



2012-08-02

# Approaches to Event Prediction in Complex Environments

Tan, Terence

Monterey, California: Naval Postgraduate School.

---

<http://hdl.handle.net/10945/44407>



Calhoun is a project of the Dudley Knox Library at NPS, furthering the precepts and goals of open government and government transparency. All information contained herein has been approved for release by the NPS Public Affairs Officer.

**Dudley Knox Library / Naval Postgraduate School**  
**411 Dyer Road / 1 University Circle**  
**Monterey, California USA 93943**

<http://www.nps.edu/library>



# Approaches to Event Prediction in Complex Environments

Terence Tan (PhD Candidate)

Advisors:

Prof Christian Darken, PhD

Prof Neil Rowe , PhD

Prof Arnold Buss , PhD

Prof Ralucca Gera , PhD

Prof John Hiles

# Scope of Presentation

- What is Relational Time Series?
- Previous Approaches
- New Learning and Prediction Approaches
- Conclusions

# Network Intrusion Detection Alerts

12/02/11-17:32:21.984133	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
--------------------------	------	---------------------------------------	-----	---------------	--------------

# Network Intrusion Detection Alerts

12/02/11-17:32:21.984133	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-17:32:24.712867	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80

## What is Relational Time Series?

Previous Approaches

New Learning and Prediction Approaches

Conclusions

# Network Intrusion Detection Alerts

12/02/11-17:32:21.984133	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-17:32:24.712867	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-18:50:13.575037	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.70

## What is Relational Time Series?

Previous Approaches

New Learning and Prediction Approaches

Conclusions

# Network Intrusion Detection Alerts

12/02/11-17:32:21.984133	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-17:32:24.712867	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-18:50:13.575037	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.70
12/02/11-18:50:13.575356	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.70

## What is Relational Time Series?

Previous Approaches

New Learning and Prediction Approaches

Conclusions

# Time Series of Network Intrusion Detection Alerts

12/02/11-17:32:21.984133	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-17:32:24.712867	2924	NETBIOS SMB-DS repeated logon failure	TCP	78.45.215.210	63.205.26.80
12/02/11-18:50:13.575037	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.70
12/02/11-18:50:13.575356	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.70
12/02/11-18:50:13.575356	3397	NETBIOS DCERPC NCACN-IP-TCP	TCP	84.0.158.110	63.205.26.70
12/02/11-18:50:15.443929	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.73
12/02/11-18:50:15.444255	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.73
12/02/11-18:50:15.444255	3397	NETBIOS DCERPC NCACN-IP-TCP	TCP	84.0.158.110	63.205.26.73
12/02/11-18:50:19.048303	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.77
12/02/11-18:50:19.048624	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.77
12/02/11-18:50:19.048624	3397	NETBIOS DCERPC NCACN-IP-TCP	TCP	84.0.158.110	63.205.26.77
12/02/11-18:50:20.346232	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.74
12/02/11-18:50:22.656974	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.79
12/02/11-18:50:22.657291	648	SHELLCODE x86 NOOP	TCP	84.0.158.110	63.205.26.79
12/02/11-18:50:22.657291	3397	NETBIOS DCERPC NCACN-IP-TCP	TCP	84.0.158.110	63.205.26.79
12/02/11-19:12:38.913940	384	ICMP PING	ICMP	66.235.66.233	63.205.26.80
12/02/11-19:12:38.914642	408	ICMP Echo Reply	ICMP	63.205.26.80	66.235.66.233
12/02/11-19:12:38.959461	384	ICMP PING	ICMP	66.235.66.233	63.205.26.80
12/02/11-19:12:38.959672	408	ICMP Echo Reply	ICMP	63.205.26.80	66.235.66.233

## What is Relational Time Series?

Previous Approaches

New Learning and Prediction Approaches

Conclusions



# Relational Time Series: Time Series of Relational Atoms

- 0.0, lookA(spock84)
- 0.0, place+(Paperville3)
- 0.0, location+(pitchfork74, Paperville3)
- 0.0, pitchfork+(pitchfork74)
- 0.0, location+(spock84, Paperville3)
- 0.0, spock+(spock84)
- 2.75, getA(pitchfork74, spock84)
- 2.75, getE(spock84, pitchfork74)
- 2.75, location-(pitchfork74, Paperville3)
- 2.75, location+(pitchfork74, spock84)
- 5.5, wA(spock84)
- 5.5, goE(spock84, west)
- 5.5, location-(spock84, Paperville3)
- 5.5, spock-(spock84)
- 5.5, place-(Paperville3)

