Mission Plan Recognition: Developing Smart Automated Opposing Forces for Battlefield Simulations and Intelligence Analyses

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Overview

- The problem
- Solution concept
- Model description
- Use case and simulation results
- Future plans

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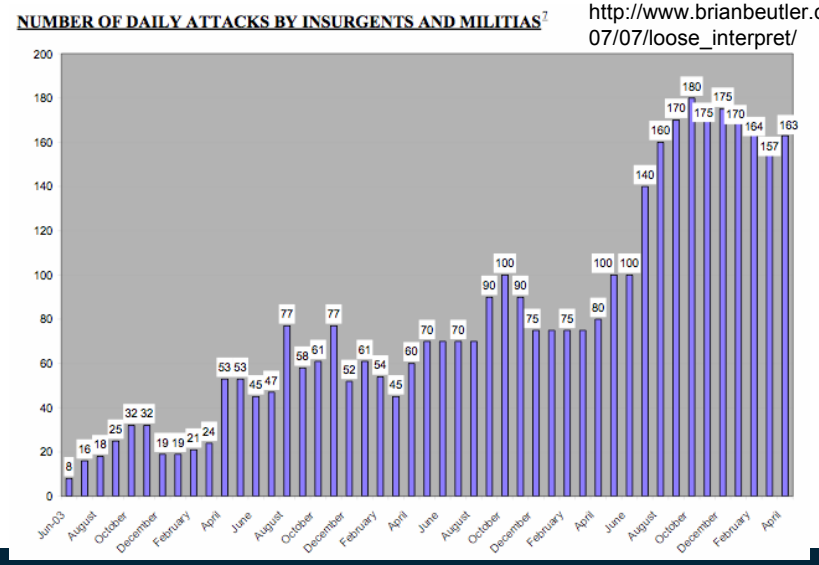
The Problem

- Adversaries constantly adapt to actions of U.S. forces
  - Need to embed adaptation in predicting the adversarial behaviors
- Current training is standardized, slow, and mismatches the asymmetric requirements of current wars and conflicts
  - Current models of OPFOR in training simulations are hard to construct and are not adaptive



http://www.brianbeutler.com/2007/07/loose_interpret/

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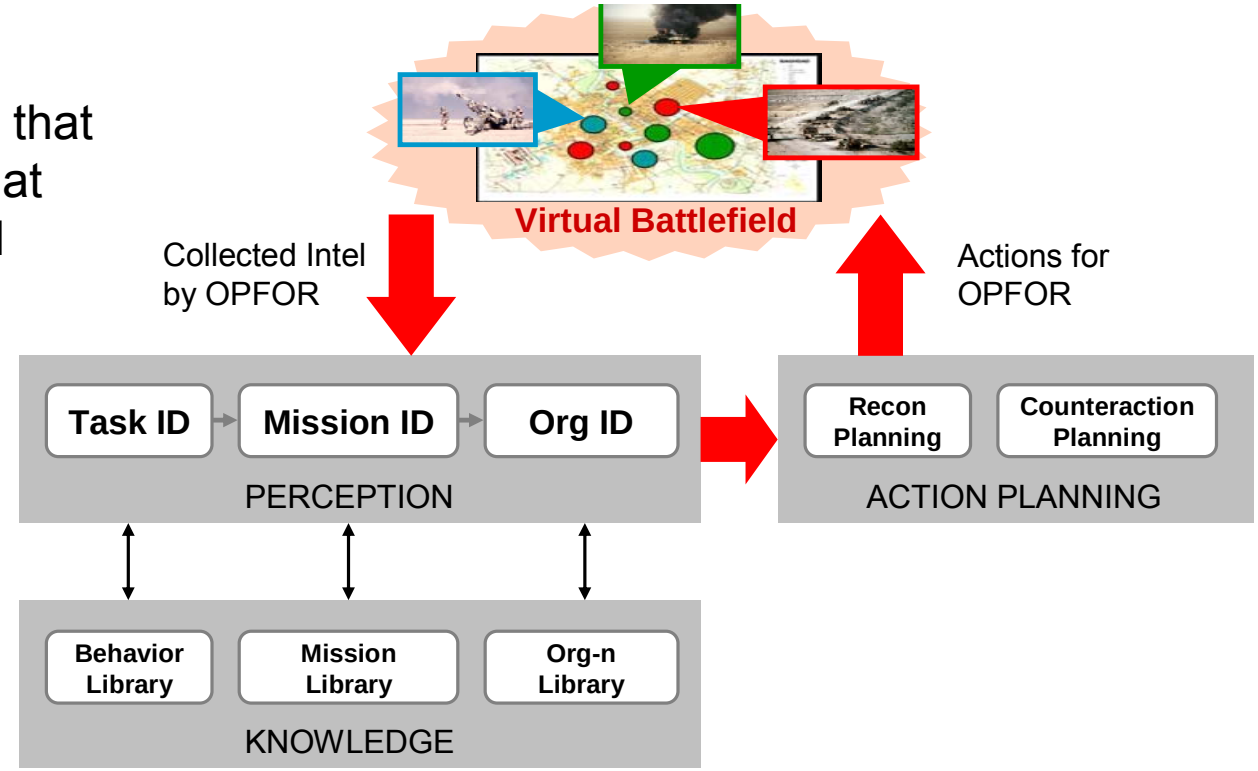
Proposed Solution

Solution

- Develop ***OPFOR agents*** that can intelligently **learn** what BLUEFOR are doing and **adapt their behaviors**



Benefits

- Better **prediction** of adaptive enemy
- Faster and more efficient **training**
- Collaborative war-gaming/**mission rehearsal**
- Use of same models for developing **BLUE decision alternatives**

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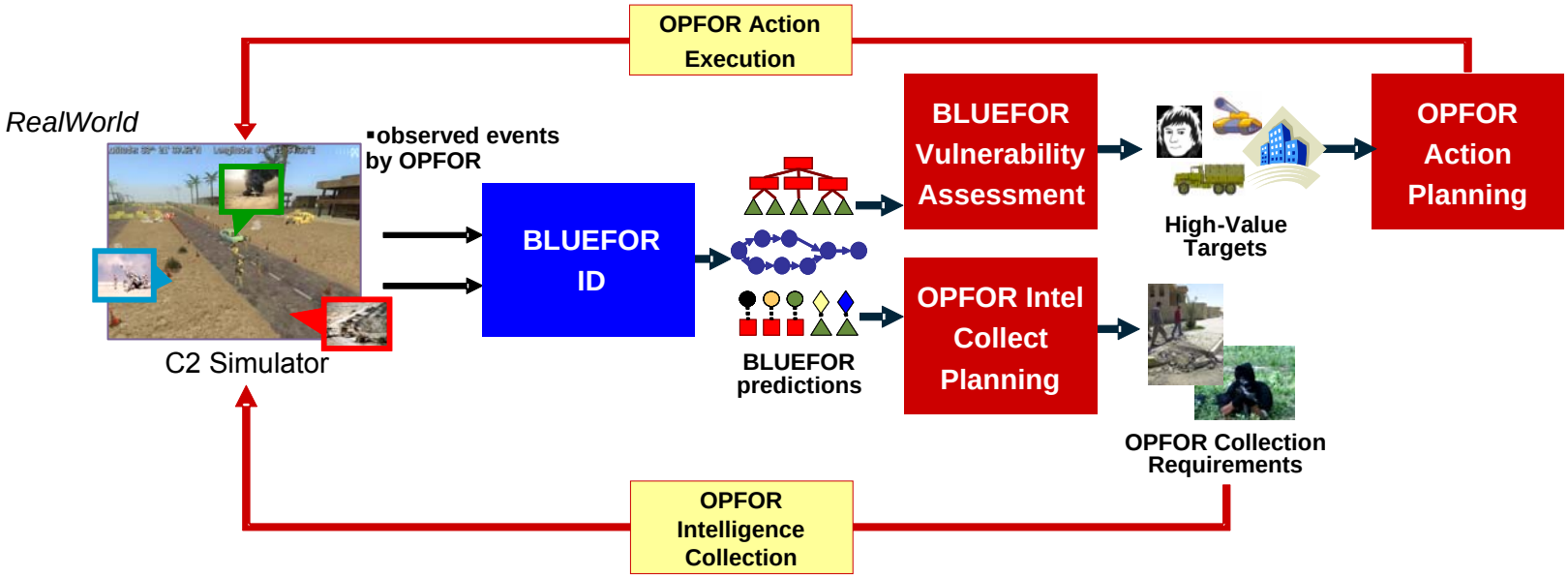
The "Big Picture"



