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Practical Data Mining

Case study : Intrusion Detection System

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25 Agustus 2020

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Iwan Syarif

Overview | Publications

ECS, Faculty of Physical Sciences and Engineering
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Interests: artificial intelligence, computer network, data mining, intrusion detection system, machine learning, network security


Iwan Syarif

Qualifications

Master of Computer Science, University of Southampton, UK, 2009

Master of Informatics, ITS Surabaya, Indonesia, 2003

Bachelor of Computer Engineering, ITS Surabaya, Indonesia, 1994

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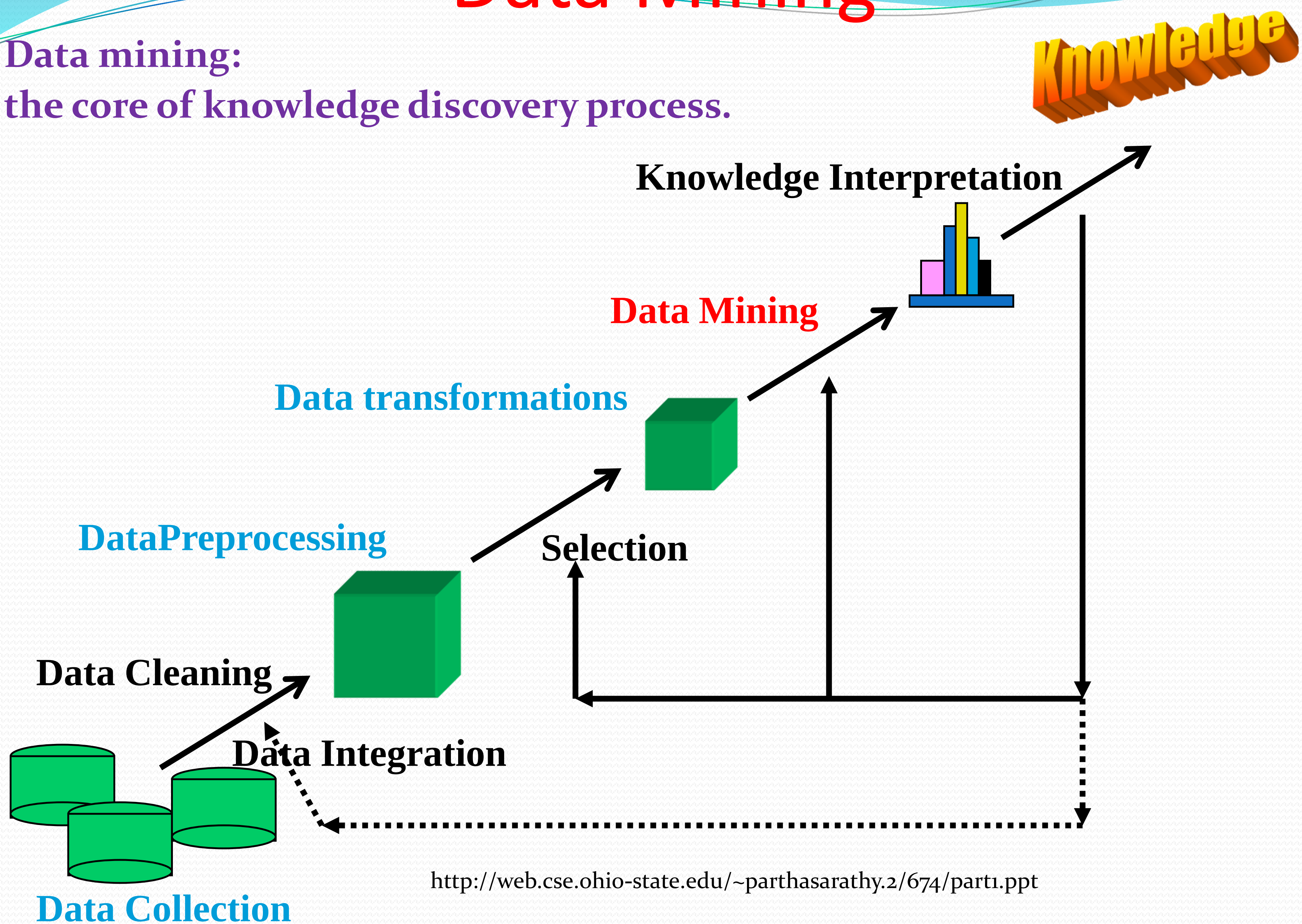
Data Mining

Data mining:
the core of knowledge discovery process.



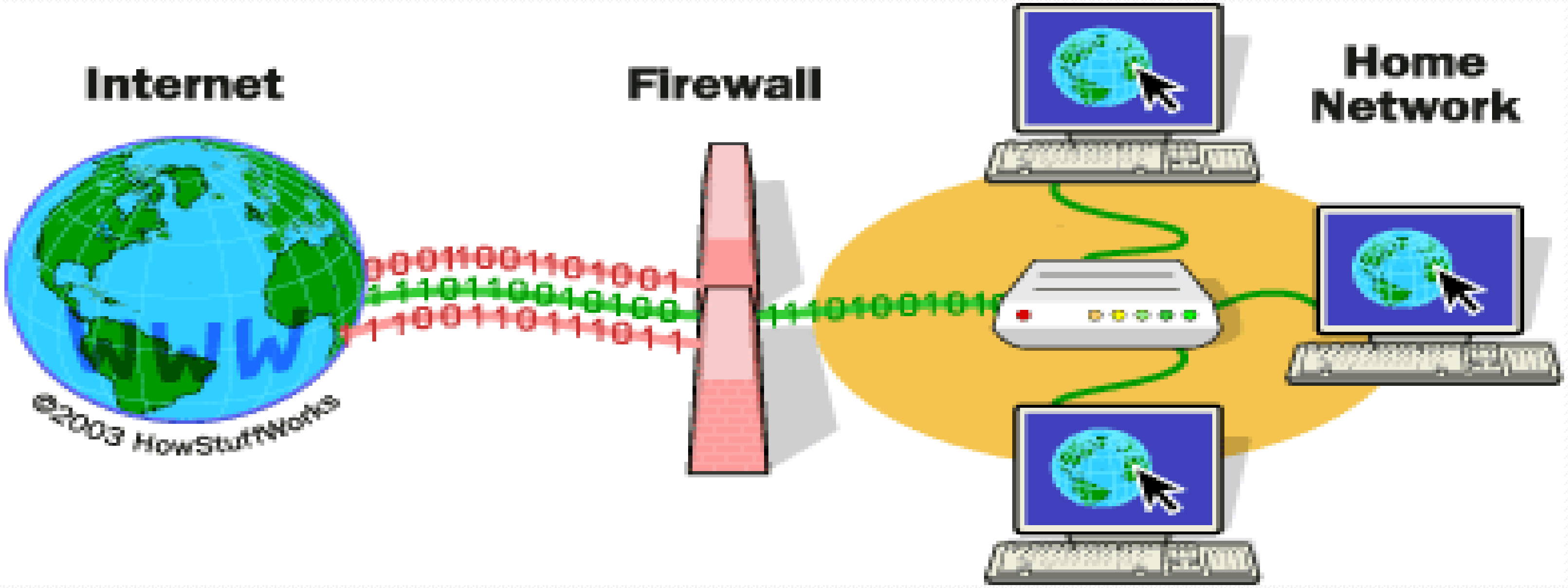
http://web.cse.ohio-state.edu/~parthasarathy.2/674/part1.ppt

Data Mining Approaches for Network Intrusion Detection System

https://norse-corp.com/map/

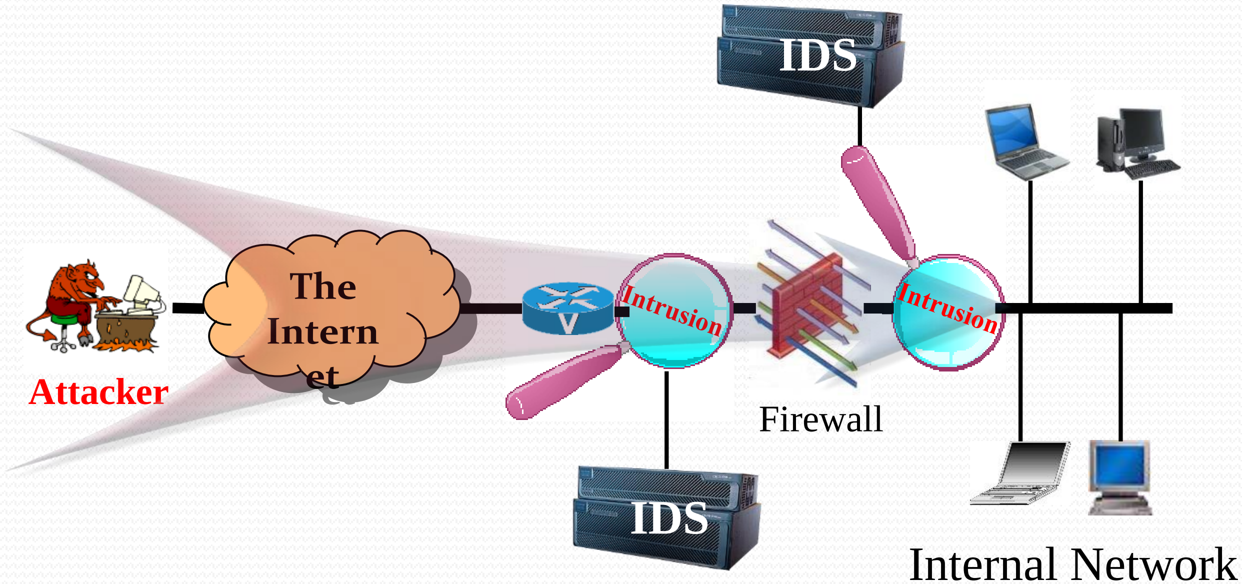
Firewalls

- Used to filter packets based on a combination of features
  - These are called packet filtering firewalls
  - Ex. Drop packets with destination port of 23 (Telnet)
- But why don't we just turn Telnet off?