$P = (t, r(c_1, c_2, \dots, c_n))$

where

P: percept

t: time

r: relation

$c_x$ : constant

## What is Relational Time Series?

Previous Approaches

New Learning and Prediction Approaches

Conclusions

# Characteristics

- No Background knowledge
  - Eg. In a unknown domain, we do not know the behaviors of any entity
- Relational Atoms
  - Multi-dimension proposition
- High variability in predicates & constants
  - Too many to predefine
- Moving Context
  - Needs online Learning

# Possible Approaches

- Approaches
  - Production Rules
  - Finite State Machines
  - Bayesian Network
  - Markov Chain
  - Statistical Relational Learning
- Recent Interest in IDS Alerts Predictions
  - 2011 Nexat a history-based approach to predict attacker actions
  - 2011 A Novel Probabilistic Matching Algorithm for Multi-Stage Attack Forecast
  - 2010 Multi stage attack Detection system for Network Administrators using Data Mining (UTN, Oak Ridge NL)
  - 2008 Alert Fusion Based on Cluster and Correlation
  - 2007 Using Network Attack Graph to Predict the Future Attacks
  - 2007 Discovering Novel Multistage Attack Strategies

What is Relational Time Series?

[Previous Approaches](#)

New Learning and Prediction Approaches

Conclusions

# Situation Learning

- Situation Learning (Darken, 2005)
  - A sliding time window identifies “Situations”
  - Forms a simple lookup table
  - Able to model trending and high variability

- 0.0, lookA(spock84)
- 0.0, place+(Paperville3)
- 0.0, location+(pitchfork74, Paperville3)
- 0.0, pitchfork+(pitchfork74)
- 0.0, location+(spock84, Paperville3)
- 0.0, spock+(spock84)
- 2.75, getA(pitchfork74, spock84)
- 2.75, getE(spock84, pitchfork74)
- 2.75, location-(pitchfork74, Paperville3)
- 2.75, location+(pitchfork74, spock84)

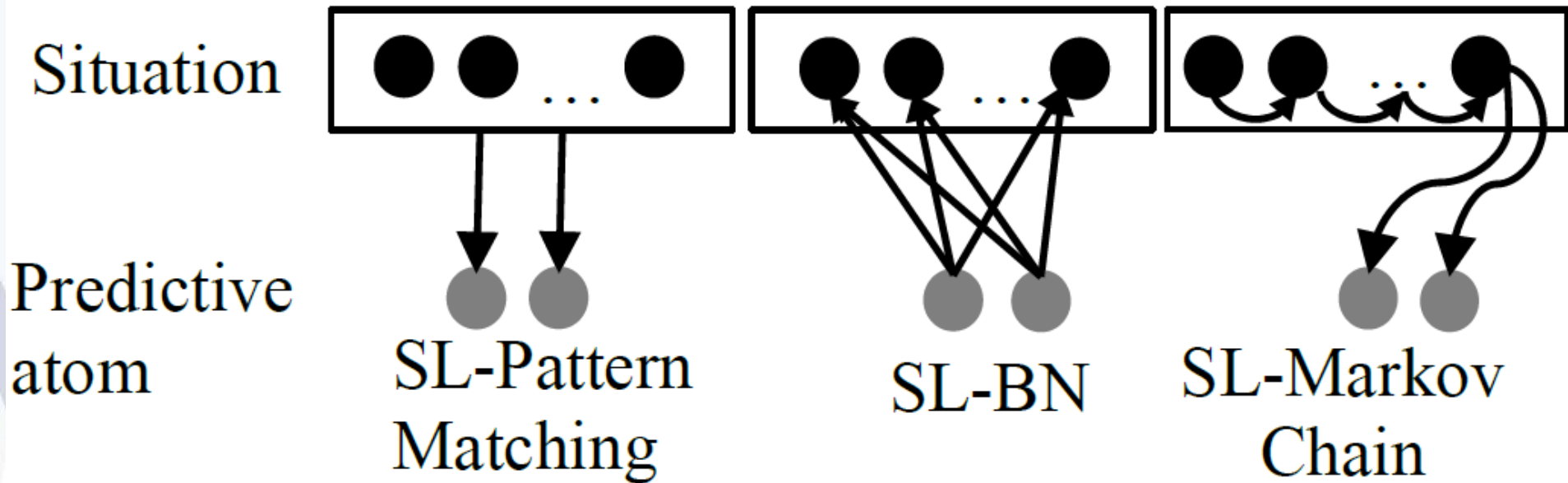
- 5.5, wA(spock84)
- 5.5, goE(spock84, west)
- 5.5, location-(spock84, Paperville3)
- 5.5, spock-(spock84)