- **Phase I effort:**
  - Models for all components
  - BLUEFOR ID Prototype
  - OPFOR Elementary Actions based on Partial BLUEFOR Vulnerability assessment
- **Phase II effort:**
  - Integrate Intel collection planning and action planning with Identification and Vulnerability assessment
  - Integrate with C2 virtual environment (RealWorld)

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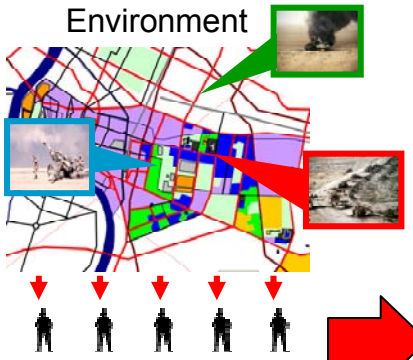
The Focus of Paper

Identification of BLUEFOR operations & plans

Battlefield Environment

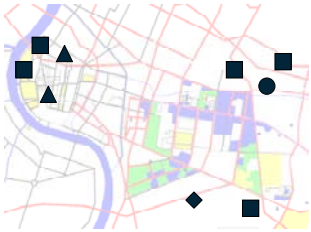


RED Sensors

Inputs:
Observations of BLUEFOR Actions/Activities

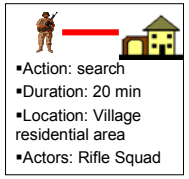
Observations of Activities

1. Geo-spatial information:
- Location of activities



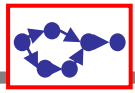
2. Temporal information:
- Time of activities

3. Feature information:
- Who
- Type/features of actors and action

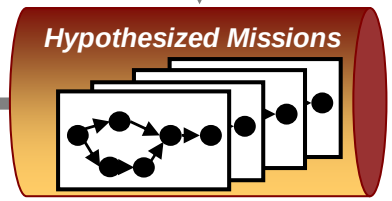


Mission Plan Recognition

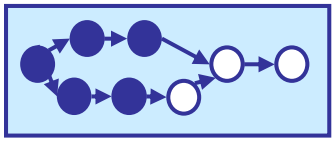
learned missions



model of mission plan



Outputs: Predictions of BLUEFOR's Mission Plan and its State



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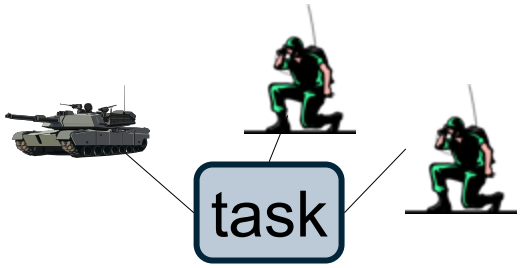
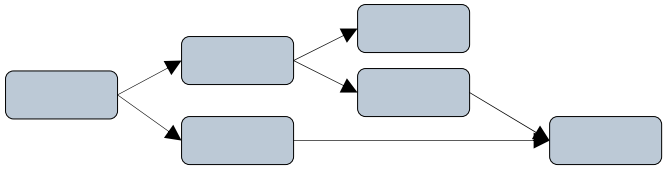
Modeling Details: Quantitative Concepts

- **Asset**
  - An object in the simulation environment
  - Ex: BLUE Recon Squad, Humwee, MP Squad, etc.

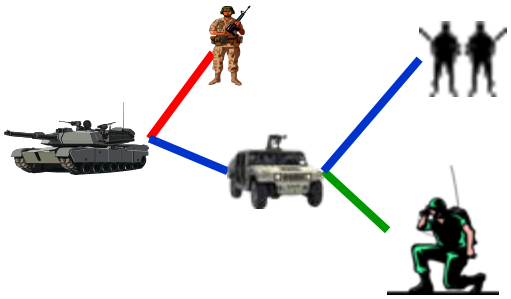
- **Tasks**
  - Coordinated actions that actors want to execute
  - Requires often multiple actions for success
  - Ex: Setup checkpoint, secure site, attack RED positions with fire, etc.



- **Mission Plan**
  - Collection of tasks with precedence
  - Ex: Reconnaissance and patrolling



- **Organization**
  - Connections & interactions between actors
  - Ex: a pattern of interactions, actions and meetings of enemy terrorist cell



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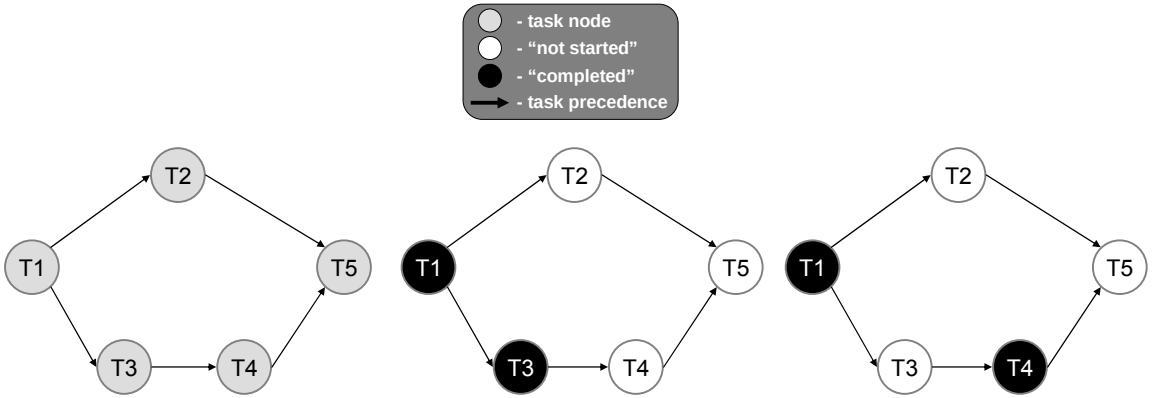
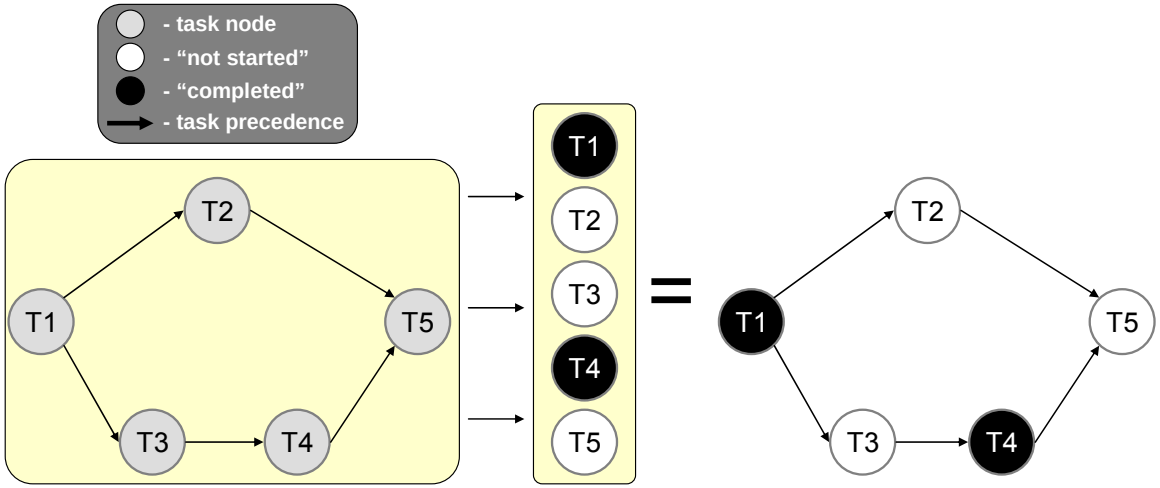
Mission and Mission State



