# A Simulated Environment for Reinforcement Learning Based Intrusion Detection Using OMNET++

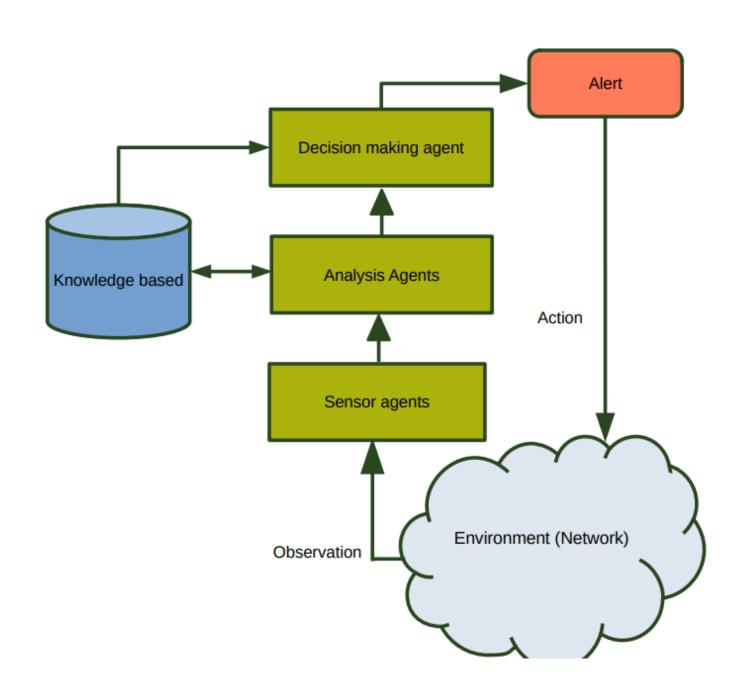
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#### Agenda

- Reinforcement environment.
- Proposed network environment.
- OSI Layers.
- Network data that sensed by the sniffer agents.
- Parameters For The HTTP Browsers and Servers
- DQN Agent (Detector).
- Network Traffic Before and After Attack using the DQN Agent.
- Performance of the DQN Algorithm (Q Value, Loss, and Epsilon)
- Detection Performance.
- Conclusion and Future Work.

### Reinforcement Learning Environment

- Reinforcement Learning (RL) environment needs to be interactive.
- An gent learns by on-line interaction with its environment.
  - 1. Takes actions
  - 2. Receives feedbacks
  - 3. Evaluates the actions
  - 4. Updates their knowledge
  - 5. Repeats steps 1-4 until convergence

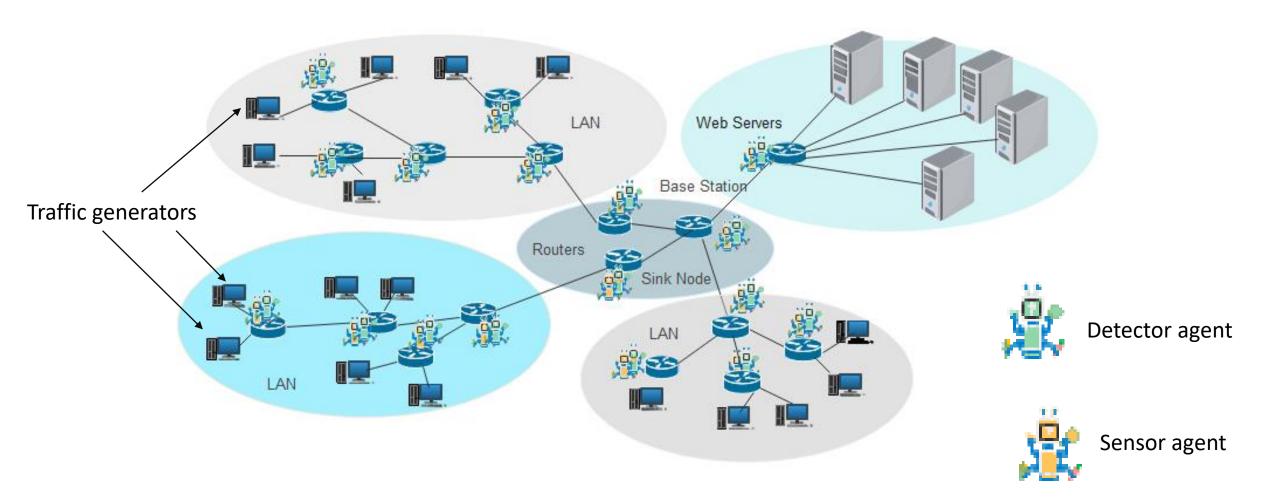


#### Reinforcement Learning Environment

- A sniffer agent function is embedded in the Data Link Layer.
- A sniffer agent continuously monitors the network state and feedback.
- An executer agent executes actions that change the network state.