$\Delta t$

Predictive atom

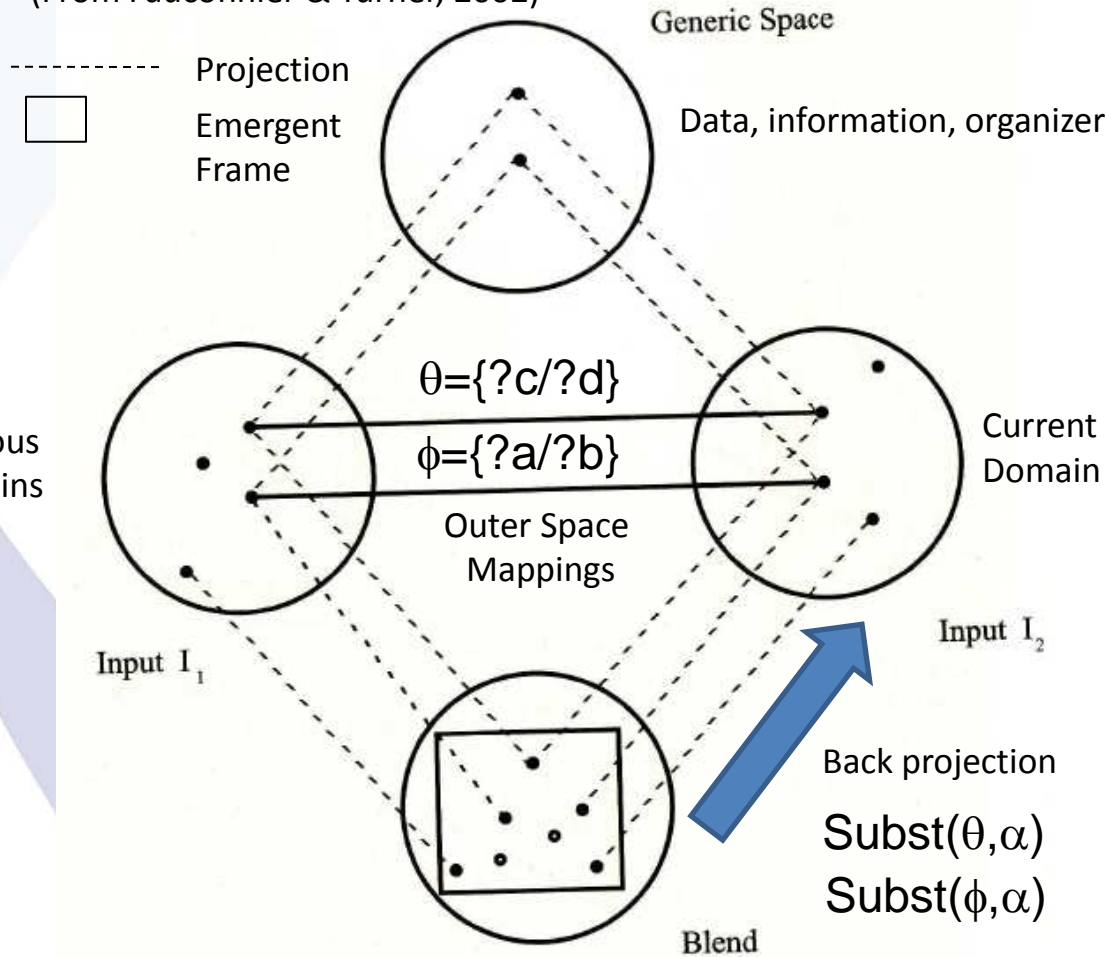
- 5.5, place-(Paperville3)

# Situation Learning (SL) + Current Approaches



# Conceptual Blending

(From Fauconnier & Turner, 2002)



**Constitution Principles**  
 Vital Relation Mapping  
 Construct Generic Space  
 Composition  
 Completion  
 Elaboration  
 Back Projection

**Optimality Principles**  
 Compression  
 Topology  
 Pattern Completion  
 Integration  
 Promoting Vital Relation  
 Web  
 Unpacking  
 relevance

**Vital Relation**  
 Change, Cause-Effect, Time,  
 Space, Identity, Change,  
 Uniqueness, Part-Whole,  
 Representation, Role, Analogy,  
 Disanalogy, Property,  
 Similarity, Category, and  
 Intentionality

# Single Scope Blending (SSB)

- Dragon-1 in Location-1
- Agent-1 enter Location-1
- Dragon-1 Kill Agent-1
- ...
- ...