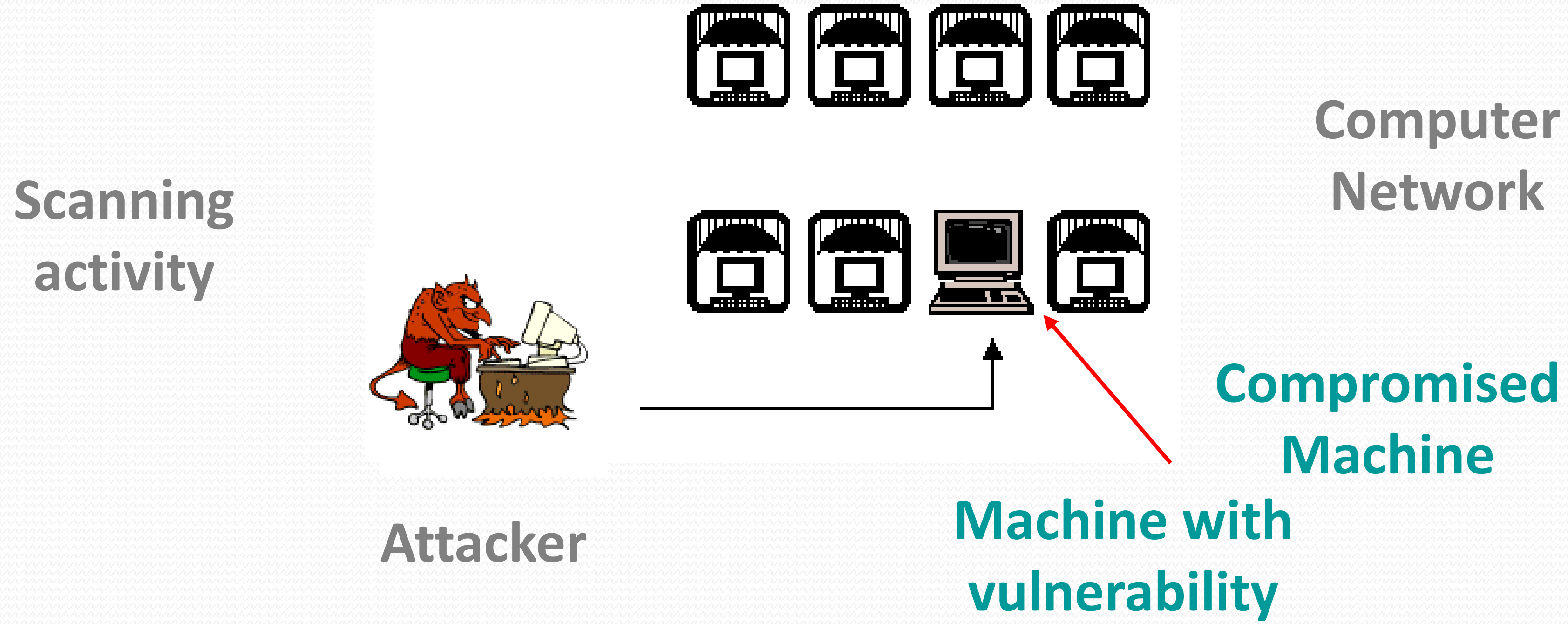
Intrusion Detection System(IDS)

- combination of software and hardware that attempts to perform intrusion detection
- raise the alarm when possible intrusion or suspicious patterns are observed

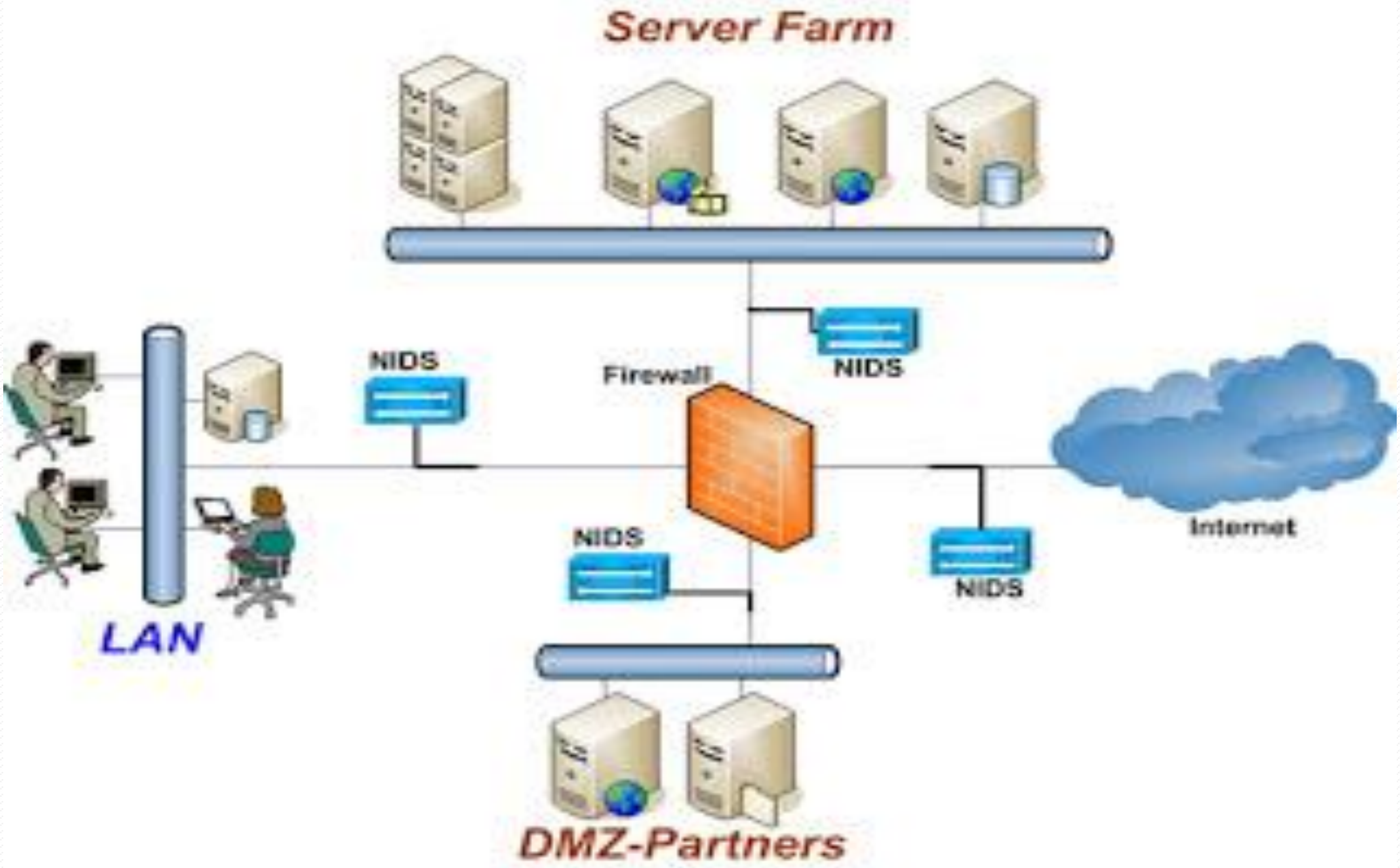


What are Intrusions?

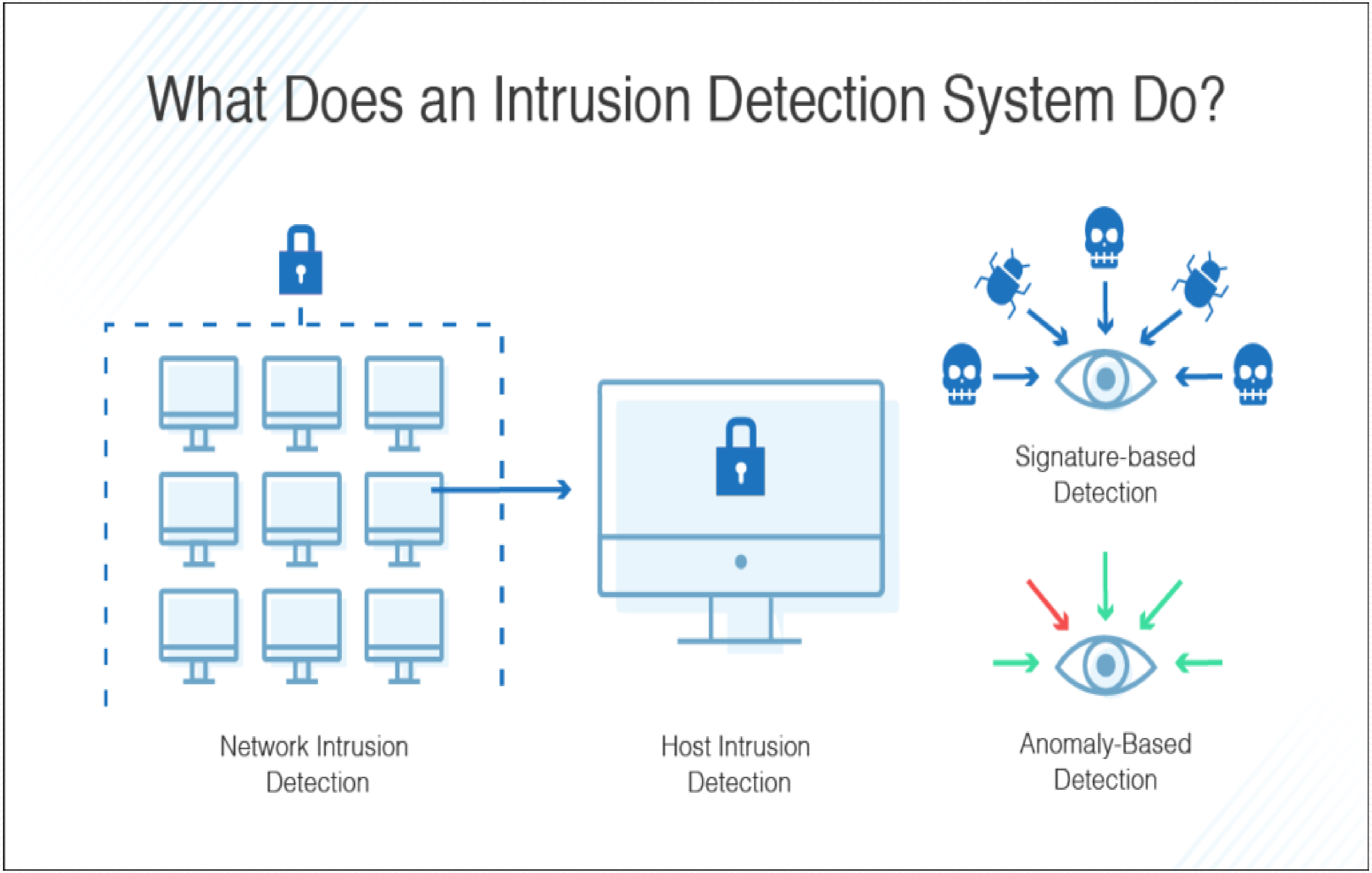
- Intrusions are actions that attempt to bypass security mechanisms of computer systems. They are usually caused by:
  - Attackers accessing the system from Internet
  - Insider attackers - authorized users attempting to gain and misuse non-authorized privileges
- Typical intrusion scenario



