Network-Aware Automated Planning

and Plan Execution

Kyle Usbeck

A Thesis Submitted to the Faculty of Drexel University in partial fulfillment of the requirements for the degree of Master of Science in Computer Science

2009-07-07

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Outline

1. Introduction
   - Motivation
   - Background
   - Approach
2. Formalization
   - Problem Statement
3. Technical Approach
   - Planning Agents
   - Execution Agents
   - Monitoring Agents
   - Mixed-initiative UI
4. Experiments
   - Plan Evaluation Benchmarking
   - Network-Aware Agent Combinations
   - Discussion

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Motivation

April 2009:

- 75% of coalition force casualties in Afghanistan are from roadside bombs.
- 40% of coalition force casualties in Iraq are from roadside bombs.

Source: Tom Vanden Brook, USA Today

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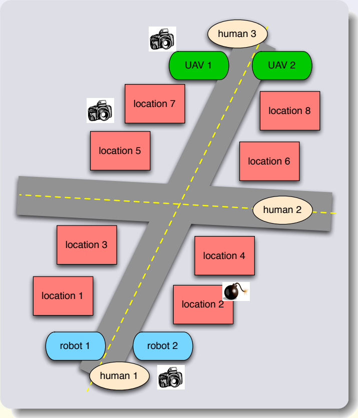
Motivating Scenario

- IED Detection.
- Monitor Locations.
- Techniques.
- Actors.
- Resources.
- Evaluators.



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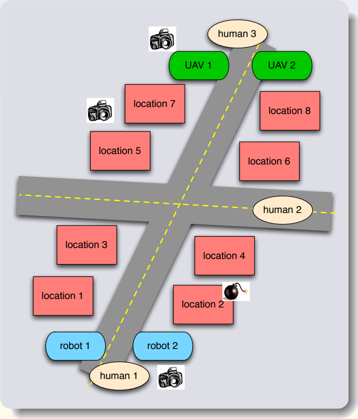

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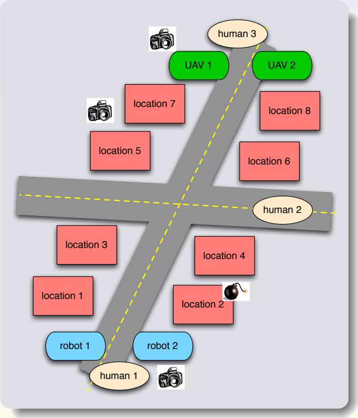

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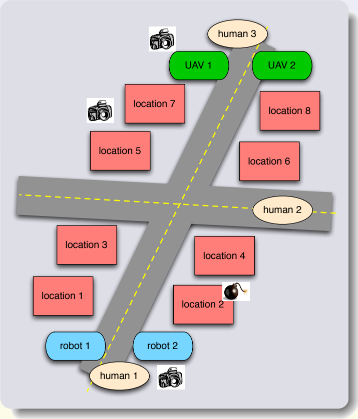

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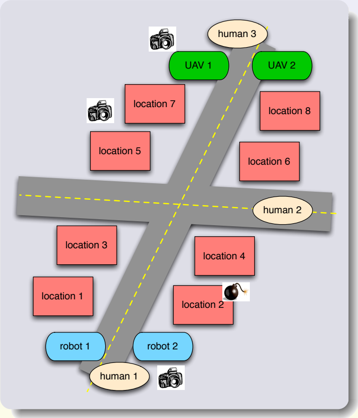

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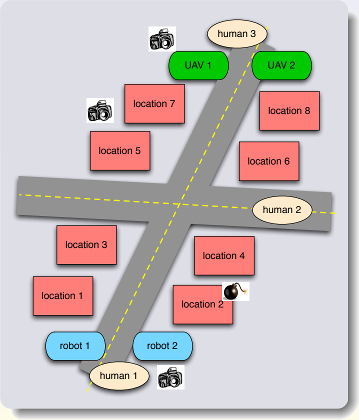


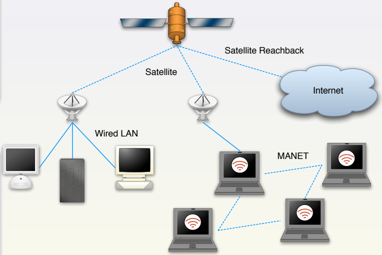
Motivating Scenario

Heterogeneous Network

multiple different network technologies are combined to work together simultaneously.

Network-Centric System

a distributed system where performance is dependent on the quality of the underlying network communication links.



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Contributions

1. Qualitatively-different plans:
    - Generating plans over a range of evaluation criteria;
    - Visualizing plan evaluations.
    - Improve plan selection.
2. Network-Aware Agents:
    - Classical planning domains for distributed service composition;
    - Measuring the performance and effectiveness of planning, execution, and monitoring agents;
    - Incorporating network-awareness.

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Service Composition to Automated Planning

Definition

"Service composition is the linking. . . of existing services so that their aggregate behavior is that of a desired service (the goal)" [Hoffmann *et al.* 09].

- Requires Semantic Web Services [Sirin *et al.* 04].
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Assumes static networking.

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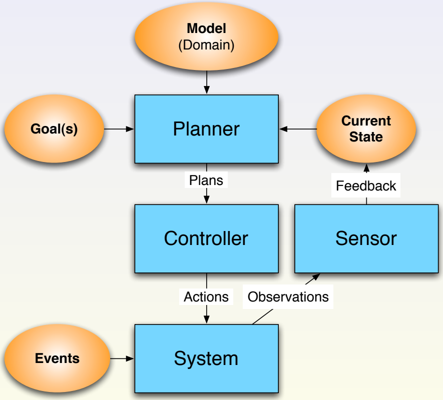
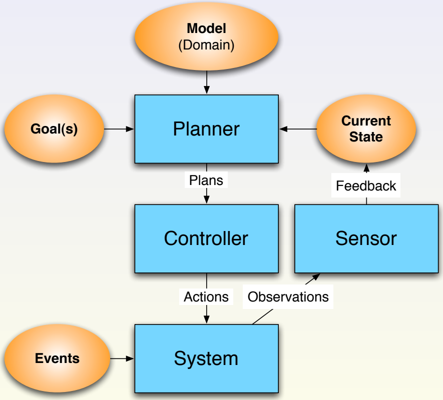


Agents:

- Planning Agent.
- Execution Agent.
- Monitoring Agent.