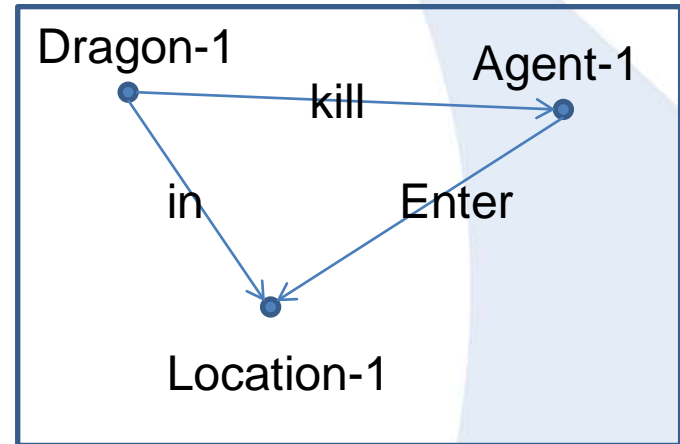
- Goblin-2 in location-2
- Dragon-2 in location-2
- Agent-2 enter location-2
- ?

One Possible Substitution:  
Dragon-1 to Goblin-2  
Agent-1 to Agent-2

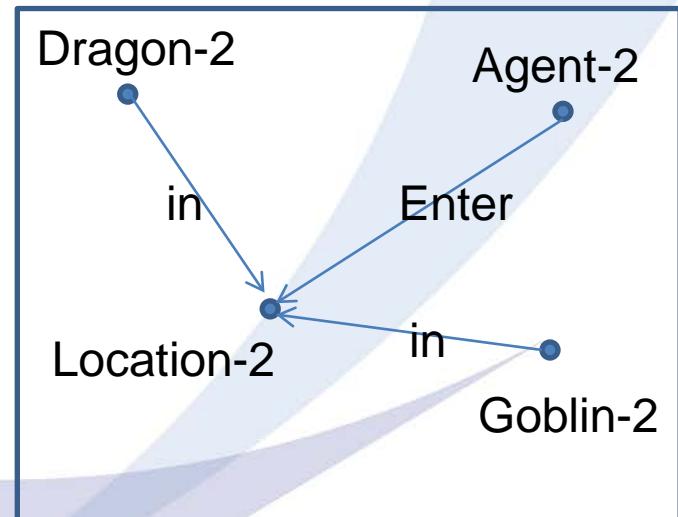
Prediction: Goblin-2 Kill Agent-2



Previous Situation

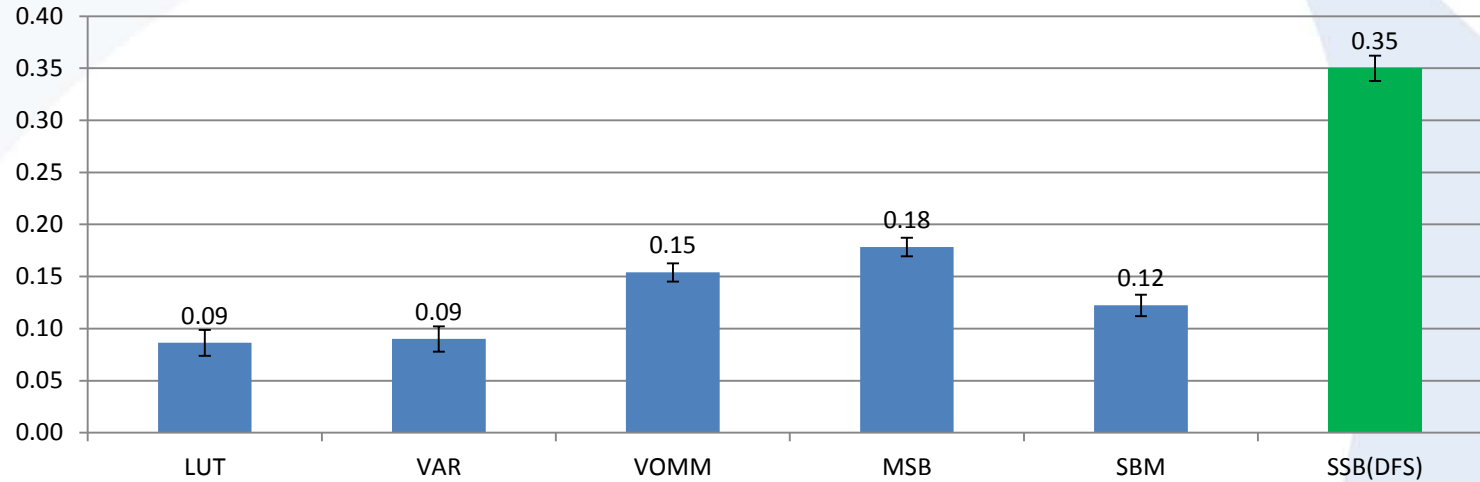


Current Situation