Network Diagram of Enterprise Network



Types of IDS


What Does an Intrusion Detection System Do?
Network Intrusion Detection
Host Intrusion Detection
Signature-based Detection
Anomaly-Based Detection

Data Mining for Intrusion Detection

- *Signature-based / Misuse detection*
  - Building predictive models from labeled labeled data sets (instances are labeled as “normal” or “intrusive”) to identify known intrusions
  - High accuracy in detecting many kinds of known attacks
  - Cannot detect unknown and emerging attacks
- *Anomaly detection*
  - Detect novel attacks as deviations from “normal” behavior
  - Potential high false alarm rate - previously unseen (yet legitimate) system behaviors may also be recognized as anomalies

Data Mining for Signature-based IDS

Misuse Detection – Building Predictive Models

Tid	SrcIP	Start time	Dest IP	Dest Port	Number of bytes	Attack
1	206.135.38.95	11:07:20	160.94.179.223	139	192	No
2	206.163.37.95	11:13:56	160.94.179.219	139	195	No
3	206.163.37.95	11:14:29	160.94.179.217	139	180	No
4	206.163.37.95	11:14:30	160.94.179.255	139	199	No
5	206.163.37.95	11:14:32	160.94.179.254	139	19	Yes
6	206.163.37.95	11:14:35	160.94.179.253	139	177	No
7	206.163.37.95	11:14:36	160.94.179.252	139	172	No
8	206.163.37.95	11:14:38	160.94.179.251	139	285	Yes
9	206.163.37.95	11:14:41	160.94.179.250	139	195	No
10	206.163.37.95	11:14:44	160.94.179.249	139	163	Yes

	categorical	temporal	categorical	continuous	class
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1	206.163.37.81	11:17:51	160.94.179.208	150	No
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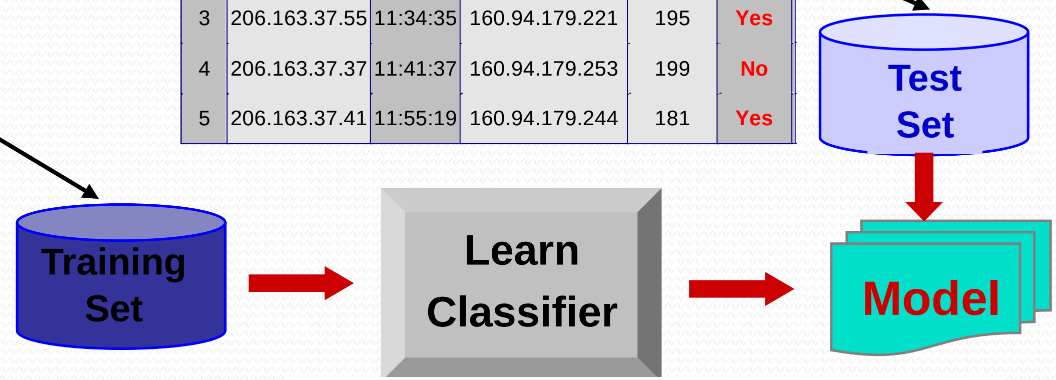
3	206.163.37.55	11:34:35	160.94.179.221	195	Yes
4	206.163.37.37	11:41:37	160.94.179.253	199	No
5	206.163.37.41	11:55:19	160.94.179.244	181	Yes

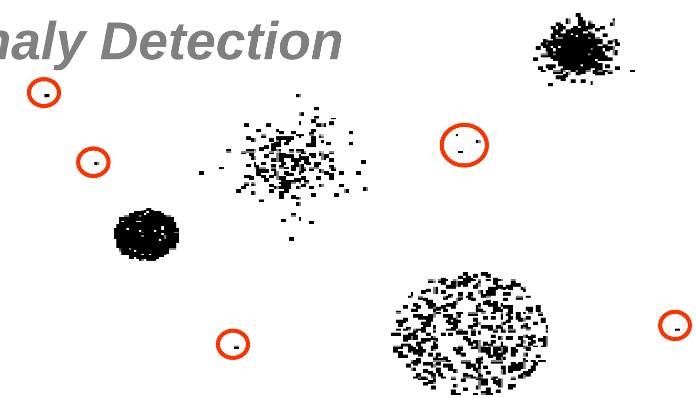


Summarization of attacks using association rules

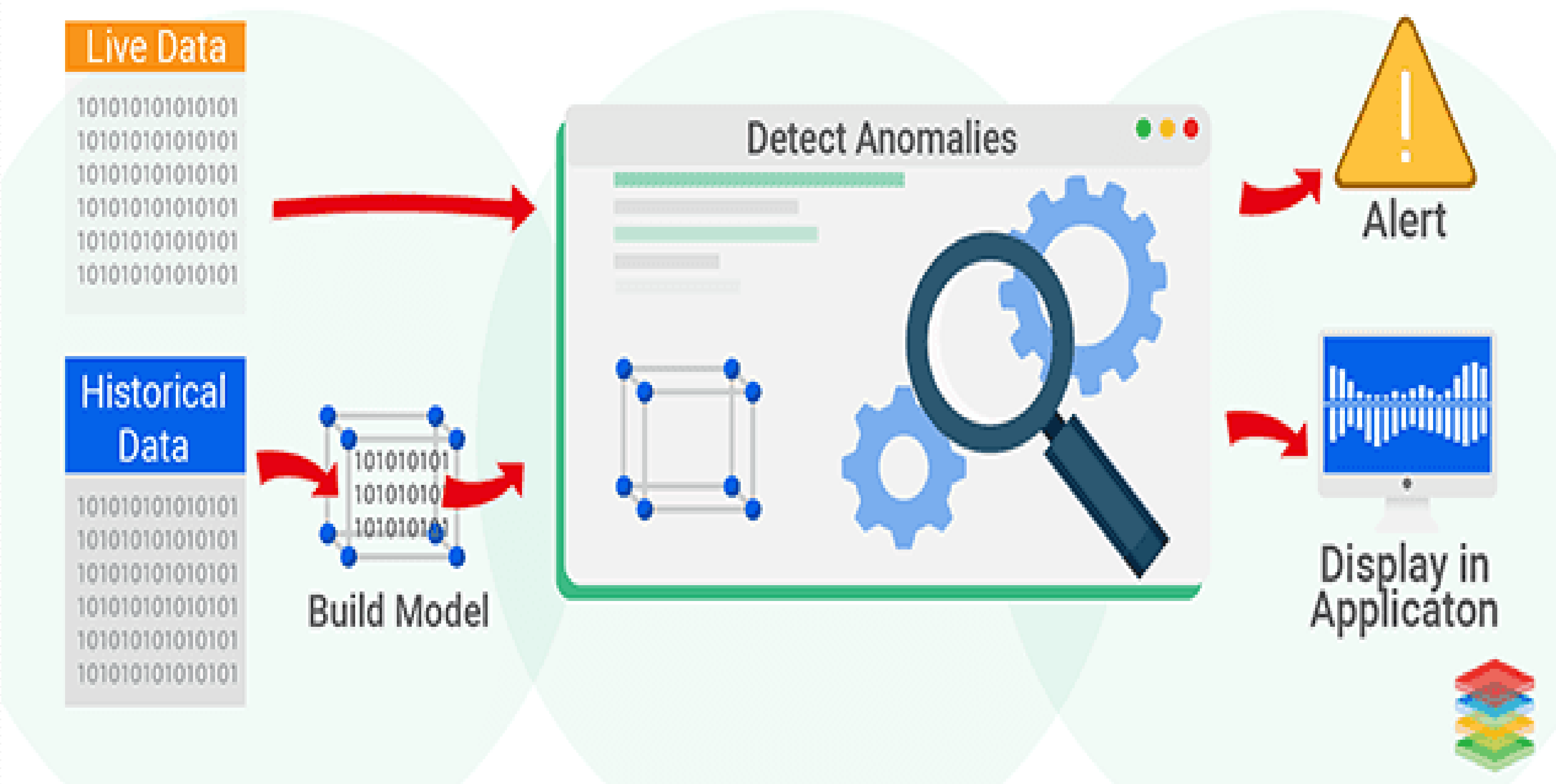
Rules Discovered:

{Src IP = 206.163.37.95,
Dest Port = 139,
Bytes ∈ [150, 200]} --> {ATTACK}

Anomaly Detection



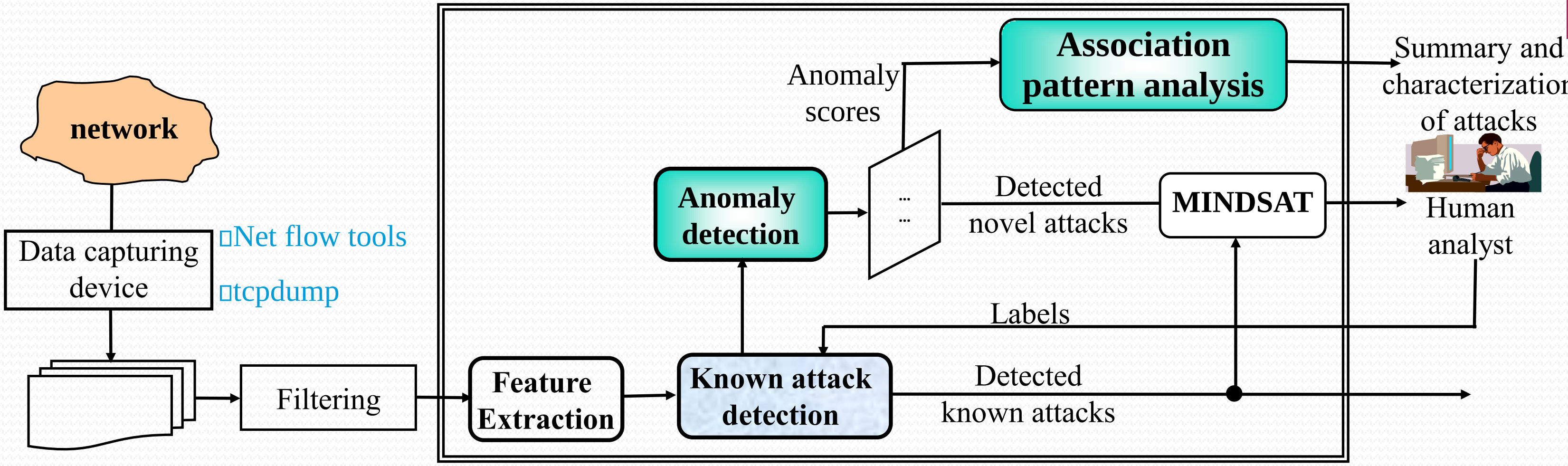
Real Time Anomaly Detection



Hybrid IDS: signature-based + anomaly detection

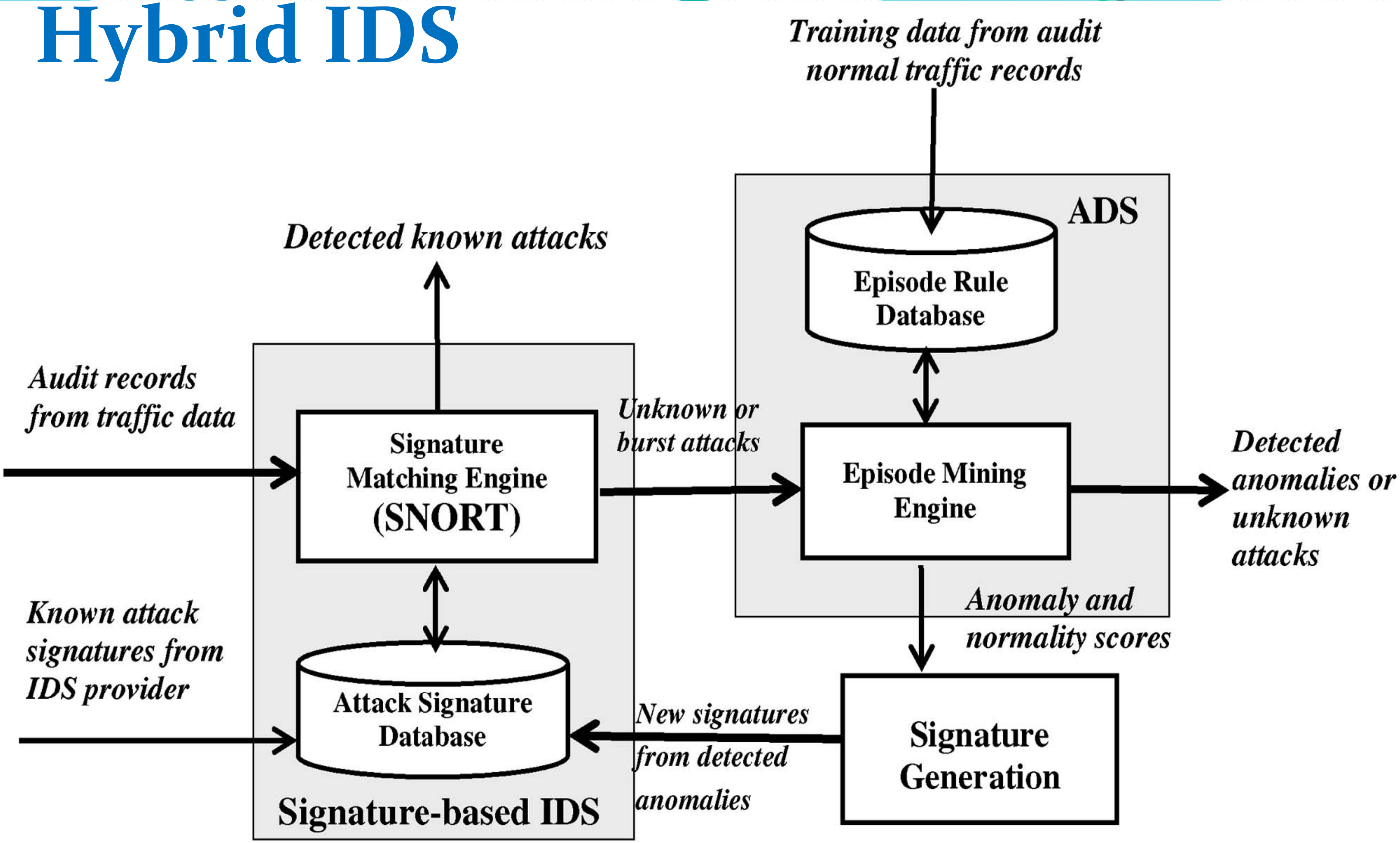
- Anomaly detection was used at U of Minnesota and Army Research Lab to detect various intrusive/suspicious activities
- Many of these could not be detected using widely used intrusion detection tools like SNORT
- Anomalies/attacks picked by *MINDS*
  - Scanning activities
  - Non-standard behavior
    - Policy violations
    - Worms

MINDS – Minnesota Intrusion Detection System



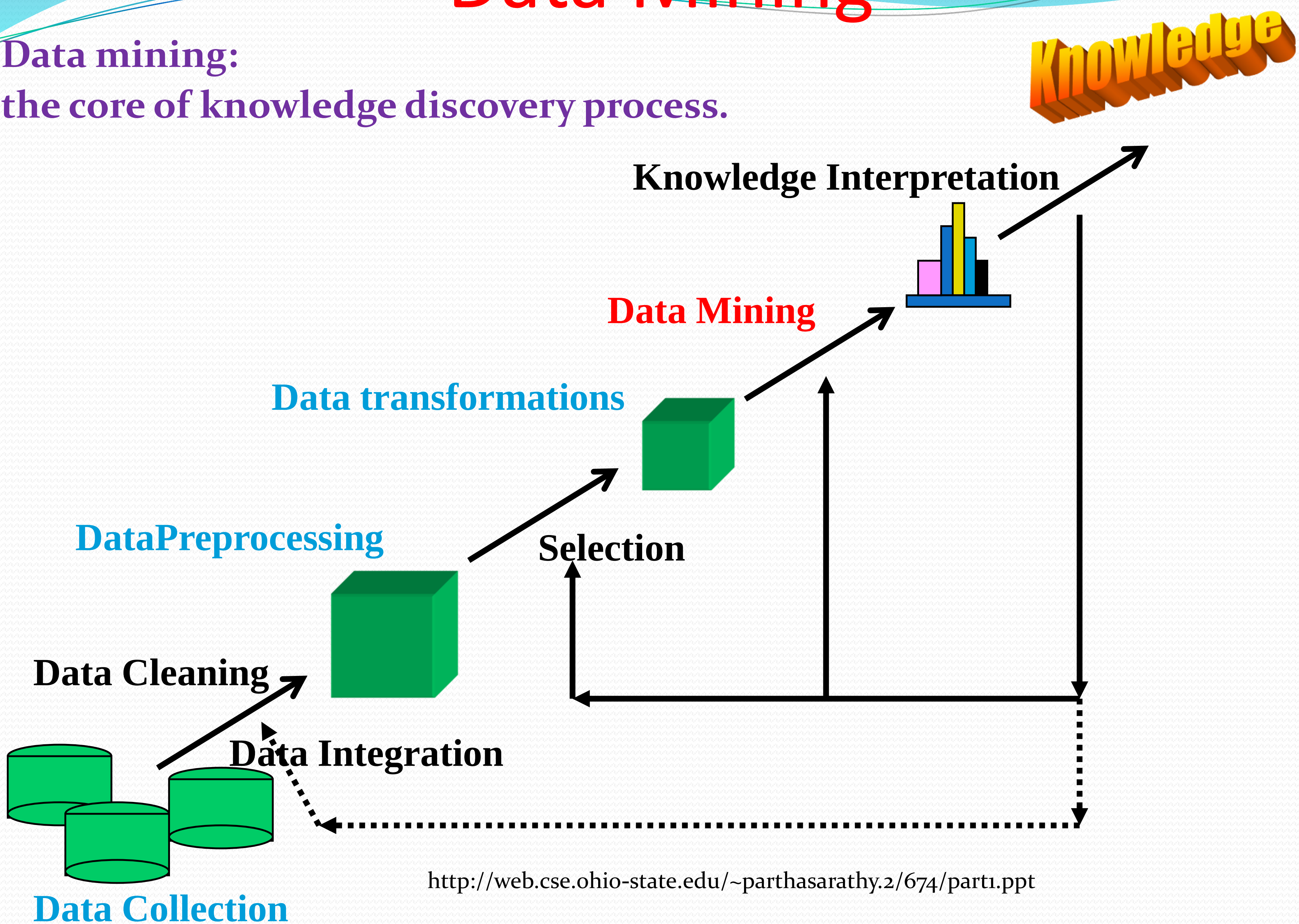
https://www-users.cs.umn.edu/~lazar027/MINDS/index.html