(a) Mission (b) Feasible Mission State (c) Infeasible Mission State



(a) Mission (b) Observations (c) Observed Mission State

Mission state is defined as **labeled graph**

- Labels = states of tasks

Mission states can be **feasible** and **infeasible**

BLUEFOR mission is **partially observable**

- BLUEFOR mission is hidden from OPFOR
- RED has observation of BLUEFOR's mission via detected actions
- Observed mission state needs to be **matched** against possible feasible states

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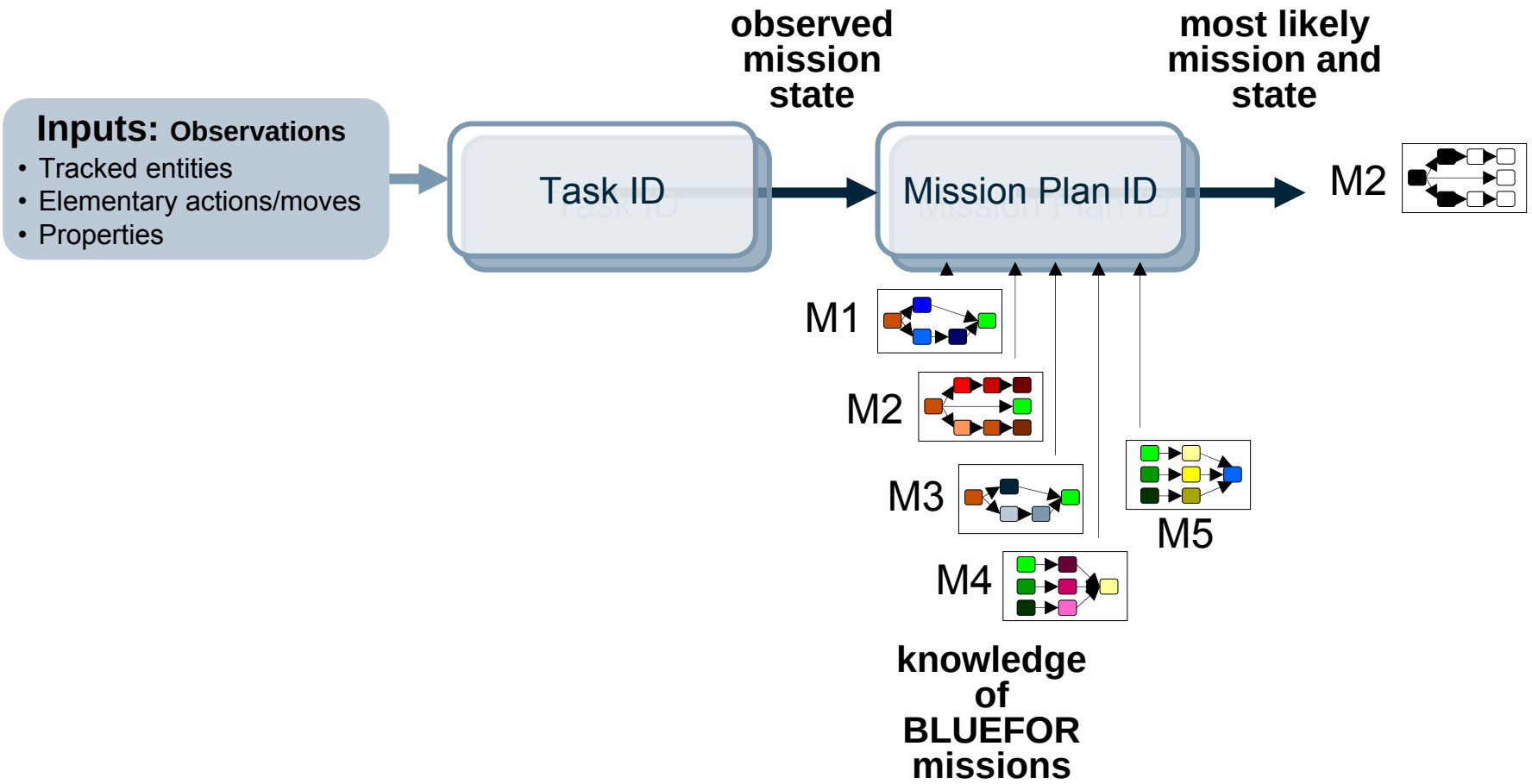
Task-Mission Identification



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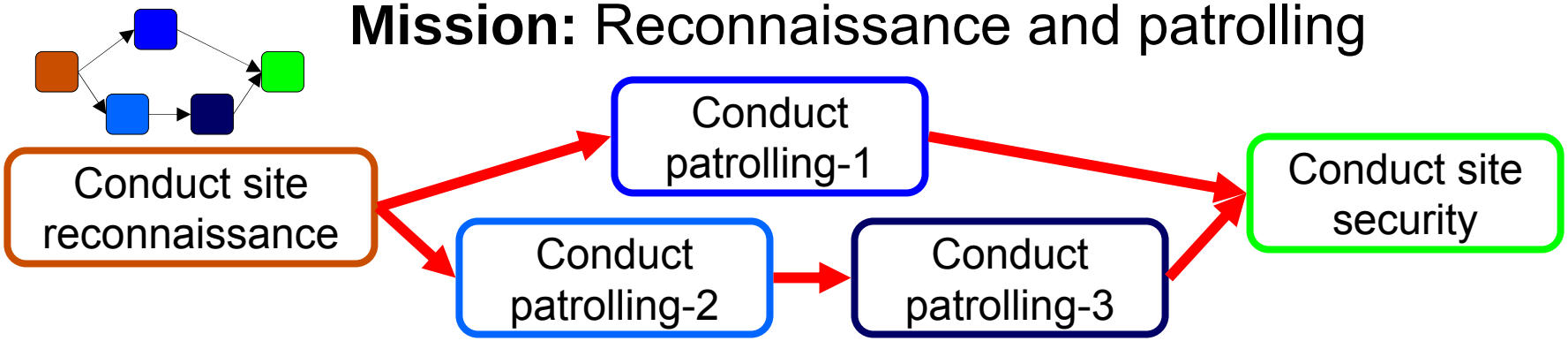
Example of Representing Missions and Tasks