[Tate 93]

Agents in Planning



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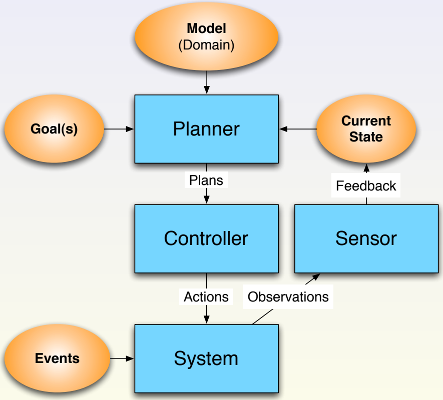

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Planning Under Uncertainty

Restrictive Assumptions:

- Determinism.
- Full observability.
- Reachability goals.

[Nau *et al.* 04]

Sources of Uncertainty:

- Partial observability.
- Unreliable resources.
- Measurement variance.
- Inherently vague concepts.

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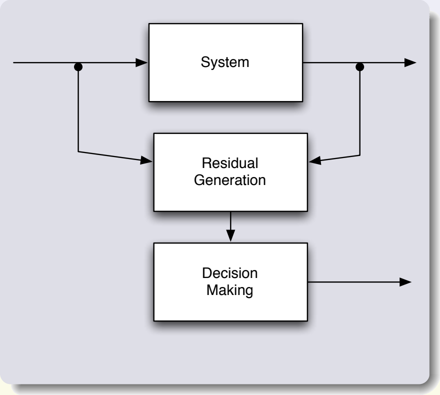

Types of FDI:

- Analytic.
- Data-driven.
- Knowledge-based.

[Pettersson 05]

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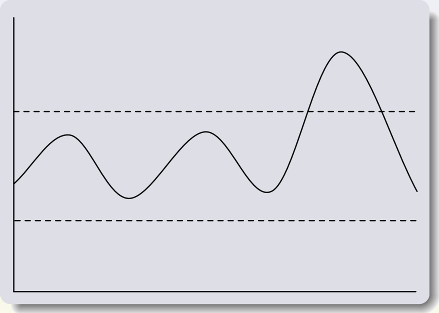

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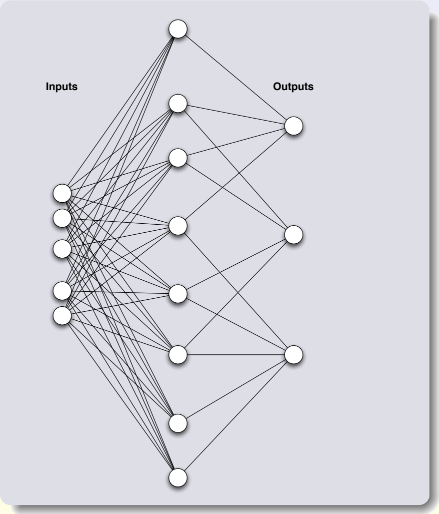

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Approach

1. Modify planner to improve the quality of the plans it produces based on evaluation criteria.
2. Add network-awareness to planning, execution, and monitoring agents.

Purpose

To improve network-centric automated planning and execution.

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Formal Problem Statement

Σ is the planning domain — the model of the world passed as input to the planner.

Σ is a Tuple

S set of states;

A set of actions;

E set of events;

γ transition function $\gamma : S \times A \to S$.

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The functions on planning actions:

For $a \in A$

precond(a) preconditions of a;

effects$^{+}(a)$ positive effects of a;

effects$^{-}(a)$ negative effects of a;

host(a) the single host h from a;

resources(a) the set of resources (parameters) of action a.

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The planning agent receives the tuple, I_P, and creates a set of plans, P_I.

I_P is a Tuple

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Network-Awareness

An agent exhibits network-awareness if changes to ω_H cause the agent's output to change while all other inputs remain constant.

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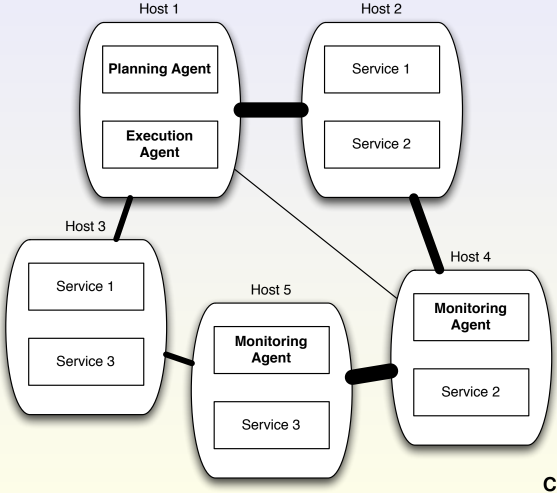

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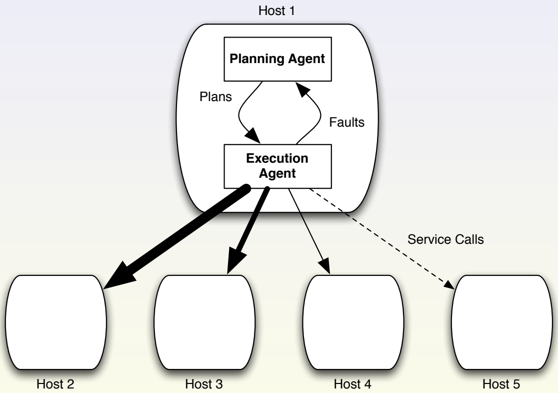

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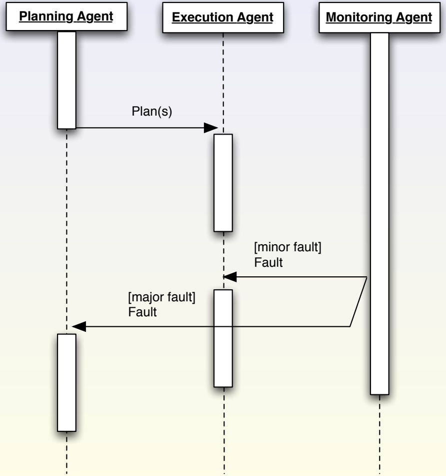

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Planning Domain Extensions

Operator distribution

- *e.g.*, NODE1ACTION(*parameters*)
- Implicit constraints.

Resource distribution

- *e.g.*, ACTION(*node1*, *parameters*)
- $s_0 \leftarrow s_0 \cup \{\textsc{Type}(node1) = \textsc{NetworkNode}\}$
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Complexity

- Operator distribution increases the number of actions in Σ to $|H| \times |A|$ in the worst case.
- Resource distributed increases the number of constraints in the world-state.

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Planning Agents

Agent Types:

- Domain-Independent.
- Random.
- Guided.

Plan Evaluators:

- Steps.
- Alternatives.
- Longest temporally ordered path.
- Duplicate plans.

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Planning Agents

Agent Types:

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Plan Evaluators:

- (none).

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Planning Agents

Plan Evaluators:

- IED detection accuracy.
- Plan execution time.
- Network link quality.
- Network bandwidth usage.