Hybrid IDS


Training data from audit
normal traffic records
ADS
Episode Rule
Database
Detected known attacks
Audit records
from traffic data
Signature
Matching Engine
(SNORT)
Unknown or
burst attacks
Episode Mining
Engine
Detected
anomalies or
unknown
attacks
Anomaly and
normality scores
Known attack
signatures from
IDS provider
Attack Signature
Database
New signatures
from detected
anomalies
Signature
Generation
Signature-based IDS

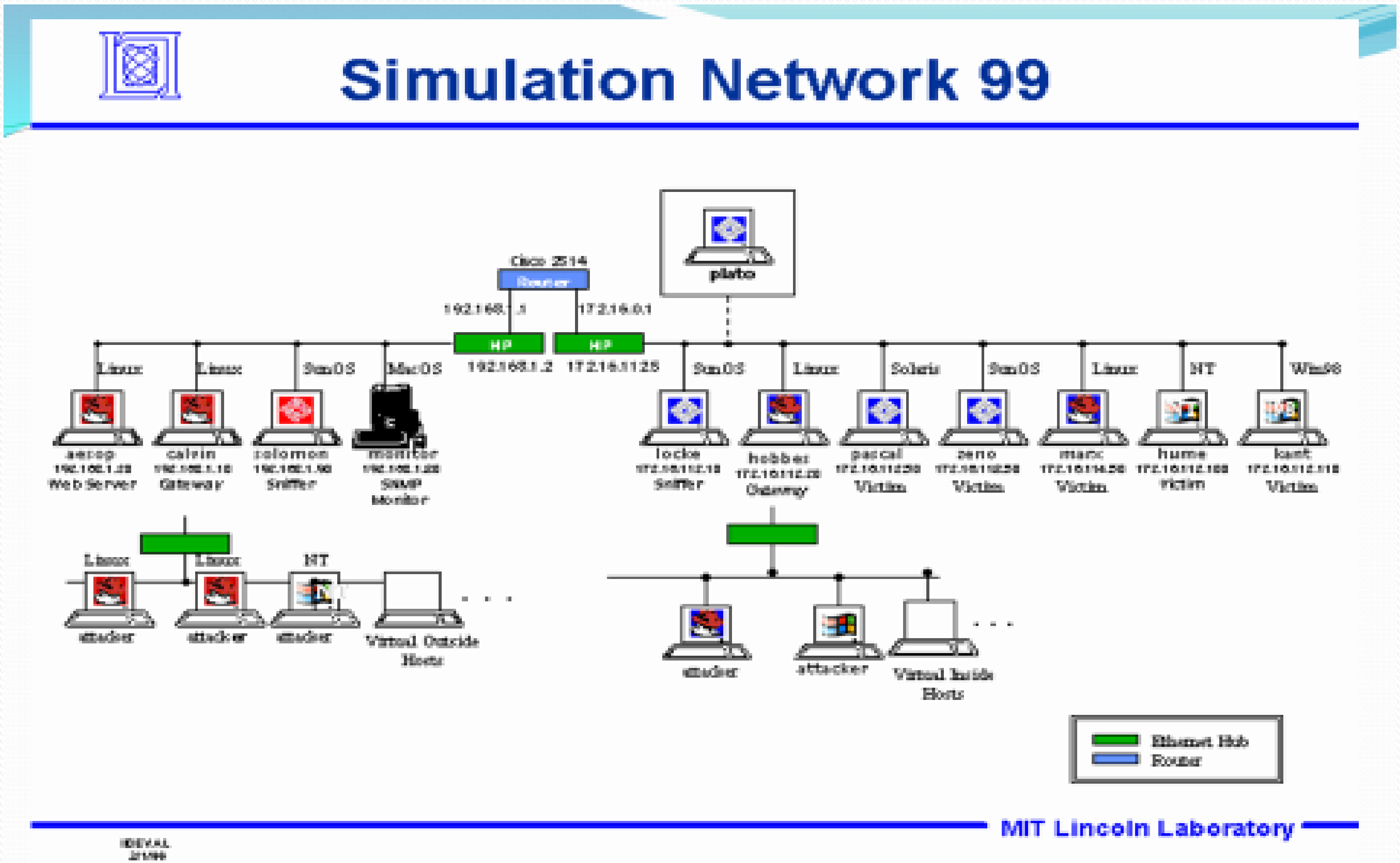
Data Mining

Data mining:
the core of knowledge discovery process.



http://web.cse.ohio-state.edu/~parthasarathy.2/674/part1.ppt

Step 1. Intrusion Data Collection
(raw data : real network traffics)



https://www.ll.mit.edu/r-d/datasets

Step 2. Data Pre-Processing
DARPA-MIT dataset : real time network traffics

- DARPA 1998 data set
  - Simulated nine weeks of raw TCP dump data
  - Probing attacks, DoS attacks, U2R, R2L attacks

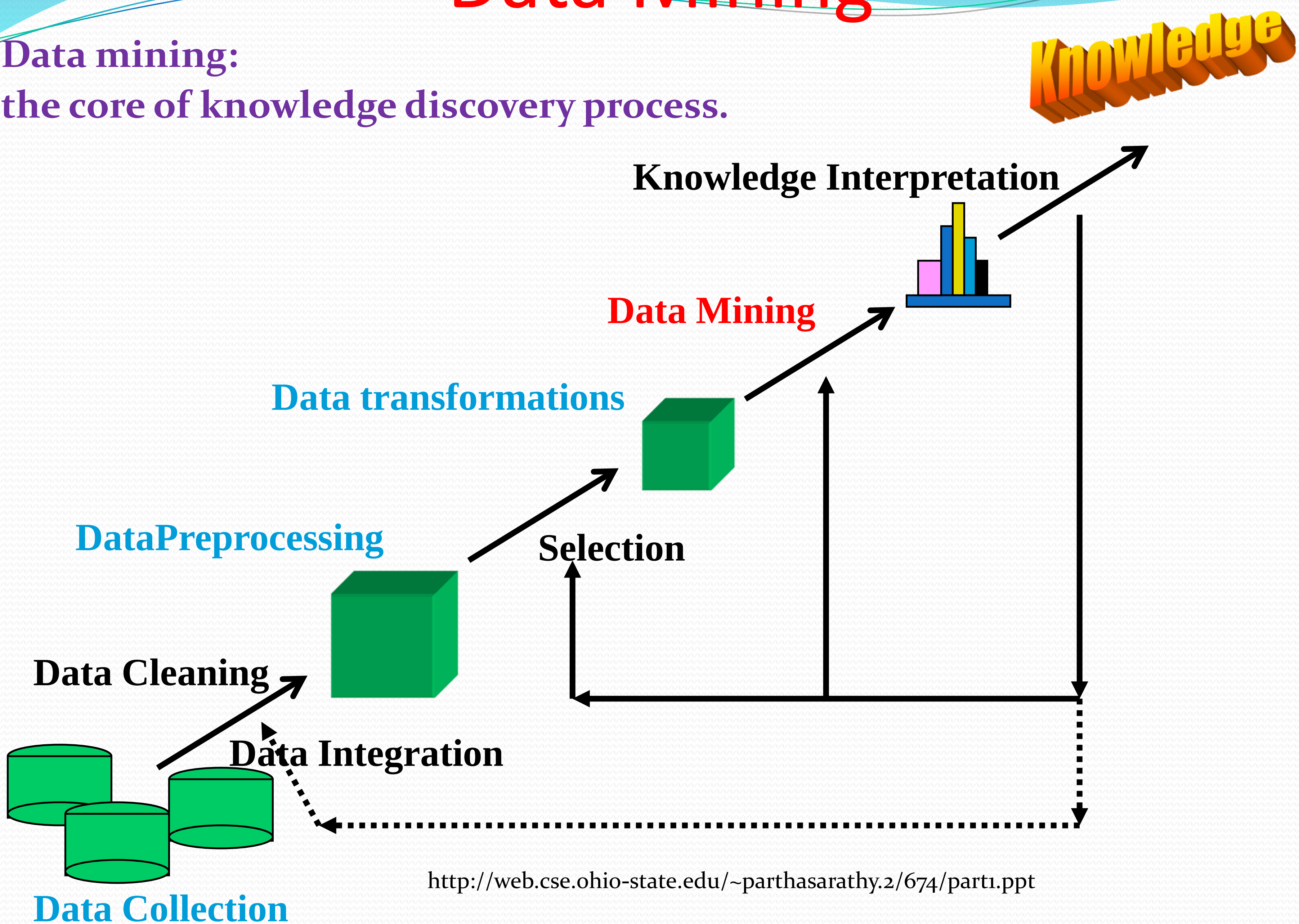
```
user@host:~$ sudo tcpdump --interface=ens33 -n host 192.168.111.1
tcpdump: verbose output suppressed, use -v or -vv for full protocol decode
listening on ens33, link-type EN10MB (Ethernet), capture size 262144 bytes
23:55:40.546464 IP 192.168.111.1 > 192.168.111.209: ICMP echo request, id 64017, seq 0, length 64
23:55:40.546517 IP 192.168.111.209 > 192.168.111.1: ICMP echo reply, id 64017, seq 0, length 64
23:55:41.551452 IP 192.168.111.1 > 192.168.111.209: ICMP echo request, id 64017, seq 1, length 64
23:55:41.551485 IP 192.168.111.209 > 192.168.111.1: ICMP echo reply, id 64017, seq 1, length 64
23:55:42.556206 IP 192.168.111.1 > 192.168.111.209: ICMP echo request, id 64017, seq 2, length 64
23:55:42.556243 IP 192.168.111.209 > 192.168.111.1: ICMP echo reply, id 64017, seq 2, length 64
23:55:43.558055 IP 192.168.111.1 > 192.168.111.209: ICMP echo request, id 64017, seq 3, length 64
23:55:43.558094 IP 192.168.111.209 > 192.168.111.1: ICMP echo reply, id 64017, seq 3, length 64
23:55:43.955857 IP 192.168.111.1.53861 > 192.168.111.209.80: Flags [SEW], seq 3194582235, win 65535, options [mss 14
60,nop,wscale 6,nop,nop,TS val 243647685 ecr 0,sackOK,eol], length 0
23:55:43.955909 IP 192.168.111.209.80 > 192.168.111.1.53861: Flags [S.E], seq 4099266365, ack 3194582236, win 65160,
 options [mss 1460,sackOK,TS val 1285093713 ecr 243647685,nop,wscale 7], length 0
23:55:43.956230 IP 192.168.111.1.53861 > 192.168.111.209.80: Flags [.], ack 1, win 2058, options [nop,nop,TS val 243
647685 ecr 1285093713], length 0
23:55:43.956250 IP 192.168.111.1.53861 > 192.168.111.209.80: Flags [P.], seq 1:80, ack 1, win 2058, options [nop,nop
,TS val 243647685 ecr 1285093713], length 79: HTTP: GET / HTTP/1.1
23:55:43.956385 IP 192.168.111.209.80 > 192.168.111.1.53861: Flags [.], ack 80, win 509, options [nop,nop,TS val 128
5093713 ecr 243647685], length 0
```