Mission: Reconnaissance and patrolling



Tasks and their requirements

Tasks	SCR	EN	TRSP	MAN	REC	INT	FIRE	DTN	PTRL
Site recon	0	0	0	0	2	0	0	0	0
Site security	3	0	0	0	0	0	0	0	0
Patrolling	0	0	0	0	0	2	0	2	0

Tasks assignment

- Site recon → Rec Sqd(2)
- Site security → Rec Sqd OR RFL Sqd(3)
- Patrolling → MP Sqd(2)

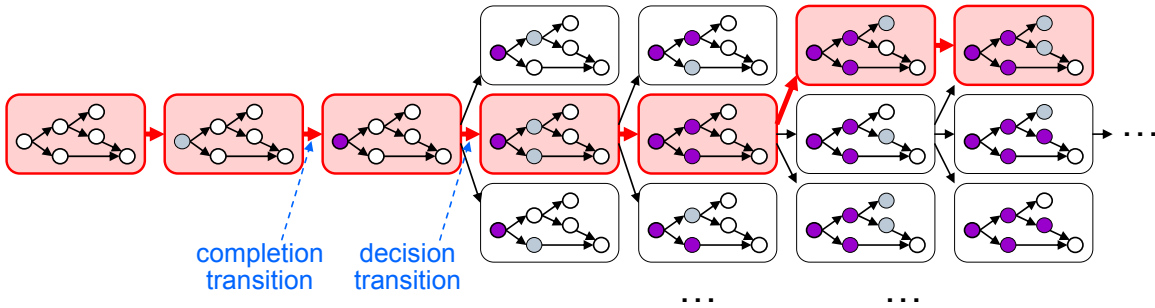
Units and their capabilities

BLUE Units	SCR	EN	TRSP	MAN	REC	INT	FIRE	DTN	PTRL
RFL Squad	1	0	0	1	0	0	0	1	1
Tank	0	1	0	0	0	0	1	0	0
Rec Squad	1	0	0	0	1	0	0	0	0
MP	0	0	0	1	0	1	0	1	1
Humwee	0	0	1	0	0	0	0	0	0

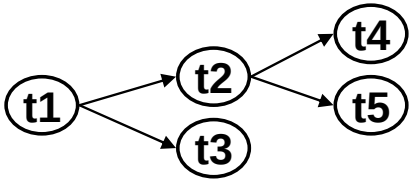
- Each BLUE unit conducts maneuvers and performs the action
- Observation of action are made by OPFOR

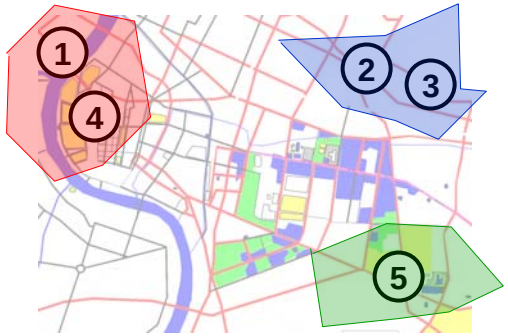
Model Property

- Allows both temporal and spatial reasoning
- Temporal:
  - Mission state changes over time
    - Actual evolution is limited significantly by precedence and available resources
    - Decision-based transitions – selecting what tasks to do, and what resources to use
- Spatial:
  - Tasks have locations



Hypothetical Mission





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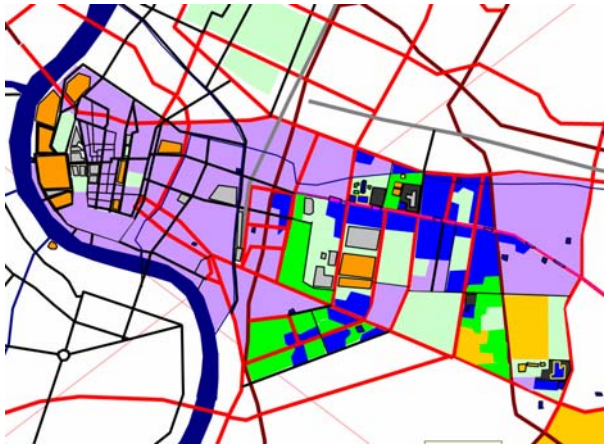
Example of Observable Data

Environment



RED Sensors

Observations of Activities

1. Geo-spatial information:

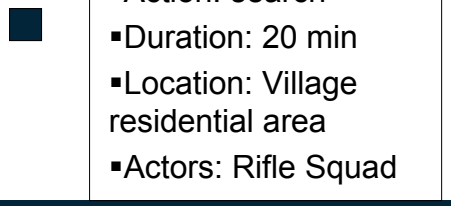
- Location of actions and movements

2. Temporal information:

- Time of activities

3. Feature information:

- Who
- Type/features of actors and action (capability applied)



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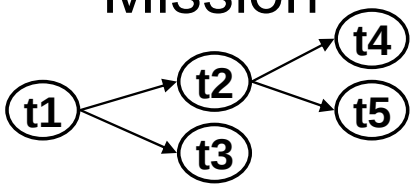
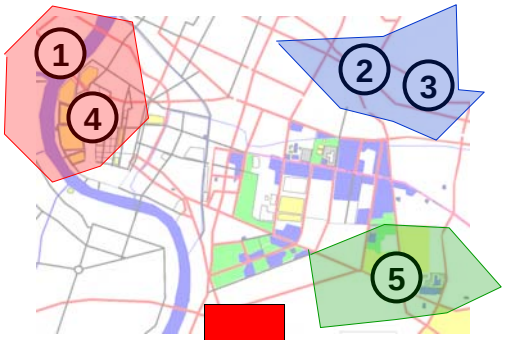
Task ID Solution (1)

Hypothetical Mission

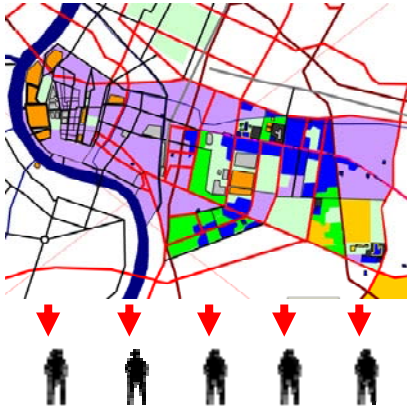




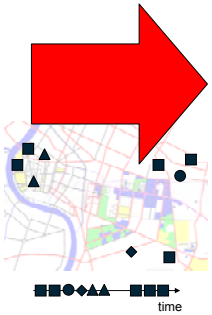
Cluster tasks according to locations

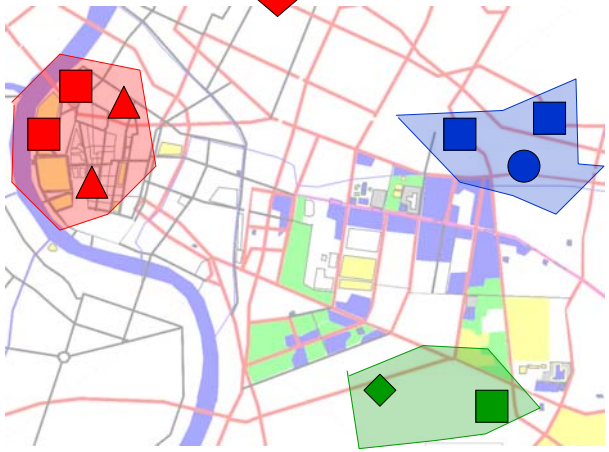
1

Environment



RED Sensors



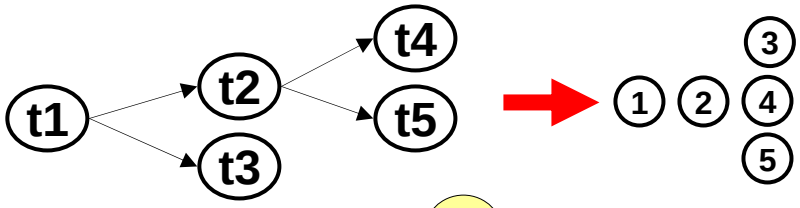


Cluster observations according to areas of tasks

2

Task ID Solution (2)