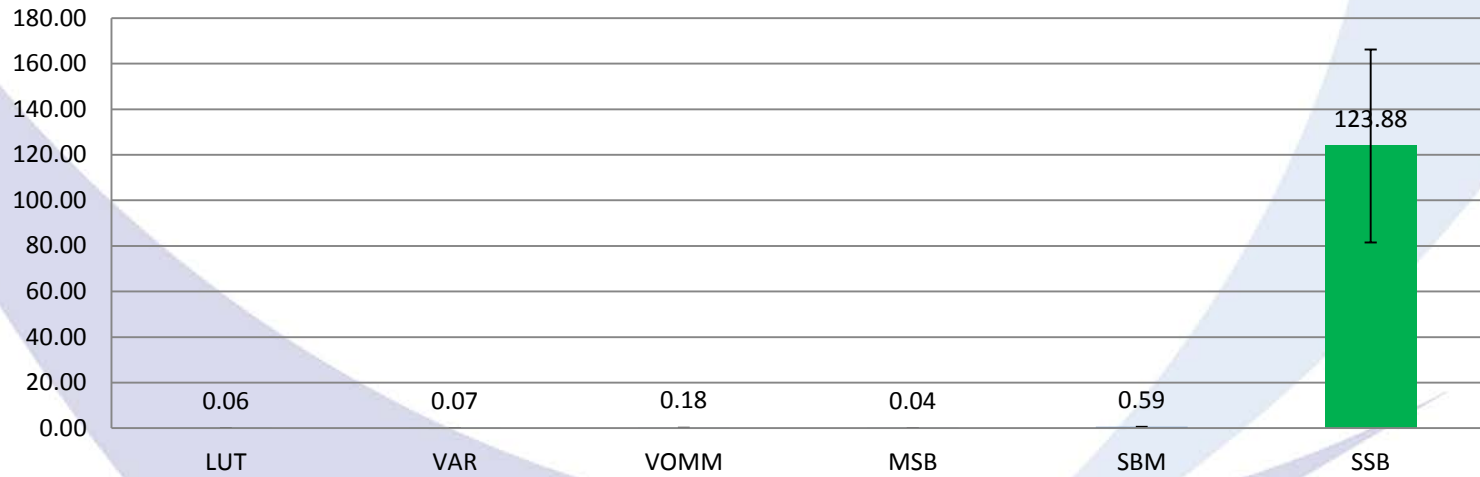


# Prediction Accuracies from a Agent Simulator

Average Prediction Accuracy, 40 batches of 100 percepts



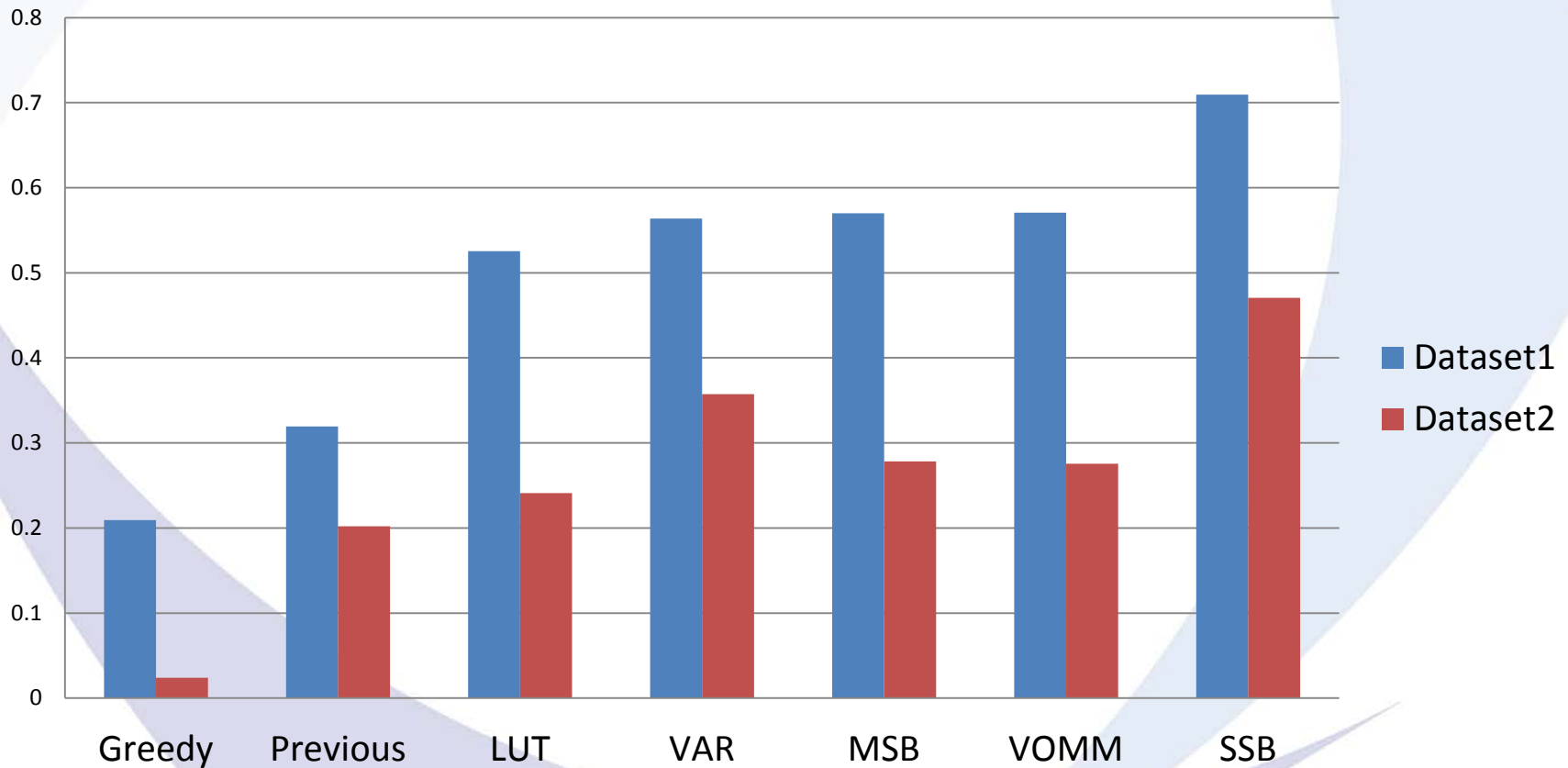
Time to run 40 batches of 100 percepts





# Network Intrusion Alerts Predictions

Final Average Prediction Accuracy



# Why is SSB Better?

- Dataset
  - 6482 alerts
  - 1590 unique alerts
- Detection Rate

	SSB	MSB	VOMM
Unique Alert Detected	947	379	375
%	59.56%	23.84%	23.58%

- Effect of Frequency on Detection Rate

Frequency	Number of Alerts	SSB Detects	MSB detects	VOMM detects
1	643	163	0	0
2	751	621	230	242
3	52	34	27	14
4	88	80	77	74
5	5	0	0	0
6	11	10	8	8
7	3	3	1	1
8	2	2	2	2
9	4	4	3	3
10	3	3	3	3