Intrusion Datasets (ready to used)

- Darpa-Intrusion Dataset 1998
- KDD Cup Intrusion Data 1999
- NSL-KDD Intrusion Dataset
- Kyoto Intrusion Dataset 2006
- Intrusion Detection Evaluation Dataset (CICIDS2017)
  - Android Botnet 2015
  - Android Adware 2017
  - Botnet 2014
  - Denial of Service Attack 2017
  - Distributed Denial of Service Attack 2017 & 2019
  - IDS 2019
  - DNS over HTTPS attacks 2020
- https://www.unb.ca/cic/datasets/index.html

Data Mining

Data mining:
the core of knowledge discovery process.



http://web.cse.ohio-state.edu/~parthasarathy.2/674/part1.ppt

Step 3 :Data Transformation

- Three groups of features
  - Basic features of individual TCP connections
    - source & destination IP *Features 1 & 2*
    - source & destination port *Features 3 & 4*
    - Protocol *Feature 5*
    - Duration *Feature 6*
    - Bytes per packets *Feature 7*
    - number of bytes *Feature 8*

dst	...	*service*	...	*flag*
h1		http		S0
h1		http		S0
h1		http		S0
h2		http		S0
h4		http		S0
h2		ftp		S0

existing features
useless

syn flood

normal

dst	...	*service*	...	*flag*	%S0
h1		http		S0	70
h1		http		S0	72
h1		http		S0	75
h2		http		S0	0
h4		http		S0	0
h2		ftp		S0	0

construct features with
high information gain

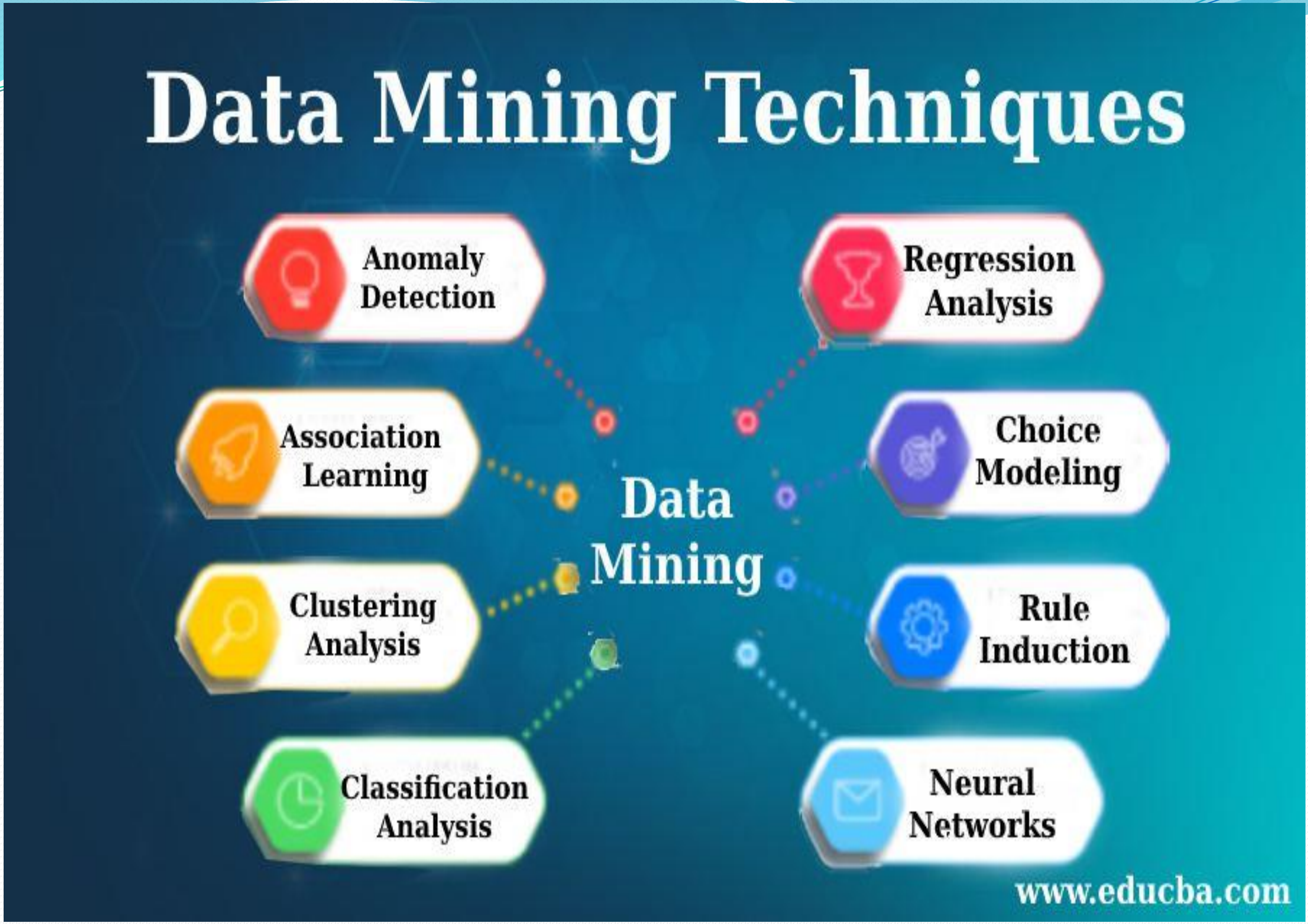
  - **Time based features**
    - For the same source (destination) IP address, number of unique destination (source) IP addresses inside the network *in last T seconds – Features 9 (13)*
    - Number of connections from source (destination) IP to the same destination (source) port *in last T seconds – Features 11 (15)*
  - Connection based features
    - For the same source (destination) IP address, number of unique destination (source) IP addresses inside the network *in last N connections - Features 10 (14)*
    - Number of connections from source (destination) IP to the same destination (source) port *in last N connections - Features 12 (16)*