#### **Simulated Network**

## Proposed Network Environment



### **Proposed Network Environment**

- HttpTools Kit of OMNET++ [1] has been utilized in developing the simulated network
- Standardhost components contain HTTP Browsers application for generating normal traffic.
- Servers are hosts but contain HTTP Servers applications to respond to requests sent by HTTP Browsers.
- Router are used for forwarding and dropping packets.
- Routers also host detector agents.
- HttpServerEvilA and HttpServerEvilB for generating malicious traffic.

#### Description of The Simulated Network Configuration

#### Simulated network configuration

General						
Service/protocol	Name	Description				
Link	Ethernet links	Ethernet connection channels with capacity				
		100Mbps				
Lookup service	HTTPControllar	Central service uses uniform popularity				
		distribution to select servers				
Web protocol	HTTP Tools kit	HTTP version 11				
	Dev	vices specifics				
Device	Number	Description				
Server	3	Uses HTTPServer				
Host	11	Uses HTTPBrowser				
	Sof	tware specifics				
Name	Parameter	Description				
HTTPServer	Start time=0s	Other parameters are specified by the HTTP				
		Tool kit				
HTTPBrowser	2 in each host.	Parameters are specified by the HTTP Tool kit				
HttpServerEvilA	number=1,	Parameters are specified by the HTTP Tool kit				
	start=0s					
HttpServerEvil	number=1,	Parameters are specified by the HTTP Tool kit				
	start=0s					

### **OSI Layers**

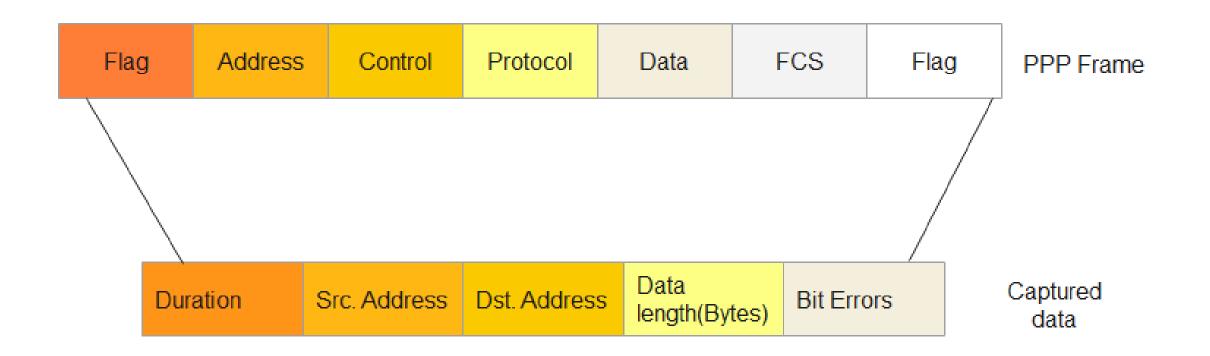
## OSI Layers

- A sniffer can see packets details after encapsulation.
- Captures relevant information
- Determines the network status based on a threshold.
- Communicates with the corresponding detector agent (on the same router)

Upper OSI Layers Network Layer Data link Layer Physical Layer

PPP

## Network State(Data) Sensed by Sniffer Agents



### Network State(Data) Sensed by Sniffer Agents

#### Features Generated by the Sensor Agents

Features	Description
IP Addresses	Sources and destinations IP addresses
Data Transferred	Data transferred during a window of time equals 5sec
Number of requests	The number of requests during a window of time equals
	5sec
Duration	The time between two recorded flows
Number of bit errors	The number of the bit error during a window of time
	equals 5sec

## Parameters For The HTTP Browsers and Servers

#### Parameters For The HTTP Browser Application

#### HTTPBrowser Paramaters

Parameter	Description	Value	
sessionInterval	The interval between activity peri-	Normally distributed, $\mu =$	
	ods	3600, $\sigma = 1800s$	
requestInterval	The interval between requests	Normally distributed, $\mu =$	
	within activity periods	600, $\sigma$ =60s	
reqInSession	The number of requests per activity	Normally distributed, $\mu =$	
	period	10, $\sigma$ =5s	