# Complexity Reduction: From Exponential to near Linear

- Default Method: Backtracking

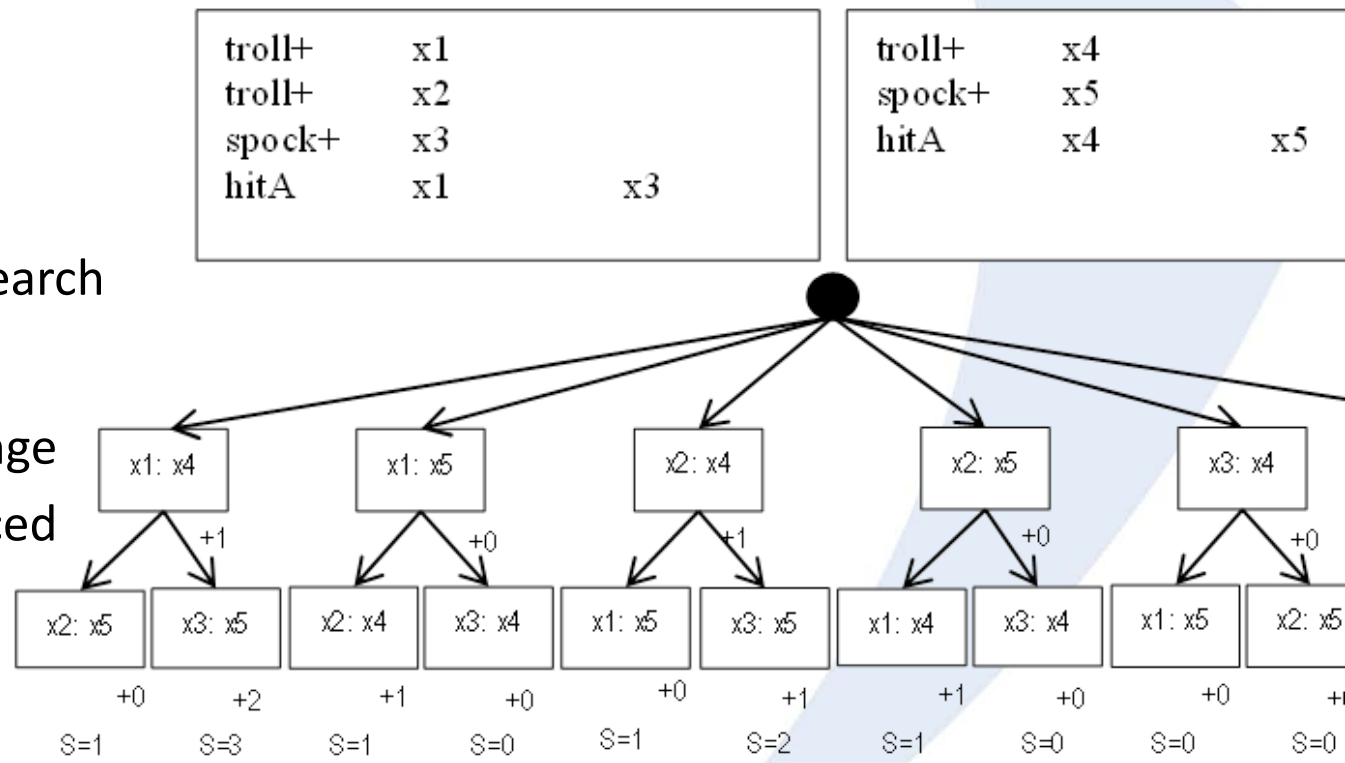
- Subgraph Isomorphism
- NP-Complete

- Improvements

- Greedy ASTAR
- Attention Based Search

- Results

- Accuracy: No Change
- Complexity: Reduced

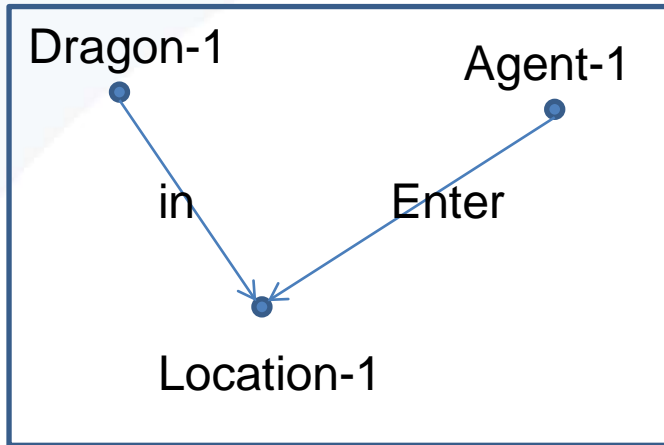


troll+	x1	
troll+	x2	
spock+	x3	
hitA	x1	x3

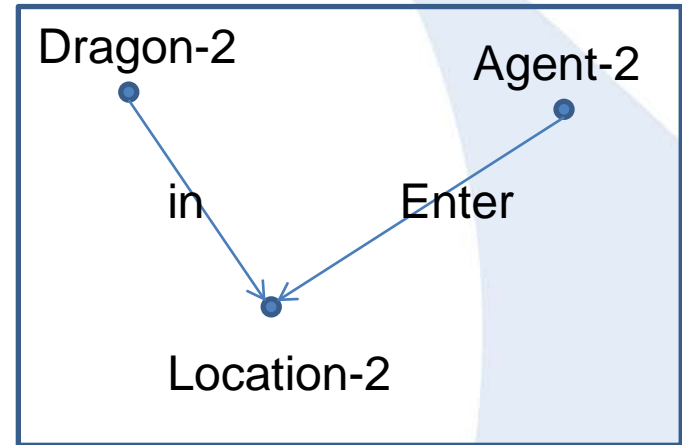
troll+	x4	
spock+	x5	
hitA	x4	x5

# Attention Based Search

Previous Situation



Current Situation



nodes	In Degree	Out Degree	Type
Dragon - 1	0	1	D
Agent - 1	0	1	A
Location - 1	2	0	L
Dragon - 2	0	1	D
Agent - 2	0	1	A
Location - 2	2	0	L