Agent Types:

- Domain-Independent.
- Random.
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Domain-Independent Planning Agent

- Uses I-Plan's default strategy.

I-Plan

University of Edinburgh, Tate *et al.* 's plan-space HTN planner which is built on an intelligent agent framework, I-X.

Process

1. Traverses search space depth-first.
2. Encounter an alternative whose constraints cannot be satisfied.
3. Backtracks using an A* search.

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Computer Science

Random Planning Agent

- DFS with random branching.

Process

```
ConstructRandomPlan($I_P$)
toVisit.push($s_0$)
while $\neg$ toVisit.empty() $\wedge$ $\neg$ solution(toVisit.peek()) do
    $v \leftarrow$ toVisit.pop()
    if $v \notin$ visited then
        visited.add($v$)
        $r \leftarrow$ randomize($v$.children())
        toVisit.push($r$)
    end if
end while
return toVisit.peek()
```

Guided Planning Agent

Generates qualitatively-different plans over:

- Domain-dependent criteria, and
- Network-centric criteria.

Process

1. A priority queue exists for each evaluator.
2. Every partial-plan is evaluated by all evaluators and placed in their respective priority queues.
3. The partial-plan at the head of each priority queue is used for the next step.

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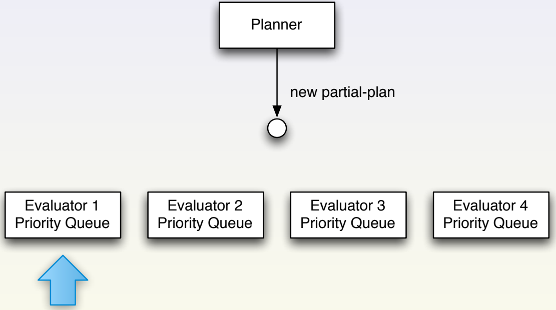
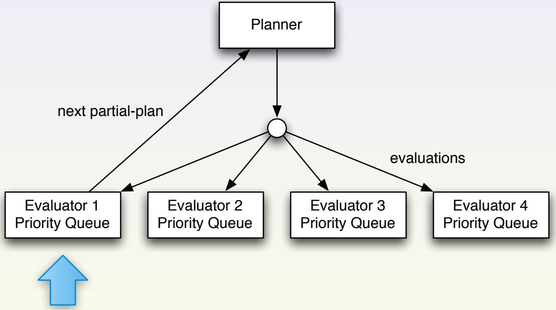
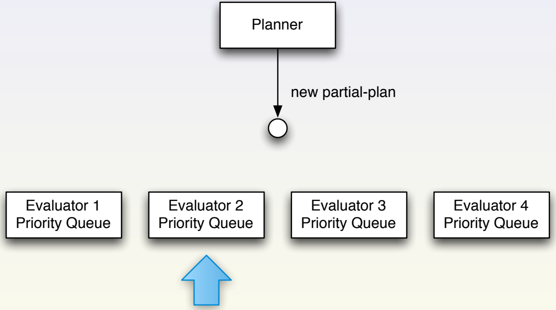

Planner
new partial-plan
Evaluator 1 Priority Queue
Evaluator 2 Priority Queue
Evaluator 3 Priority Queue
Evaluator 4 Priority Queue

Guided Planning Agent



Guided Planning Agent



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   - Motivation
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   - Monitoring Agents
   - Mixed-initiative UI
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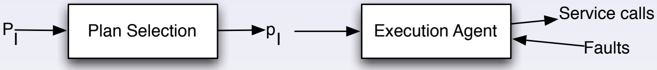
Execution Agents



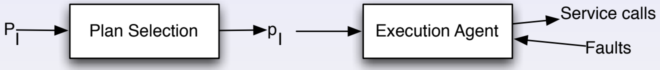
Agent types:

- Naïve.
- Reactive.
- Proactive.

Defined by:

- Service invocation.
- Error handling.

Execution Agents



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Naïve Execution Agent

Naïve Execution Agent Properties

Service Invocation Invokes services exactly as described by p_I. The naïve agent requires that $\forall$ actions $a \in p_I, \text{host}(a) \neq \emptyset \wedge \text{resources}(a) \neq \{\}$.

Error Handling Ignores execution errors.

- **Not** network-aware.

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Reactive Execution Agent

Reactive Execution Agent Properties

Service Invocation Invokes services exactly as described by p_I. The reactive agent requires that $\forall$ actions $a \in p_I$, host$(a) \neq \emptyset \wedge$ resources$(a) \neq \{\}$.

Error Handling Repairs the failed p_I by replacing failed service call(s) with new ones, creating p'_I.

- Network-aware recovery — plan repair.
- Uses routing protocol neighbors & link quality.

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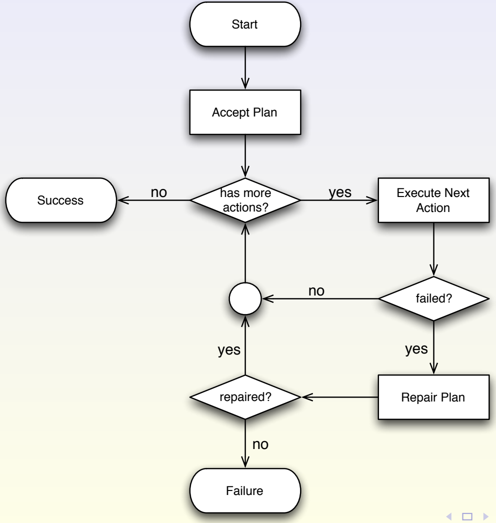

Proactive Execution Agent

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Service Invocation Invokes services using network-aware logic to choose the host and resources at execution time. The proactive execution agent uses only service descriptions from actions $a \in p_I$, meaning $\forall a \in p_I, \text{host}(a) = \emptyset \wedge \text{resources}(a) = \{\}$

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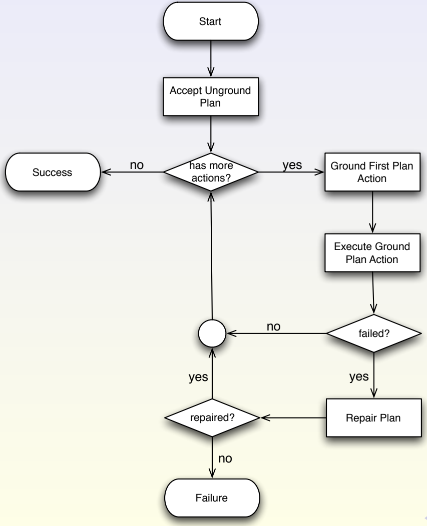

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Monitoring Agents

Methods of FDI

1. Analytic.
2. Data-driven.
3. Knowledge-based.

Monitoring Agents

Methods of FDI

1. Analytic. ← Active Monitor
2. Data-driven. ← Passive Monitor
3. Knowledge-based.

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Analytic Monitoring Agent

Given the ordered plan $p_I = \{a_0, a_1, \ldots, a_{|p_I|}\}$

An analytic monitoring agent:

1. Constructs $p_M = \{m_0, m_1, \ldots, m_{|p_I|+1}\}$, an ordered set of monitoring actions;
2. Creates the new execution plan $p_I' = \bigcup_{i=0}^{n} \{m_i, a_i\}$;
3. The result is $p_I' = \{m_0, a_0, m_1, a_1, \ldots, m_{|p_I|}, a_{|p_I|}, m_{|p_I|+1}\}$.
4. Each $m \in p_M$ calculates the residual between expected and actual bytes transferred.