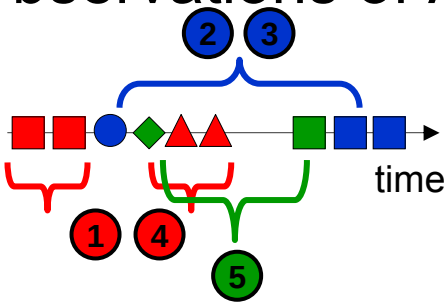
Hypothetical Mission



3a

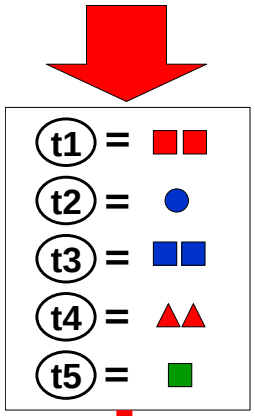
Prioritize tasks according to precedence constraints

Observations of Activities



3b

Cluster observations over time

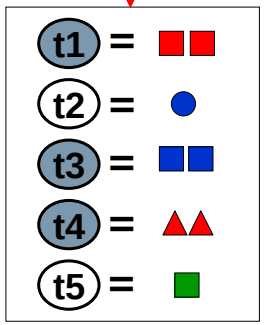


4

Associate tasks with observations in the order of task priority

5

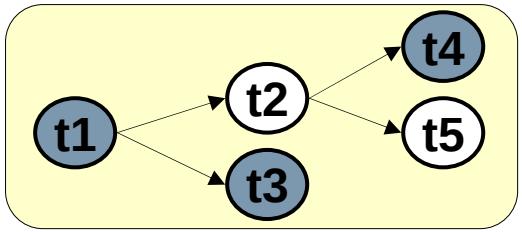
Perform max-likelihood estimation of task state



Observed Mission State:

Max Likelihood for Task State Estimates

$$O^* = \max_O \prod_j p(a_j \mid o_j)$$



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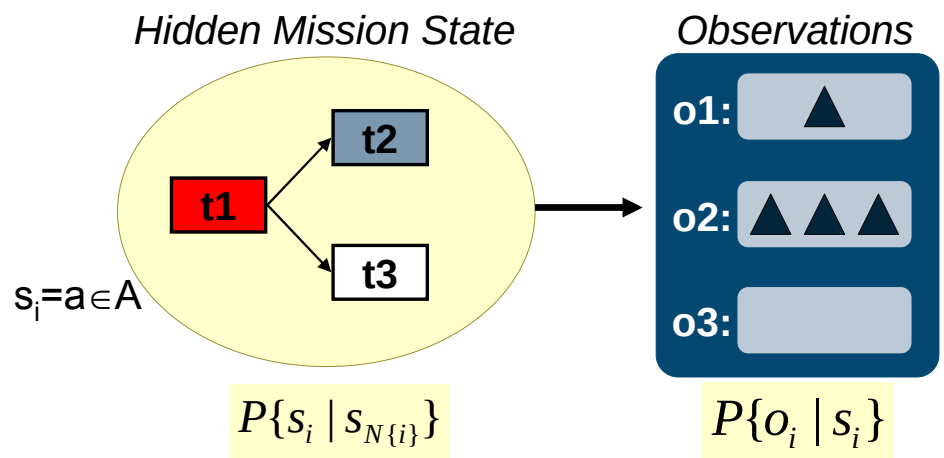
Mission Plan Recognition Model

- **Finding Mission State:** max a-posteriori estimator

$$S^* = \arg\max_S p(S \mid O, m) = \arg\max_S \frac{1}{Z} \prod_i p_i(o_i \mid s_i) p_i(s_i \mid s_{N\{i\}})$$

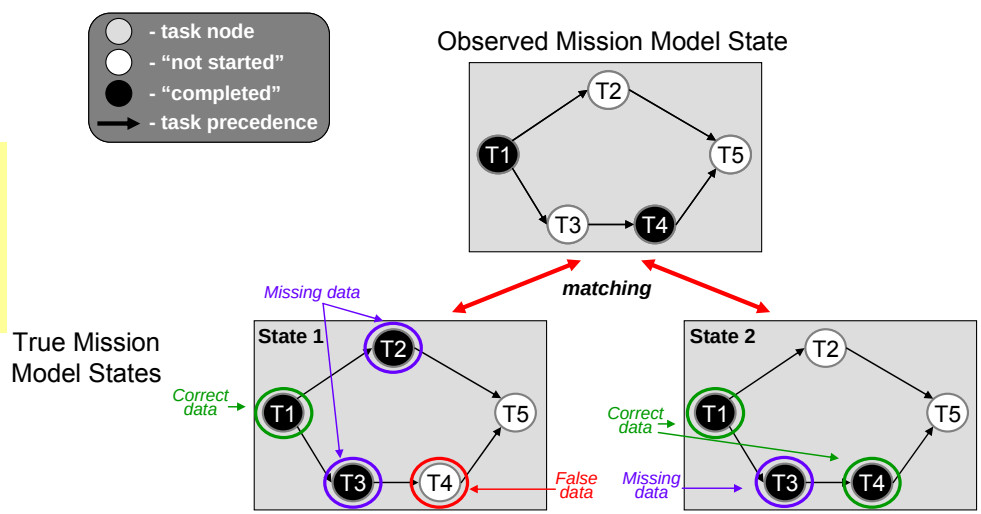
$$\cong \arg\max_S \sum_i \log p_i(o_i \mid s_i) + \sum_i \log p_i(s_i \mid s_{N\{i\}})$$



- **Finding Mission:** max likelihood estimator

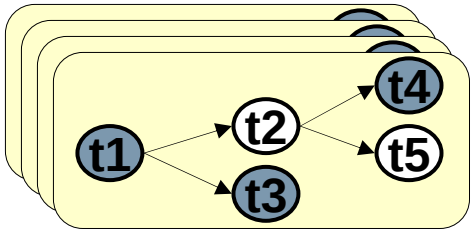
$$m^* = \arg\max_m p(O \mid m) = \arg\max_m \sum_S p(O \mid S, m) p(S \mid m)$$

$$= \arg\max_m \sum_S \prod_i p_i(o_i \mid s_i) p_i(s_i \mid s_{N\{i\}})$$

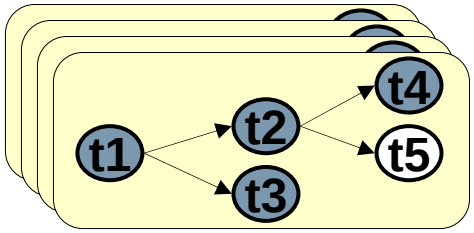


Mission ID Solution

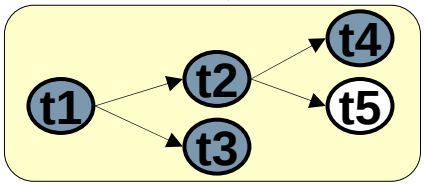
Observed Mission State



Max-posterior Mission States



Predicted RED mission & its state



1

Conduct max a-posteriori mission state estimation assuming that task states are uncertain observations

$$S^* = \arg\max_S \prod_i p(o_i^* \mid s_i)\, p(s_i \mid s_{N\{i\}})$$

Can be solved by dynamic programming, Hidden Markov Random Fields, etc.