#### Parameters For The HTTP Server Application

#### **HTTPServer Paramaters**

Parameter	Description	Value		
pageSize	The number of referenced re-	exponential, mean		
	sources per HTML page 10000 bytes, min=100			
numResources	The number of referenced re-	uniform [0, 20]		
	sources per HTML page			
textImageResourceRatio	The ratio of images to text	uniform [0.2, 0.8]		
	resources on HTML pages			
imageResourceSize	The size of image resources	exponential, mean		
		20000bytes, min=1000		
textResourceSize	The size of text resources, e.g.,	exponential, mean		
	CSS documents	10000, bytes,		
		min=1000		

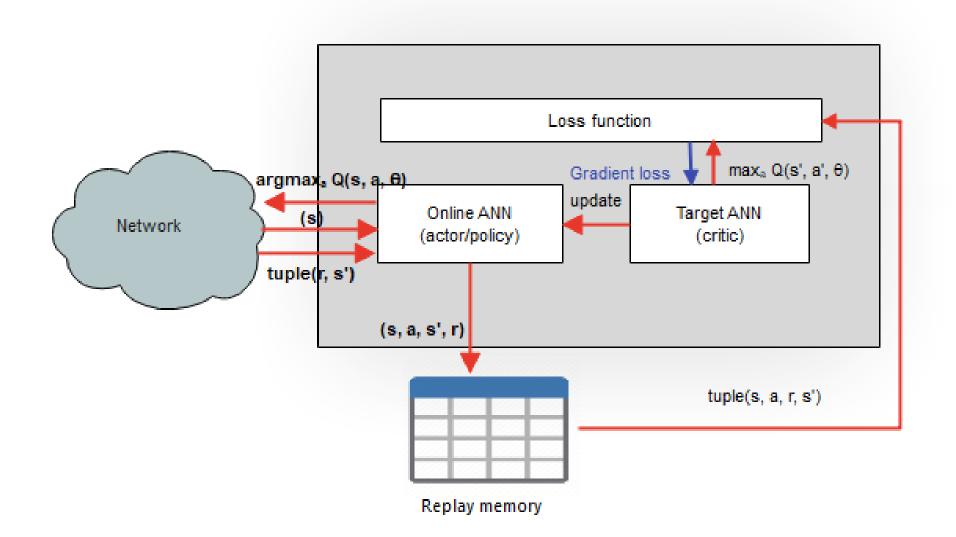
#### Parameters For The HTTP ServerEvilA and HTTP ServerEvilB Applications

#### HttpServerEvilA and HttpServerEvilB Paramaters

Parameter	Description	HttpServerEvilA	HttpServerEvilB
minBadRequests	minimum requests number	3	3
maxBadRequests	maximum requests number	8	8

### **DQN Agent (Detector)**

#### **DQN Agent Architecture**



#### **DQN Agent Algorithm**

```
Algorithm 1: DQN Algorithm for Single Agent Model
set replay memory m to size n
set random weights to online network
set random weights to target network
set episodes= e and interval=T
for episodes = 1, 2, \dots e do
  Set s_1 = x, x = current network state \phi_1 = \phi(s_1)
  for t = 1, 2, ..., T do
     Select action a_t using \epsilon – greedy
     Or select action with \max_a Q^*(\phi(s_t), a, \theta)
     Observe r, s_{t+1}
     Save tuple(\phi_t, a_t, r_t, \phi_{t+1})inm
     Check if memory m.size >= limit otherwise continue
     Select random sample from m #select a minibatch
     for i = 1, 2, \dots size(minibatch) do
        y_{j} = \begin{cases} r_{j} & if \phi_{t+1} = terminal \ state \\ r_{j} + \gamma \max_{a'} Q(\phi_{j+1}, a', \theta) & if \phi_{t+1} = non - terminal \ state \end{cases}
        Calculate \nabla = (y_i - Q(\phi_i, a_i, \theta))^2
        Update weights of both networks using ∇
        Accumulate Q(\phi, a, \theta)
     end for
  end for
end for
Use model for classification
for each tuple in dataset do
  Find an action with \max_a Q^*(\phi(s_t), a, \theta)
end for
Find true and false classifications
Evaluate model
```