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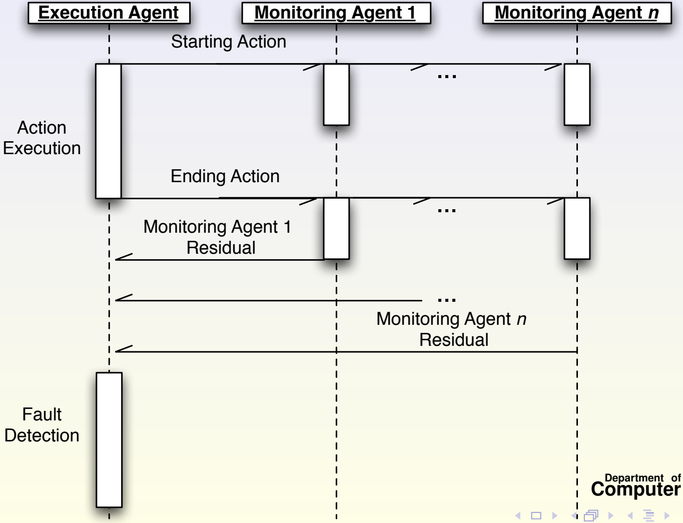
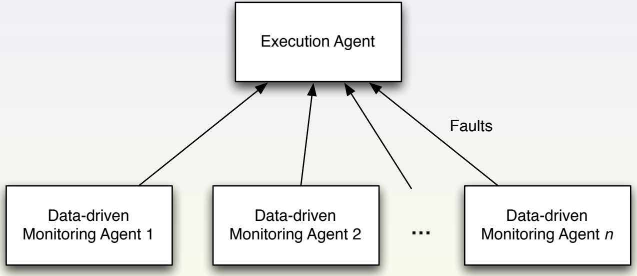
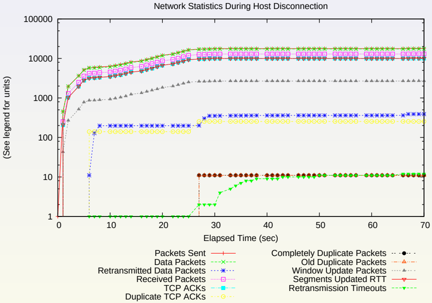


Data-driven Monitoring Agent


Execution Agent
Faults
Data-driven Monitoring Agent 1
Data-driven Monitoring Agent 2
...
Data-driven Monitoring Agent *n*

Data-driven Monitoring Agent



- Multivariate monitor.
- Data packets.
- Retransmission timeouts.

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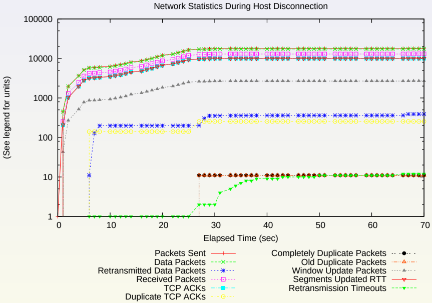
Data-driven Monitoring Agent



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Plan Evaluation Criteria Statistics

Aspects

- Range (effective and theoretic).
- Direction (minimize or maximize).
- Statistics (e.g., mean, median, mode, standard deviation).

Benefit

Plans can be positioned along an absolute continuum of evaluation values.

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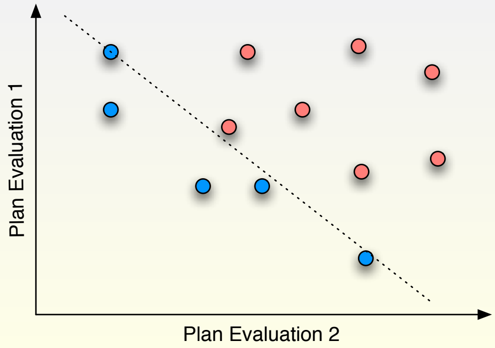
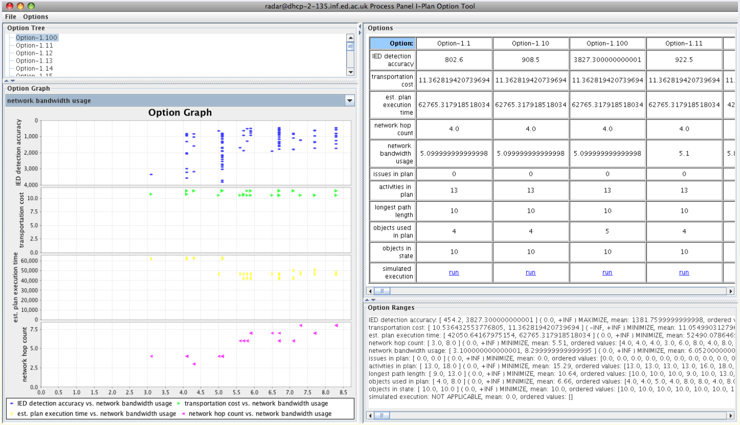
Dominant Plans

Definition

A plan, p, is **dominant** to a set of other plans, P^- in respect to two or more plan evaluators $e_{1\dots k} \in E$ when $\forall e \in E, p^- \in P^- [e(p) \geq e(p^-)]$.