2

Select the mission plan with highest likelihood score

$$\mu(m) = \prod_j p(a_j \mid o_j^*) \sum_S \prod_i p(o_i^* \mid s_i)\, p(s_i \mid s_{N\{i\}})$$

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Experiment Summary

- Measures
  - % correct predictions
- Power of the prediction
  - Entropy (inverse of ambiguity)
- Runs
  - For each ground-truth BLUE mission
  - Vary the probability of action/event detection by OPFOR elements
  - Vary time at which predictions are performed

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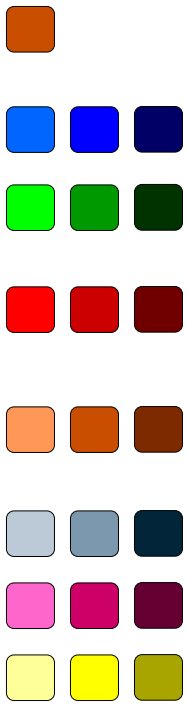
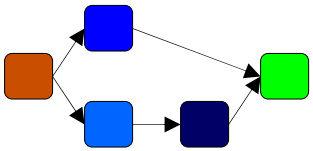
Use-case Details: BLUEFOR Missions

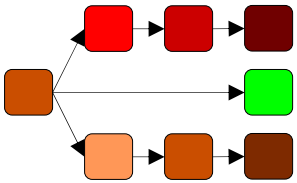
- Tasks (operations)
  - Site reconnaissance
  - Patrolling
  - Site security
  - Attack OPFOR positions
  - Detain OPFOR members
  - Building search
  - Resupply ops
  - Checkpoint setup



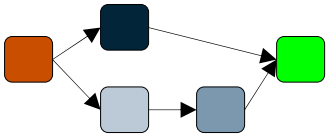
M1: Reconnaissance and patrolling
Site reconnaissance(1)
Patrolling(3)
Site security(1)



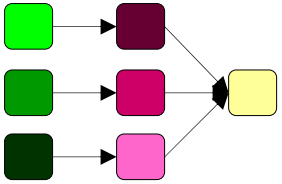
M2: Ground Stability and Defensive Ops
Site reconnaissance(1)
Attack OPFOR positions(3)
Detain OPFOR members(3)
Site security(1)



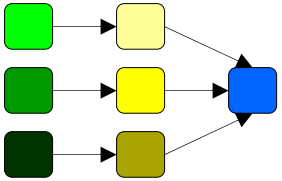
M3: Search
Site reconnaissance(1)
Building search(3)
Site security(1)



M4: Security and supplies
Site security(3)
Resupply ops(3)
Checkpoint setup(1)



M5: Area and site security
Site security(3)
Checkpoint setup(3)
Patrolling(1)



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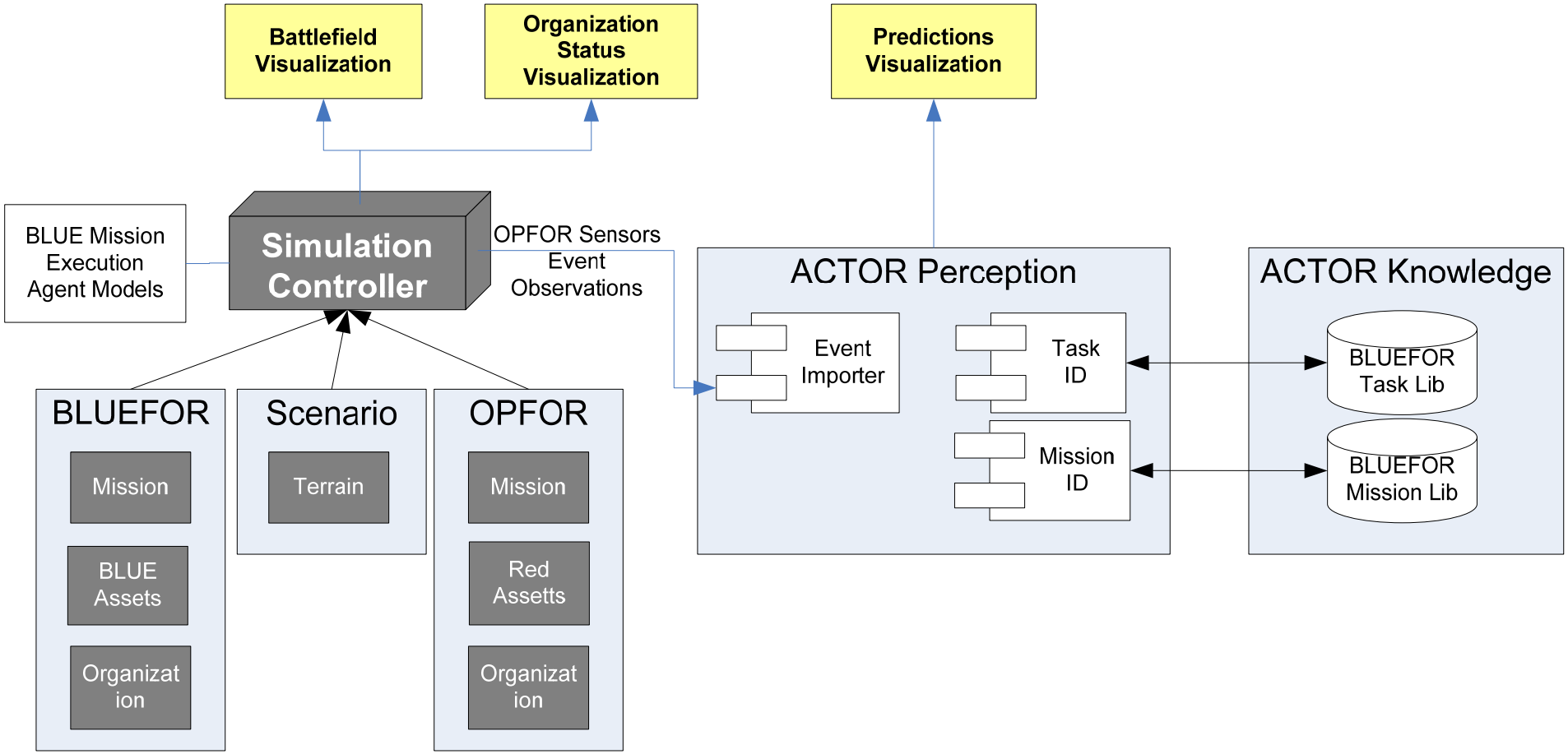
Validation Prototype Architecture



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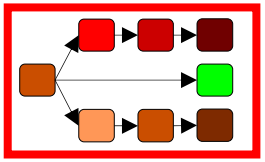
Inference over time-1