Step 3 :Data Transformation

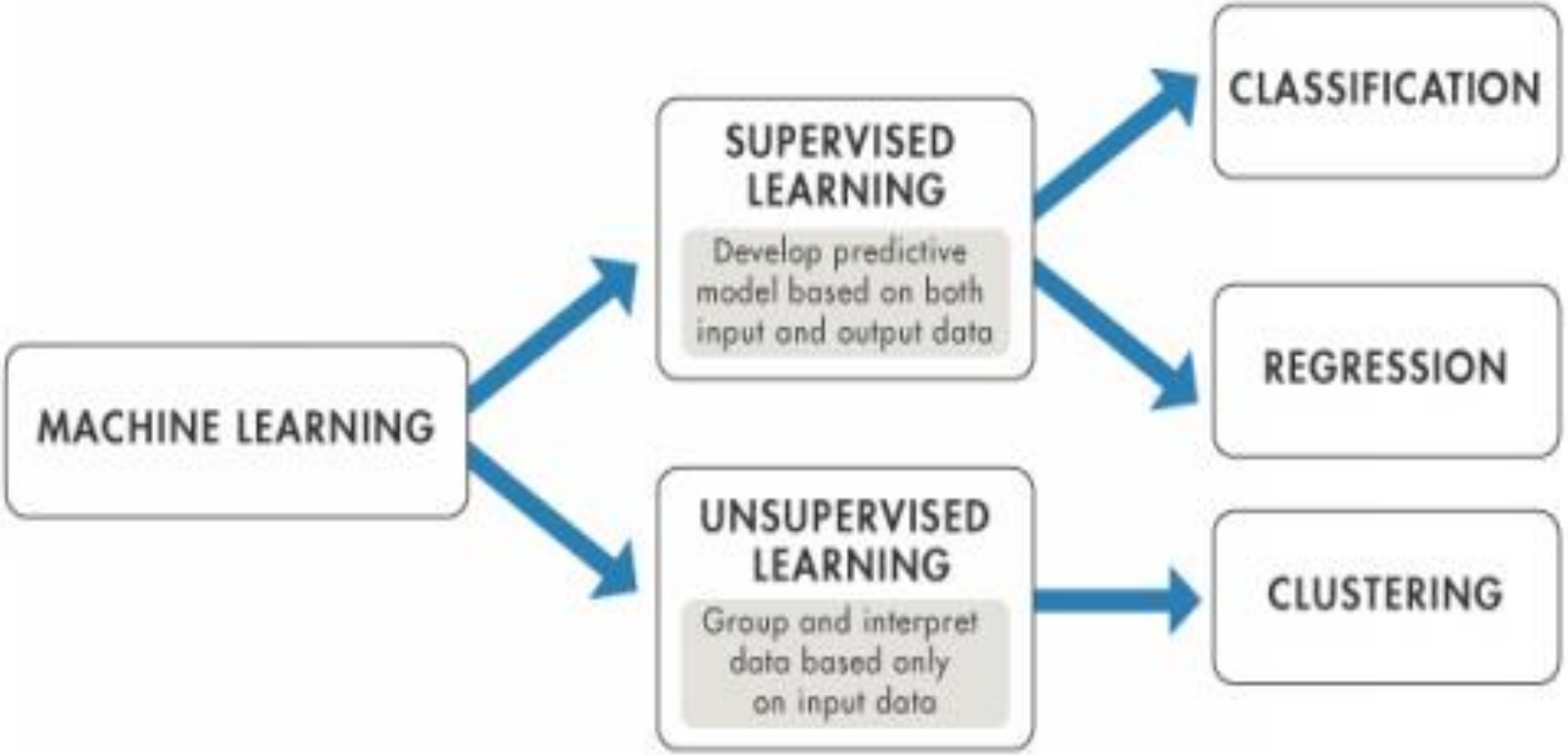
KDD Cup 99 Data Set : 41 attributes + label

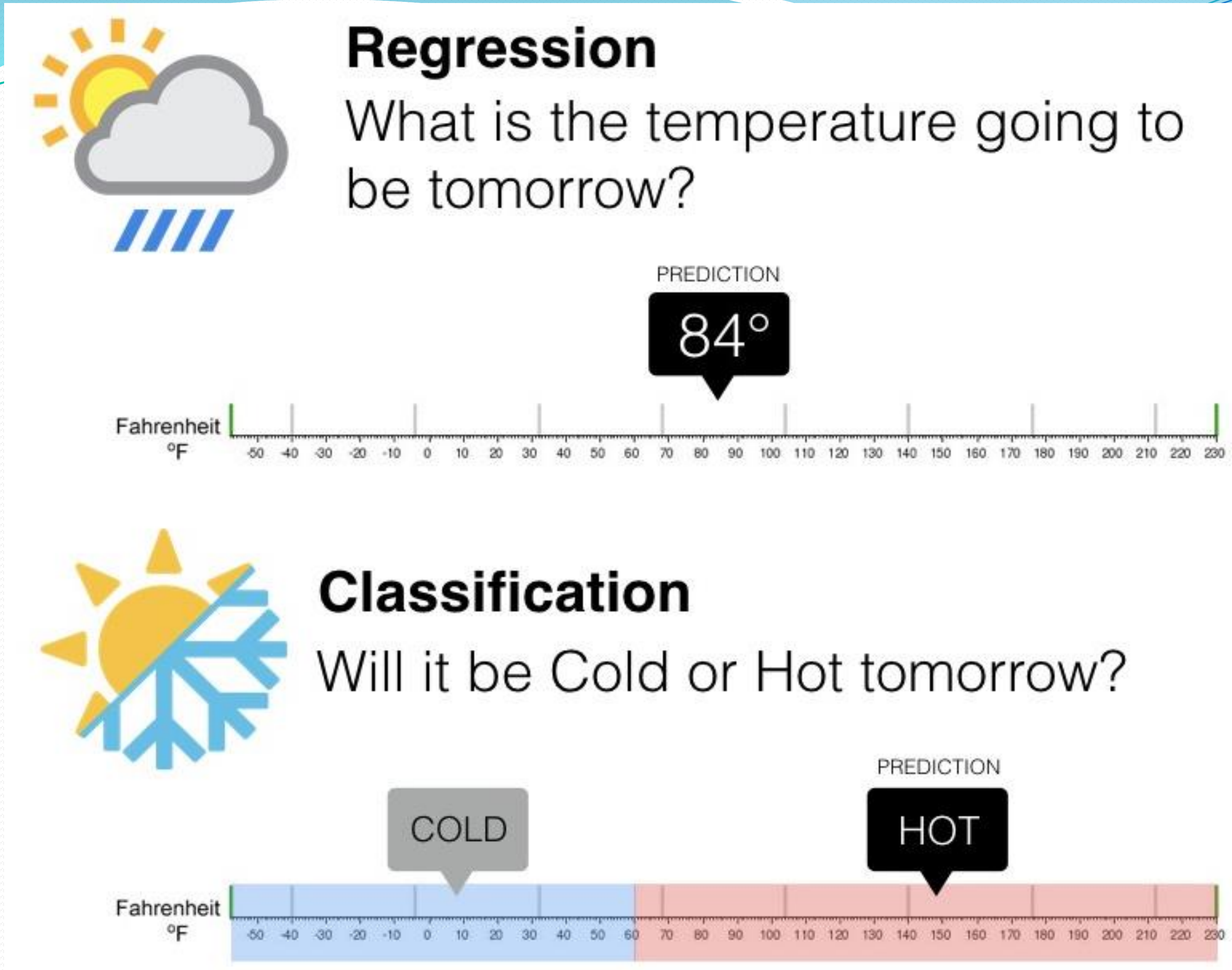
S.NO	FEATURE NAME	S.NO	FEATURE NAME
1	Duration	22	Is_guest_login
2	Protocol type	23	Count
3	Service	24	Serror_rate
4	Src_byte	25	Rerror_rate
5	Dst_byte	26	Same_srv_rate
6	Flag	27	Diff_srv_rate
7	Land	28	Srv_count
8	Wrong_fragment	29	Srv_serror_rate
9	Urgent	30	Srv_rerror_rate
10	Hot	31	Srv_diff_host_r
11	Num_failed_logins	32	Dst_host_coun
12	Logged_in	33	Dst_host_srv_c
13	Num_compromised	34	Dst_host_same
14	Root_shell	35	Dst_host_diff_s
15	Su_attempted	36	Dst_host_same
16	Num_root	37	Dst_host_srv_diff_host_rate
17	Num_file_creations	38	Dst_host_serror_rate
18	Num_shells	39	Dst_host_srv_serror_rate
19	Num_access_shells	40	Dst_host_rerror_rate
20	Num_outbound_cmds	41	Dst_host_srv_rerror_rate
21	Is_hot_login		

Category	Class label(attack) in dataset
DOS-Denial of service	back,land, pod, neptune, smurf, teardrop
R2L-Remote to local	ftp_write, guess_passwd, imap, multihop, phf, spy, warezclient
U2R-User to root	Buffer_overflow, loadmodule, perl, rootkit
Probe	Ipsweep, nmap, portsweep, satan