Plan Evaluation Visualization



radar@dhcp-2-135.inf.ed.ac.uk Process Panel I-Plan Option Tool

File Options

Option Tree

- Option-1.100
- Option-1.11
- Option-1.12
- Option-1.13
- Option-1.14
- Option-1.15

Option Graph

network bandwidth usage

Options

Option:	Option-1.1	Option-1.10	Option-1.100	Option-1.11	
IED detection accuracy	802.6	908.5	3827.300000000001	922.5	
transportation cost	11.362819420739694	11.362819420739694	11.362819420739694	11.362819420739694	11.
est. plan execution time	62765.317918518034	62765.317918518034	62765.317918518034	62765.317918518034	42
network hop count	4.0	4.0	4.0	4.0	
network bandwidth usage	5.099999999999998	5.099999999999998	5.099999999999998	5.1	5.8
issues in plan	0	0	0	0	
activities in plan	13	13	13	13	
longest path length	10	10	10	10	
objects used in plan	4	4	5	4	
objects in state	10	10	10	10	
simulated execution	run	run	run	run	

Option Ranges

IED detection accuracy: [454.2, 3827.300000000001] (0.0, +INF) MAXIMIZE, mean: 1381.7599999999998, ordered v
transportation cost: [10.536432553776805, 11.362819420739694] (-INF, +INF) MINIMIZE, mean: 11.05499031279
est. plan execution time: [42050.64167975154, 62765.317918518034] (0.0, +INF) MINIMIZE, mean: 52490.078646:
network hop count: [3.0, 8.0] (0.0, +INF) MINIMIZE, mean: 5.51, ordered values: [4.0, 4.0, 4.0, 3.0, 6.0, 8.0, 4.0, 8.0,
network bandwidth usage: [3.100000000000001, 8.299999999999995] (0.0, +INF) MINIMIZE, mean: 6.0520000000
issues in plan: [0.0, 0.0] (0.0, +INF) MINIMIZE, mean: 0.0, ordered values: [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0
activities in plan: [13.0, 18.0] (0.0, +INF) MINIMIZE, mean: 15.29, ordered values: [13.0, 13.0, 13.0, 13.0, 16.0, 18.0,
longest path length: [9.0, 13.0] (0.0, +INF) MINIMIZE, mean: 10.64, ordered values: [10.0, 10.0, 10.0, 9.0, 10.0, 13.0,
objects used in plan: [4.0, 8.0] (0.0, +INF) MINIMIZE, mean: 6.66, ordered values: [4.0, 4.0, 5.0, 4.0, 8.0, 8.0, 4.0, 8.0
objects in state: [10.0, 10.0] (0.0, +INF) MINIMIZE, mean: 10.0, ordered values: [10.0, 10.0, 10.0, 10.0, 10.0, 10.0, 1
simulated execution: NOT APPLICABLE, mean: 0.0, ordered values: []

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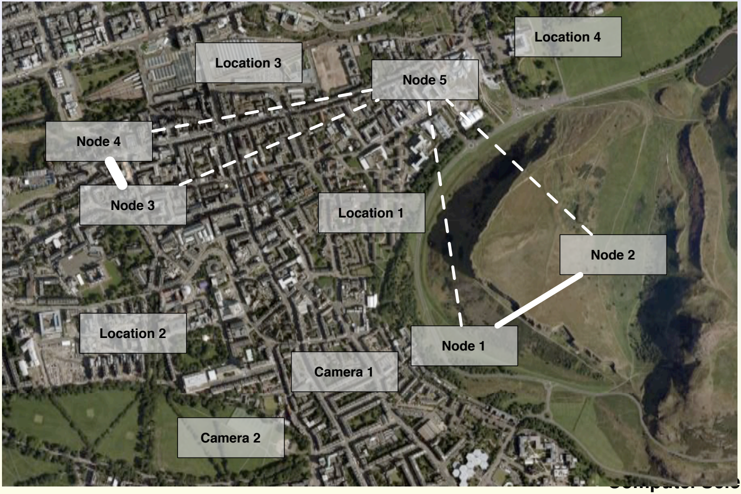
Experiment: Plan Evaluation Benchmarking



Plan Evaluation Benchmarking

Action	Providing Hosts
PHYSICALMOVE	all
ACQUIRECAMERA	all
TAKEPHOTO	all
GETOLDPHOTO	all
RELEASECAMERA	all
CHECKFORIEDAT	1, 2, and 5
MANUALSEARCH	1, 2, 3, and 4
PHOTOGRAPHICSEARCH	3, 4, and 5
PHOTOARCHIVE	5
PHOTOCOMPARE	4 and 5
RESULTREPORT	2 and 5

Plan Evaluation Benchmarking

Camera	Resolution
Camera 1	3.2 MP
Camera 2	8.0 MP

Node	Speed (max mph)	Transportation Cost ($ per mile)
Node 1	30	6.0
Node 2	40	6.5
Node 3	20	5.1
Node 4	10	4.9
Node 5	45	6.2

Plan Evaluation Benchmarking Results

Each planning algorithm ran in I-Plan for five minutes.

σ Plan Evaluations

	ω_H	Bandwidth	IED Acc.	Time
I-Plan Default	0.949	0.759	291.4	8216
Random	1.647	**1.476**	177.9	7220
Guided	**1.916**	1.141	**392.6**	**14050**

Dominant Plans

Search Strategy	**% Dominant Plans Produced**
I-Plan Default	7.4%
Random	33.3%
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Experiment: Network-Aware Agent Combinations

Agent	**Technique**
Planning	Random
	Domain-independent (I-Plan)
	Guided
Execution	Naïve
	Reactive
	Proactive
Monitoring	Data-driven
	Analytic
	(none)

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Experimental Setup

- Multi-objective Optimization (MOO) Function.
- Implemented agents with I-X and I-Plan.
- Network emulation.
- Mobility models.

MOO function

$$\text{MOO}(p_I) = \text{IEDDetectAcc}(p_I) + 3 \times \text{TranspCost}(p_I) + 5 \times \text{ExecTime}(p_I) + \text{LinkQuality}(p_I) + \text{BandwidthUse}(p_I)$$

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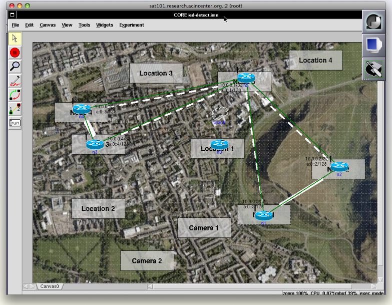
CORE



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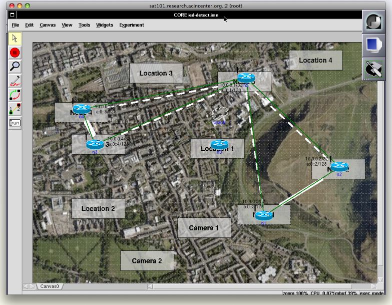

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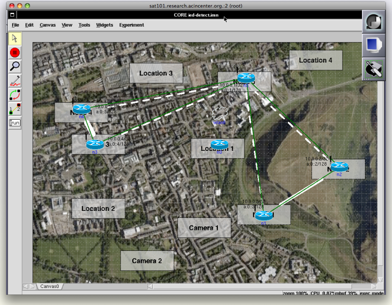

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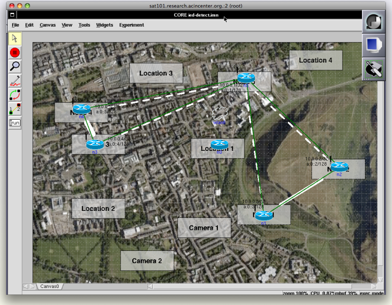

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Mobility Models

Purpose

- Dictate geographical node locations.
- Dynamic ω_H.