Ground Truth



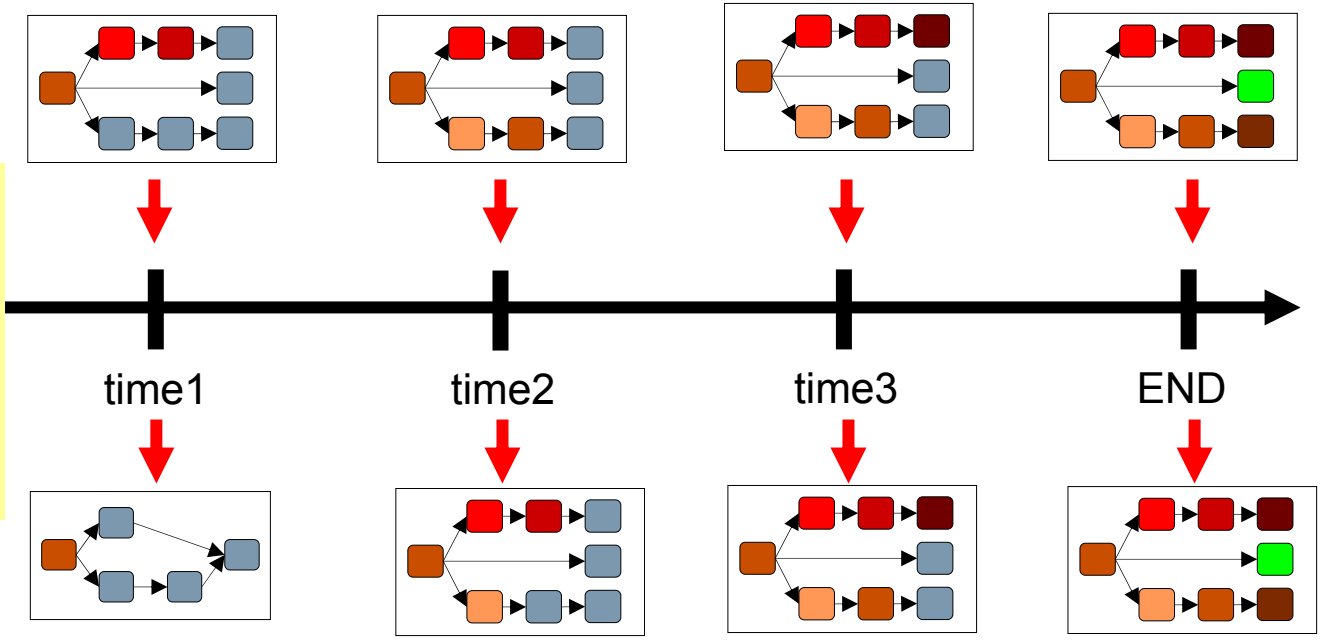
M2: Ground Stability and Defensive Ops

Site reconnaissance(1)

Attack OPFOR positions(3)

Detain OPFOR members(3)

Site security(1)



M1

Predictions

Incorrect mission plan

Correct mission plan, wrong state

P(detection)=.5

- **Conclusions:**
  - Prediction improves with time as more events are collected

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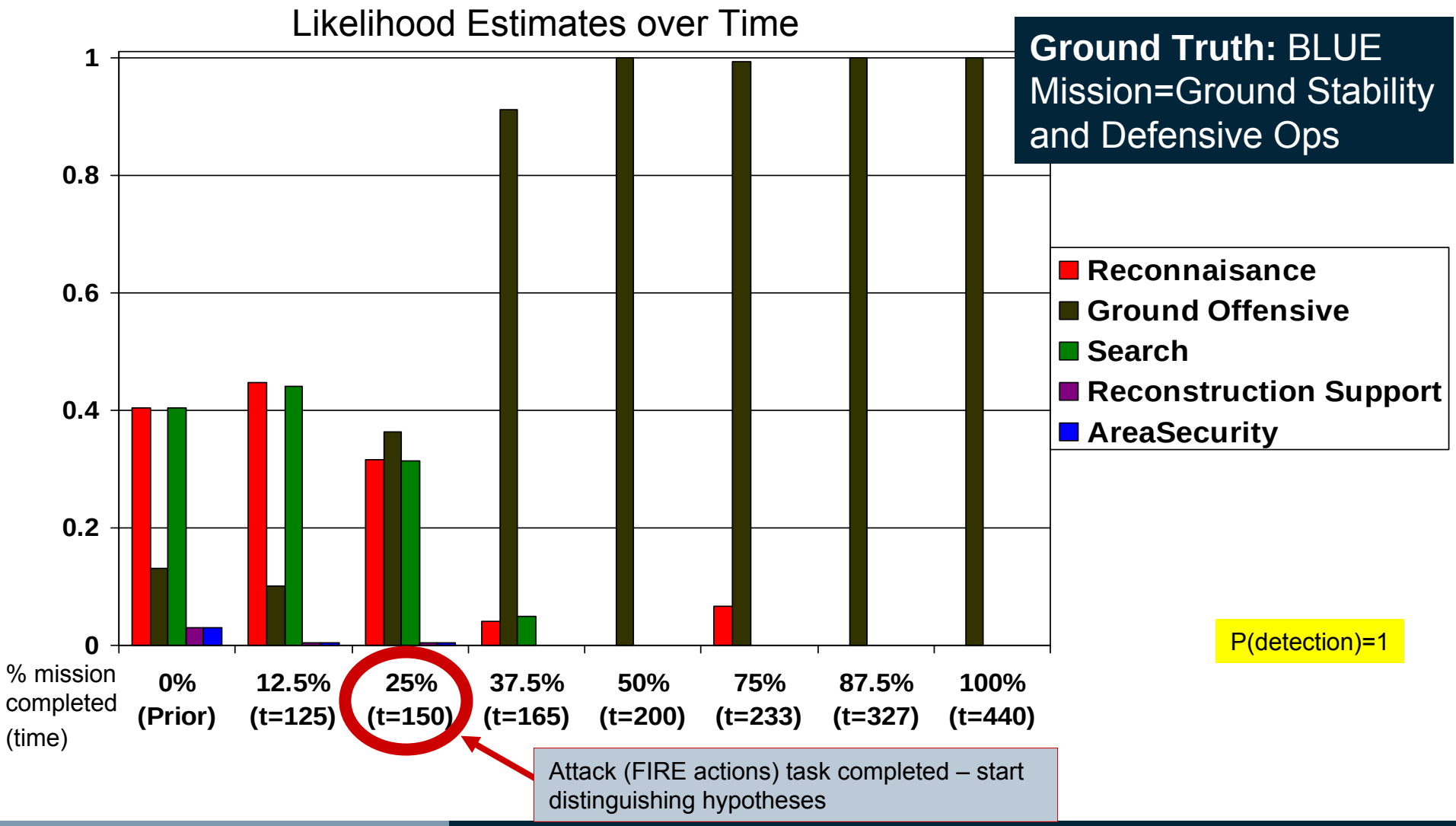
Inference over time-1