#### Parameters used with the DQN agent

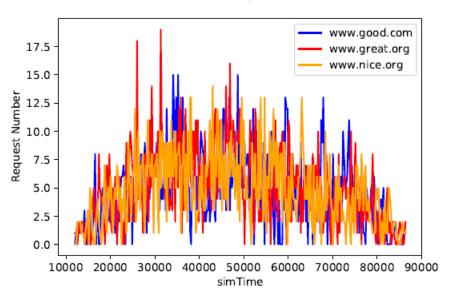
#### Parameters used with the DQN agent

ANN Parameters					
Parameter	Value	Description			
layers (deep)	4	The number of layers of the ANN			
Inputs (s)	3	The number of inputs of the ANN			
Outputs (a)	2	The number of actions of the ANN			
eta $(\eta)$	0.01	Is used as a training rate for the ANN			
alpha (α)	0.05	Is used as a training rate for the ANN			
	DQN I	Parameters			
Parameter	Value	Description			
Input (s)	3	The number of inputs of the DQN			
Actions (a)	2	The number of actions of the DQN			
lr (α)	0.01	Learning rate of the DQN			
gamma ( $\gamma$ )	0.05	Discount factor for the DQN			
Minibatch size	20	The memory size the agent samples			
		for training			
epsilon $(\epsilon)$	1	Probability used for balancing be-			
		tween exploration and exploitation			
min-epsilon	0.90	minimum limit for epsilon			
decay-epsilon	0.995	decay rate for epsilon			

## Network Traffic Before and After Attack using the DQN Agent

#### **Three Servers in A Normal Situation**

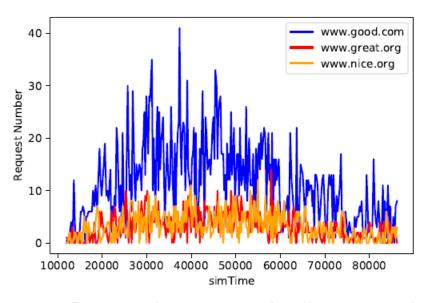
#### Uniform Distribution of Requets on Three Servers



Uniformly distributed requests among servers in a normal situation

#### www.goog.com Server Under Attack

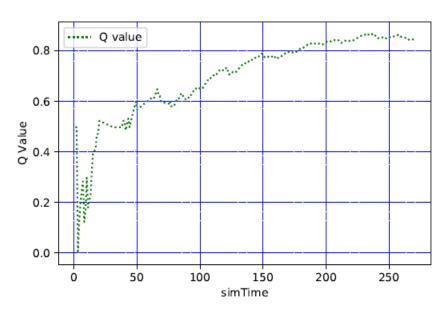
Server www.good.com Requets Deviation from Uniform Distribution



Comparing between servers' traffic statuses under attack

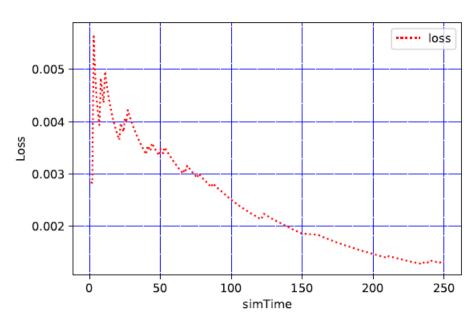
## Performance of the DQN Algorithm (Q Value, Loss, and Epsilon)

#### Q value



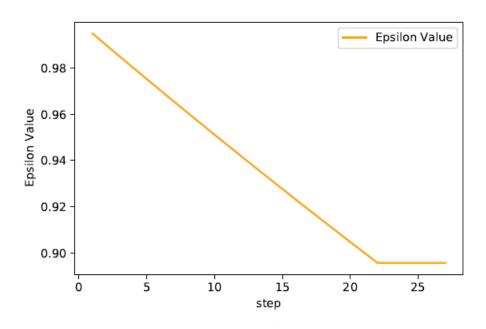
Plotting Cumulative Q value over episodes

#### LOSS



Loss values during training episodes

#### **Epsilon Decay**



Epsilon value for agent exploration

#### **Detection Performance**

#### **Detection Performance**

Model performance using typical multiagent IDS architecture

	Total cases	TP	TN	FP	FN	Accuracy	Precision
Classification	5651	624	682	2301	3350	0.19	0.21

#### Conclusion

- An environment has been simulated for Reinforcement Learning based intrusion detection using simulation.
- Network performance measurement.
- Reinforcement Learning algorithm evaluation based on a single agent.
- Detection performance (accuracy, precision etc) is to be measured.

#### **Future Work**

- Other Reinforcement Learning algorithms can be tested using the framework.
- Cooperative Reinforcement Learning algorithms can also be tested and evaluated.

Thank you

#### References

1. Jonsson, K. V. HttpTools: a toolkit for simulation of web hosts in OMNeT++. *Proceedings of the 2nd International Conference on Simulation Tools and Techniques*. Rome, Italy. 2009. 1–8.