Mobility Patterns

1. Local.
2. Static.
3. Dynamic.
4. Partition-merge.

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Mobility Models

Purpose

- Dicta
- Dyna

Mobility P

1. Loca
2. Stati
3. Dyna
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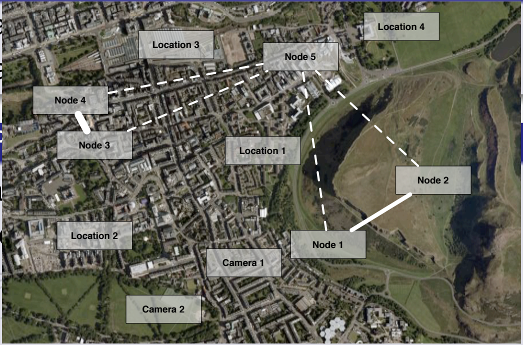

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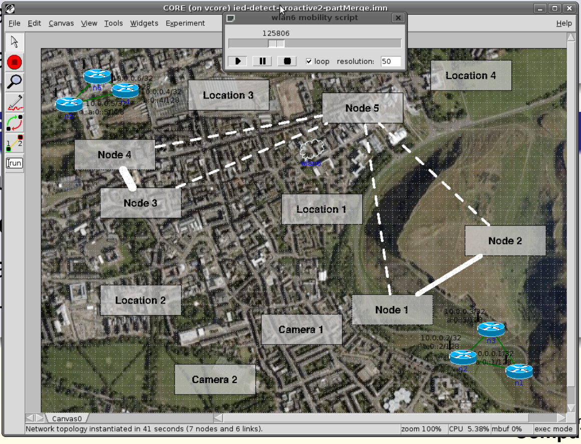
Purpose

- Dicta
- Dyna

Mobility F

1. Loca
2. Stati
3. Dyna
4. Parti



Network topology instantiated in 41 seconds (7 nodes and 6 links).

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Domain-independent Plan

```
checkForIEDAt  location1
manualSearch   node1  location1
physicalMove   node1  location1
conductScan    node1  location1
physicalMove   node2  location1
reportResults  node2  location1
checkForIEDAt  location2
manualSearch   node1  location2
physicalMove   node1  location2
conductScan    node1  location2
physicalMove   node2  location2
reportResults  node2  location2
checkForIEDAt  location3
manualSearch   node1  location3
physicalMove   node1  location3
conductScan    node1  location3
physicalMove   node2  location3
reportResults  node2  location3
```

Random Plan

```
checkForIEDAt location1
photographicSearch node3 location1
physicalMoveToCamera node3 camera1
acquireCamera node3 location1 camera1
physicalMove node3 location1
getOldPhoto node5 to photo-0
takePhoto node3 location1 camera1 to photo-1
comparePhotos node4 photo-1 photo-0
reportResults node2 location1
checkForIEDAt location2
manualSearch node1 location2
physicalMove node1 location2
conductScan node1 location2
physicalMove node2 location2
reportResults node2 location2
checkForIEDAt location3
manualSearch node1 location3
physicalMove node1 location3
conductScan node1 location3
physicalMove node2 location3
reportResults node2 location3
```

Guided Plan

```
checkForIEDAt location1
photographicSearch node5 location1
physicalMoveToCamera node5 camera2
acquireCamera node5 location1 camera2
physicalMove node5 location1
getOldPhoto node5 to photo-0
takePhoto node5 location1 camera2 to photo-1
comparePhotos node5 photo-1 photo-0
reportResults node5 location1
checkForIEDAt location2
manualSearch node3 location2
physicalMove node3 location2
conductScan node3 location2
physicalMove node5 location2
reportResults node5 location2
checkForIEDAt location3
manualSearch node4 location3
physicalMove node4 location3
conductScan node4 location3
physicalMove node2 location3
reportResults node2 location3
```

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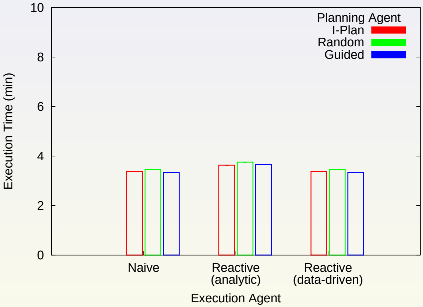
Local Results: Mean Time



- Network **not** a factor.
- Network-awareness did not hurt.

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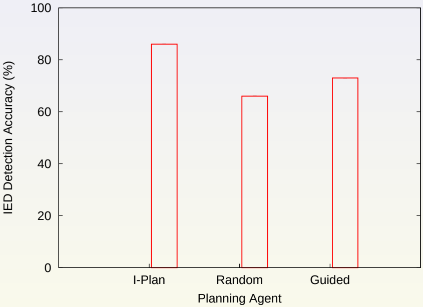
Local Results: Mean IED Detection Accuracy



- Ideal values of IED detection accuracy.

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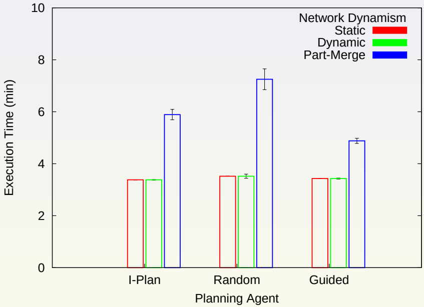
Planning Agent Comparison



- Network disruptions adversely effect plan execution times.
- Guided was 16.7% faster than I-Plan and 28.8% faster than random in part-merge.

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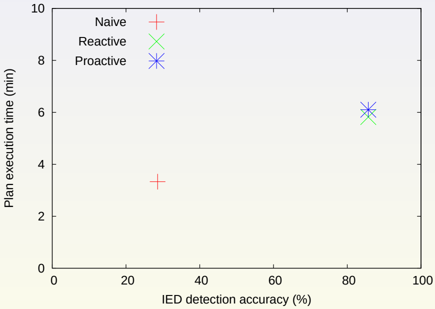
Execution Agent Effectiveness

Planning Agent: domain-independent (I-Plan default)



- Naïve agent has the lowest IED detection accuracy and exec. time.
- Reactive and proactive agents achieved ideal IED detection accuracies.

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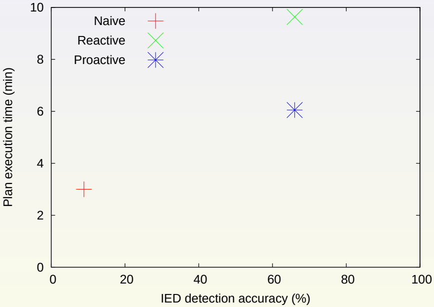
Execution Agent Effectiveness

Planning Agent: random



- Naïve agent failed most often.
- Proactive agent finished considerably faster than reactive.