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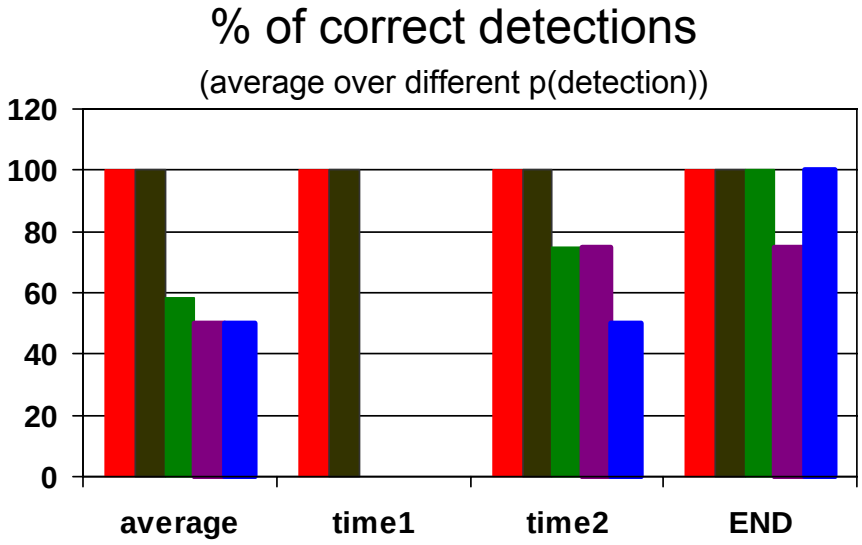
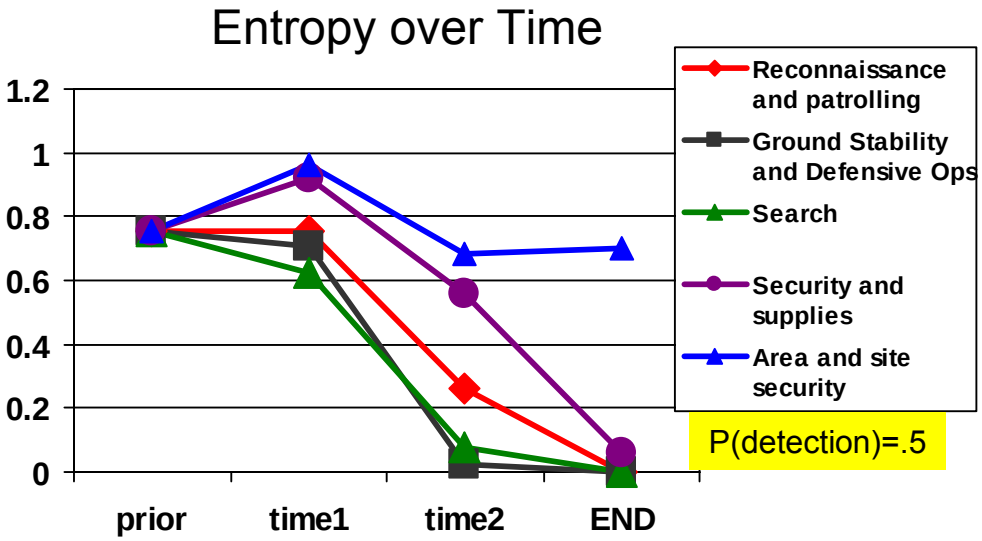
Simulation Results-2: Recognition over time





- **Conclusions:**
  - High detection accuracy (>=75%) in the middle of the mission
  - Detection accuracy data supported by entropy (power of estimator)
  - Detection improves towards the end of the mission as more actions are detected

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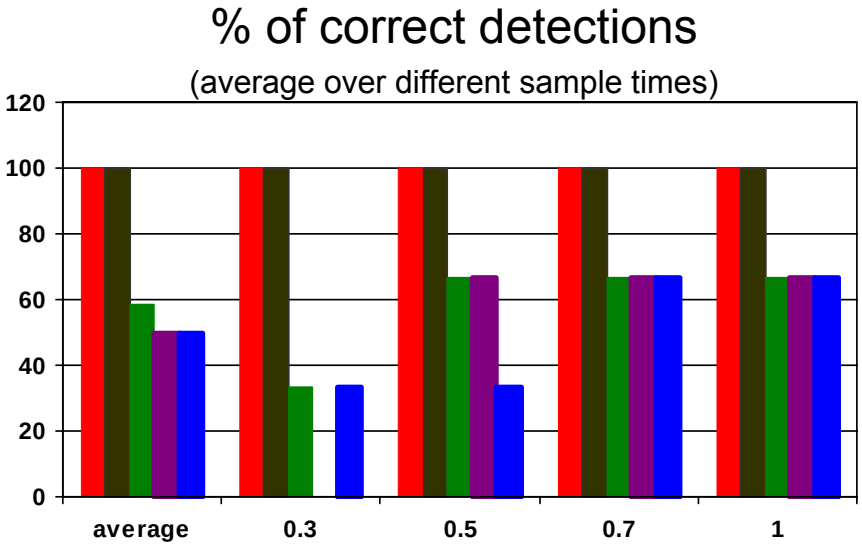
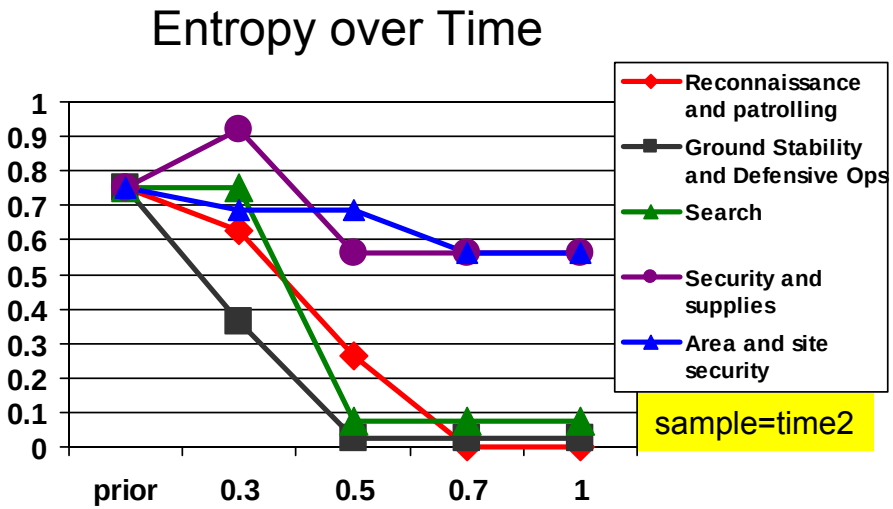
Simulation Results-3: Effect of Detection Probability





- **Conclusions:**
  - Improved accuracy of event detection increases accuracy of predictions
  - Sensitivity to specific mission plan classes is observed

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Using Mission Estimates for RED Planning

- Action plans based on org impact:
  - **Effects on organizational resources:** enemy attacks for the *geographic or functional areas* creating resource misutilization and correspondingly a resource shortage at the commander level
  - **Effects on organizational interactions:** events and task requirements that force commanders of BLUEFOR to increasingly *coordinate and synchronize* their activities, resulting in inefficient coordination patterns, loss of information, and correspondingly delayed actions and erroneous decision making by BLUEFOR
  - **Effects on mission/objectives:** vignettes and obstacles that prevent BLUE C2 from *performing specific individual and mission tasks*, thus requiring it to change or abort the mission

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Future Plans: Ideas for Phase II

- Automated model building & updating
  - RED ***discovers*** over time the "patterns of BLUEFOR missions/TTPs"
- RED adaptation for plan generation
  - RED ***learns*** over time the impact of its actions and responses of BLUEFOR
- Integration of predictions with OPFOR intelligence collection/sensor planning
  - RED ***designs*** actions to collect data for highest SA

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