node1	node2	Difference
Dragon - 1	Dragon - 2	[1, 0, 1, 1, 0]
	Agent - 2	[0, 0, 1, 1, 0]
	Location - 2	[0, 0, 0, 0, -3]
Agent - 1	Dragon - 2	[0, 0, 1, 1, 0]
	Agent - 2	[1, 0, 1, 1, 0]
	Location - 2	[0, 0, 0, 0, -3]
Location - 1	Dragon - 2	[0, 0, 0, 0, -3]
	Agent - 2	[0, 0, 0, 0, -3]
	Location - 2	[1, 0, 1, 1, 0]

What is Relational Time Series?

Previous Approaches

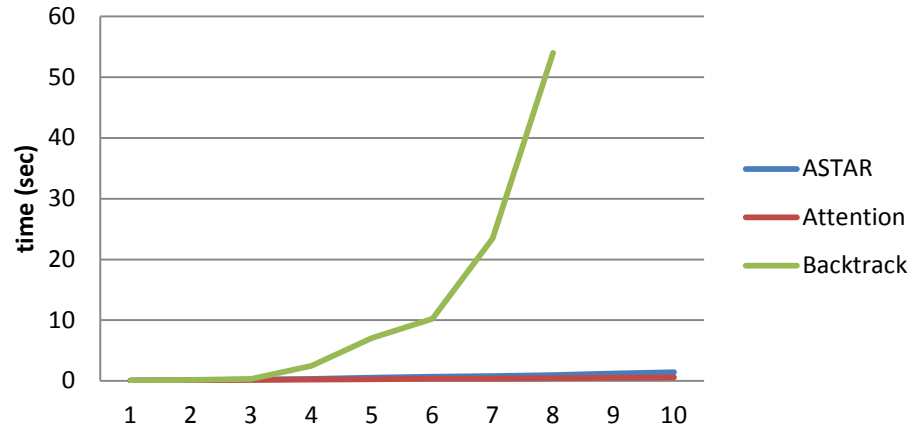
New Learning and Prediction Approaches

Conclusions

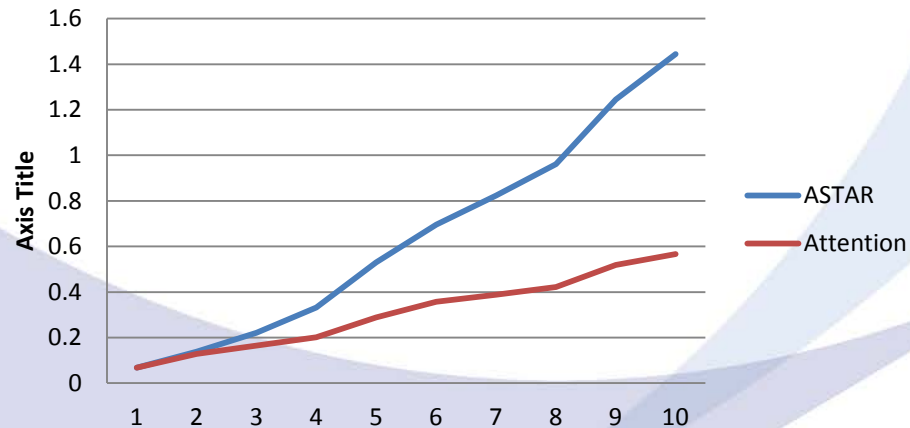
score = [Type, ExactNameMatch, BothExactDegreeMatch, AtLeastOneDegreeMatch, DegreeDiff]

# Scalability Test

Processing Time over number of atom in each situation (Pymud)



Processing Time over number of atom in each situation (Pymud)



# Conclusions

- Single Scope Blending Prediction Approach predicts better
- Reduces NP-Complete complexity to Linear through Greedy ASTAR and Attention based search

Thank you