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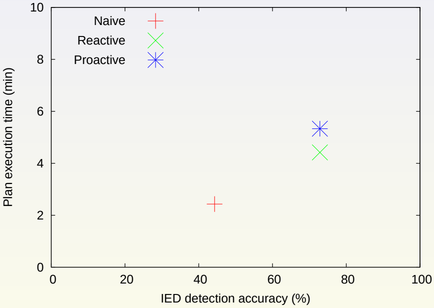
Execution Agent Effectiveness

Planning Agent: guided (network-aware)



- Naïve agent failed most often.
- The guided algorithm advice significantly helped the execution agent.

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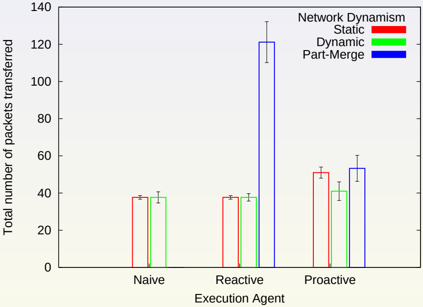
Execution Agent Performance



- Proactive agent uses slightly more network transmissions under connected mobility patterns.
- Under part-merge, the proactive agent sent fewer than half as many packets as the reactive agent.

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Monitoring Agent Comparisons

Analytic Monitoring Agent

- High percentage of false-positives.
- Communication errors → incorrect residuals.
- Active monitor.

- Analytic monitors are less-suitable for network-centric domains.

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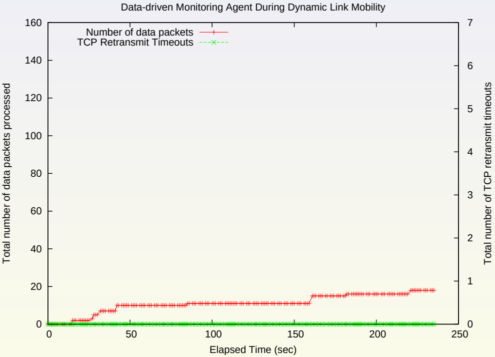
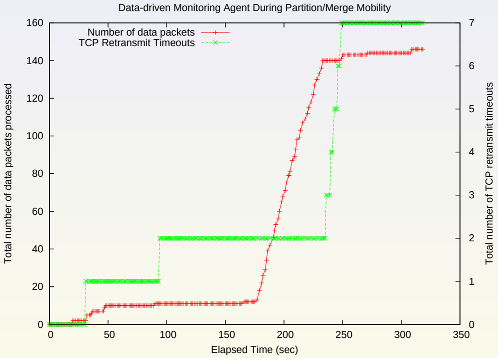
Data-driven Monitoring Agent

Normal execution:



Data-driven Monitoring Agent

Network disconnection:



Data-driven Monitoring Agent

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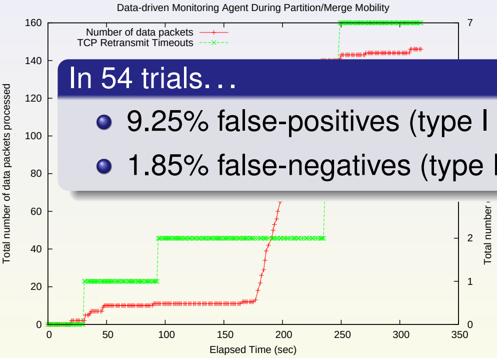

In 54 trials. . .

- 9.25% false-positives (type I error).
- 1.85% false-negatives (type II error).

Outline

1 Introduction
- Motivation
- Background
- Approach

2 Formalization
- Problem Statement

3 Technical Approach
- Planning Agents
- Execution Agents
- Monitoring Agents
- Mixed-initiative UI

4 Experiments
- Plan Evaluation Benchmarking
- Network-Aware Agent Combinations
- Discussion

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Main Contributions

1. Qualitatively-different plan generation:
    - Qualitatively different plans over a range of plan evaluation criteria.
    - Visualizing plan evaluations.
2. Network-aware agents:
    - Network-aware planning agent.
    - Network-aware execution agents.
    - Network-aware monitoring agents.

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Future Work

- Knowledge-based monitoring agents.
- Incorporate the effects of planning actions into heuristics.

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  - Evan Sultanik
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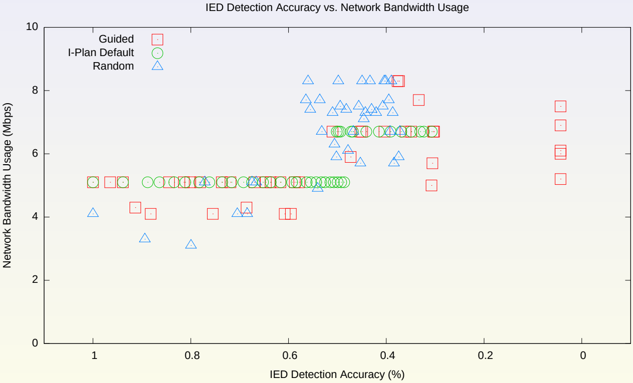
IED Detection Accuracy and Bandwidth Usage



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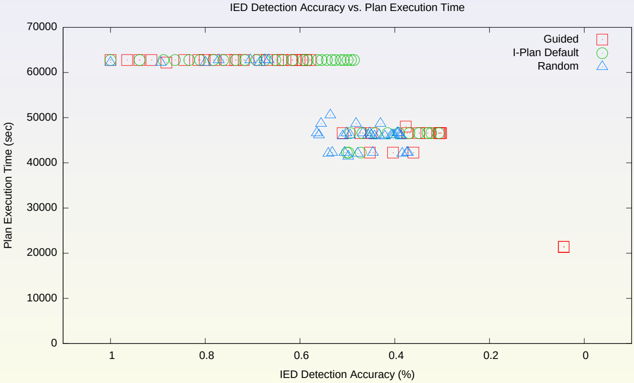
IED Detection Accuracy and Execution Time



