predominates. Human involvement useful even if training is limited, or with low level of malicious clients (20%) if training is good.

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Analysis results: strategy selection (Scenario 2 – optimize user experience)

Outgun predominates. Human involvement only useful if operator has extensive training (>0.55) and malicious clients >50%.

Current and Future Work

- Adaptation and architecture models can be combined with formal techniques to improve the predictability of SAS in a systematic manner
  - Latency-aware proactive adaptation [SEAMS14]
  - Self-protecting systems
    - Adversarial environments that might include potential attackers
      - Denial-of-Service Mitigations [HotSoS14]
      - Moving Target Defense [MTD14]
  - Human-in-the-loop
    - System formed by a coalition of adaptation manager and human participants [SEAMS15]
- Future work
  - Explicit resolution of uncertainty
  - Machine learning to improve models at run time
  - Combining off-line and on-line analysis/synthesis.

References

- [SEAMS14] Javier Cámara, Gabriel A. Moreno and David Garlan. Stochastic Game Analysis and Latency Awareness for Proactive Self-Adaptation. In *9th International Symposium on Software Engineering for Adaptive and Self-Managing Systems*, Hyderabad, India, 2-3 June 2014.
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