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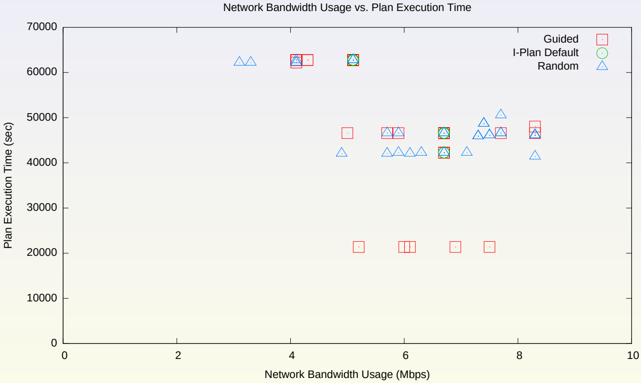
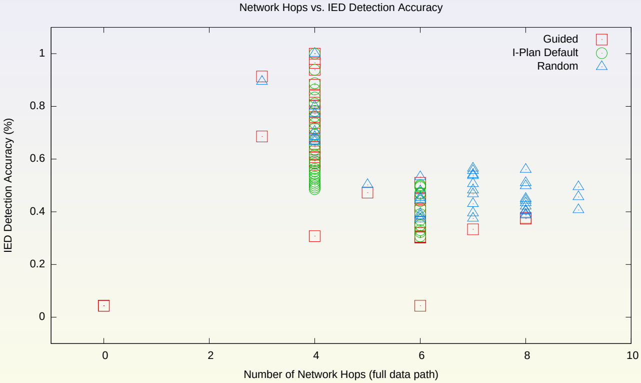
Network Bandwidth Usage and Execution Time



Network Hops and IED Detection Accuracy



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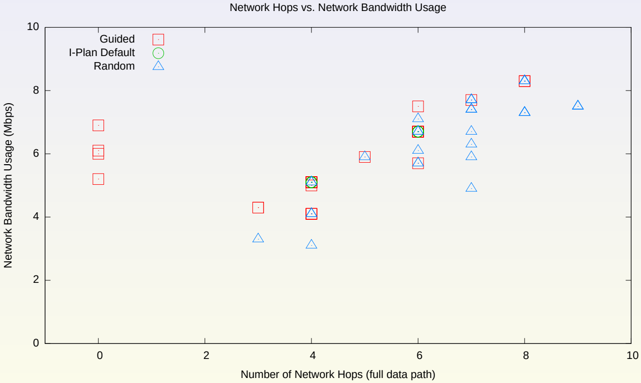
Network Hops and Bandwidth Usage



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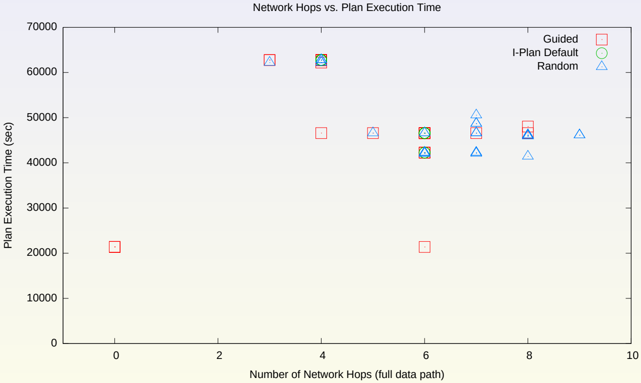

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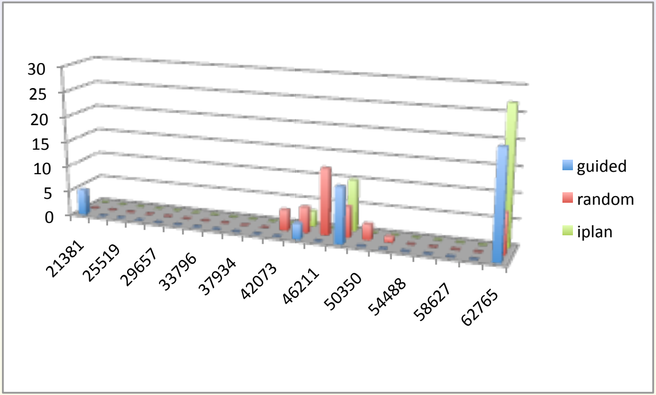
Plan Eval. Benchmarking Execution Time Distribution



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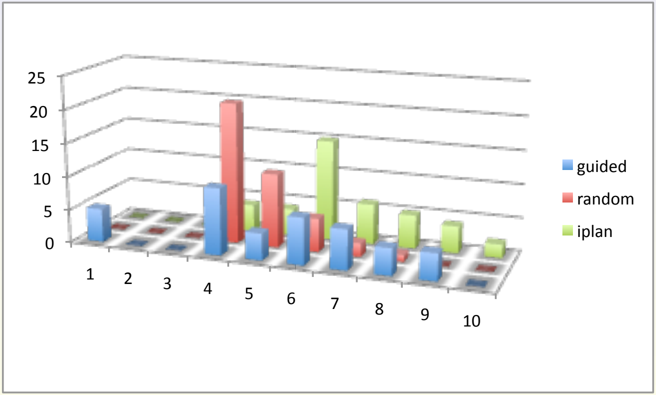
Plan Eval. Benchmarking IED Detect. Acc. Distribution



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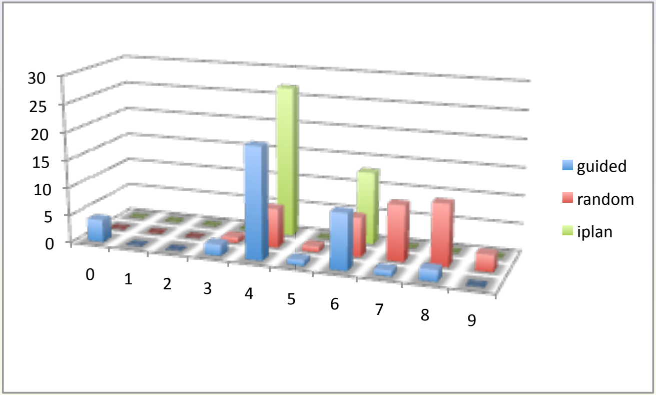
Plan Eval. Benchmarking Link Quality Distribution



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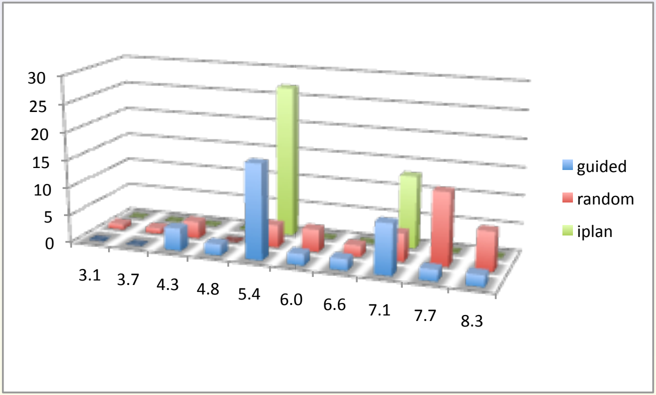
Plan Eval. Benchmarking Bandwidth Usage Distribution


guided
random
iplan