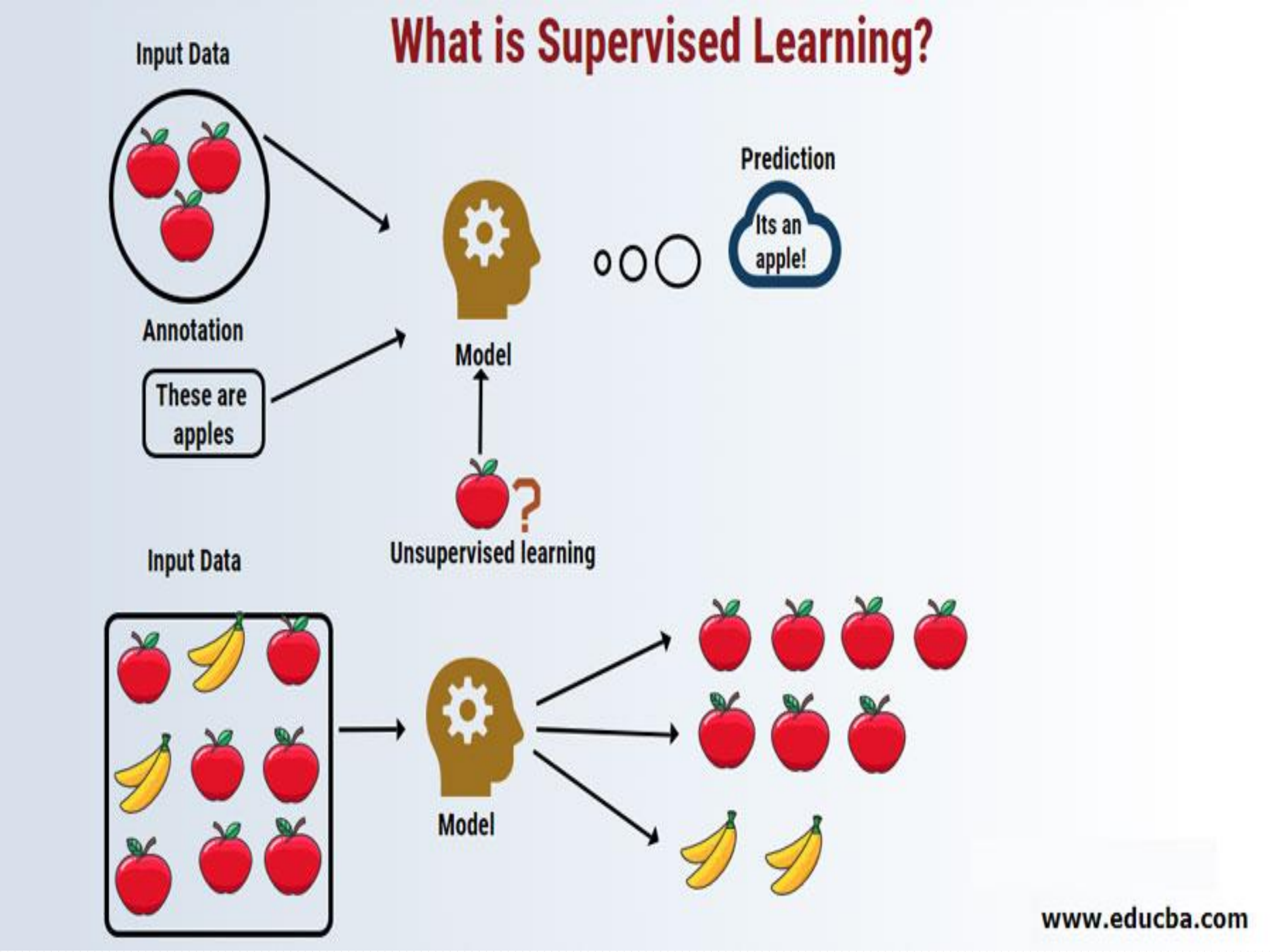

Data Mining Techniques
Anomaly Detection
Regression Analysis
Association Learning
Choice Modeling
Data Mining
Clustering Analysis
Rule Induction
Classification Analysis
Neural Networks
www.educba.com

Supervised Learning vs Unsupervised Learning




Regression
What is the temperature going to be tomorrow?
PREDICTION
84°
Fahrenheit
°F
-50 -40 -30 -20 -10 0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180 190 200 210 220 230
Classification
Will it be Cold or Hot tomorrow?
PREDICTION
COLD
HOT
Fahrenheit
°F
-50 -40 -30 -20 -10 0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180 190 200 210 220 230

Supervised Learning



Data Mining for Signature-based IDS

Misuse Detection – Building Predictive Models

Tid	SrcIP	Start time	Dest IP	Dest Port	Number of bytes	Attack
1	206.135.38.95	11:07:20	160.94.179.223	139	192	No
2	206.163.37.95	11:13:56	160.94.179.219	139	195	No
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6	206.163.37.95	11:14:35	160.94.179.253	139	177	No
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	categorical	temporal	categorical	continuous	class
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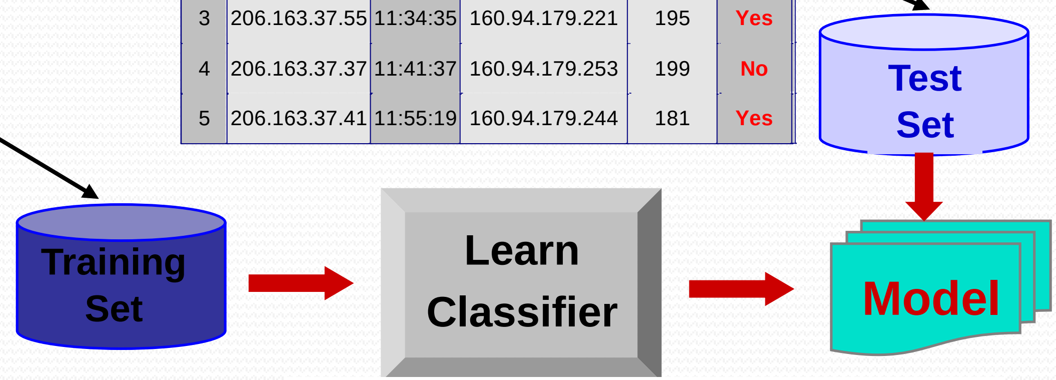
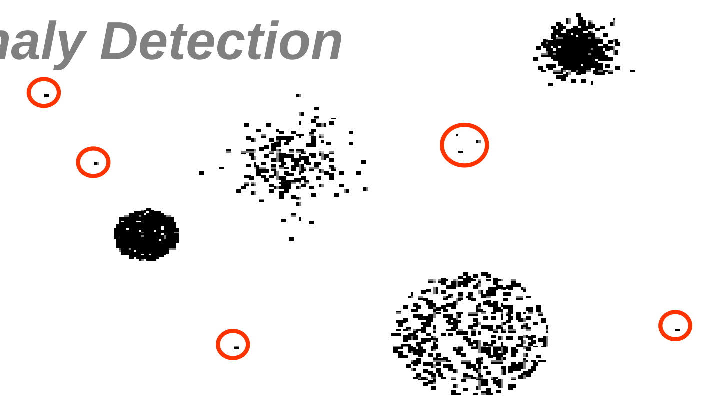


Summarization of attacks using association rules

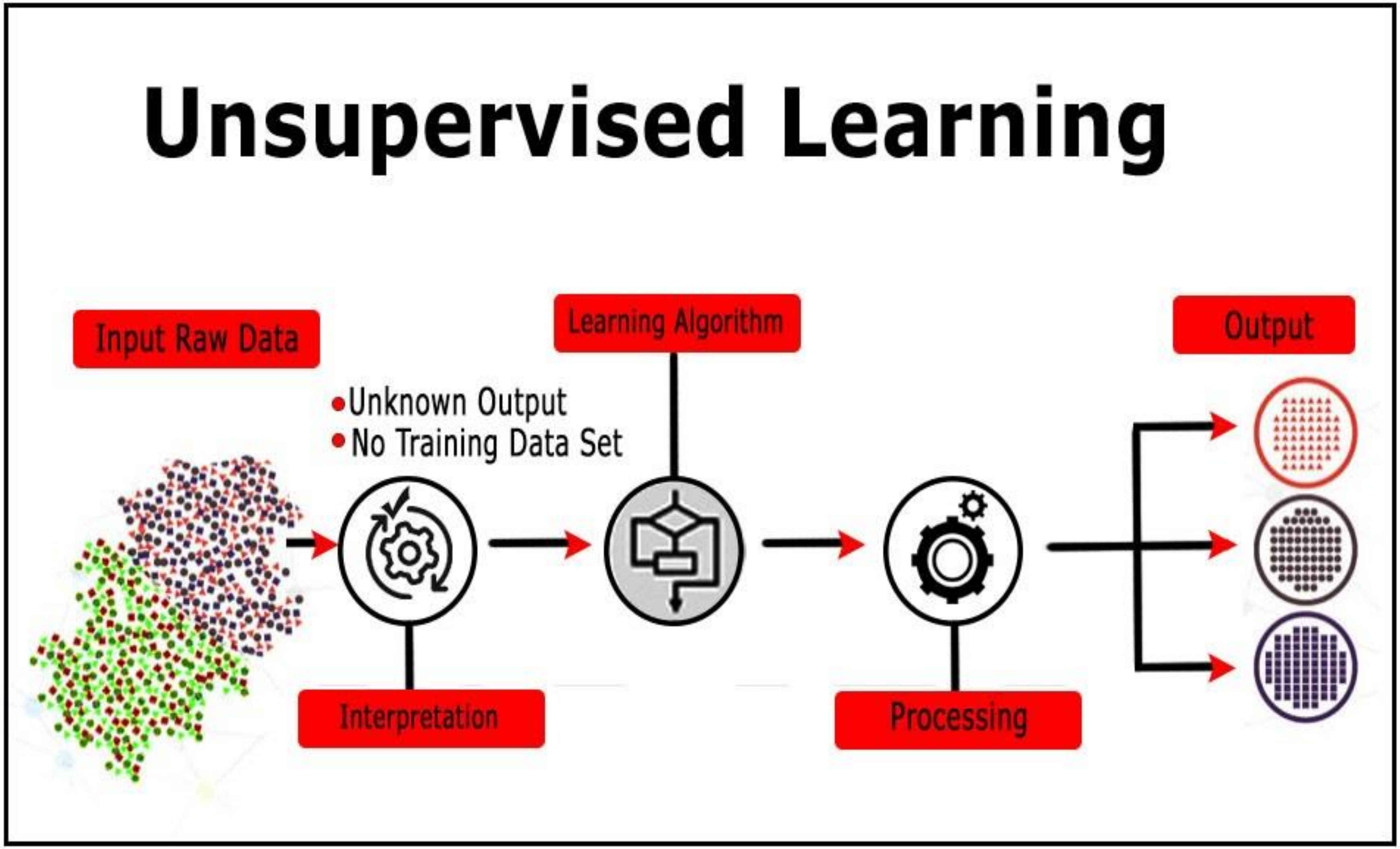
Rules Discovered:

{Src IP = 206.163.37.95,
Dest Port = 139,
Bytes ∈ [150, 200]} --> {ATTACK}

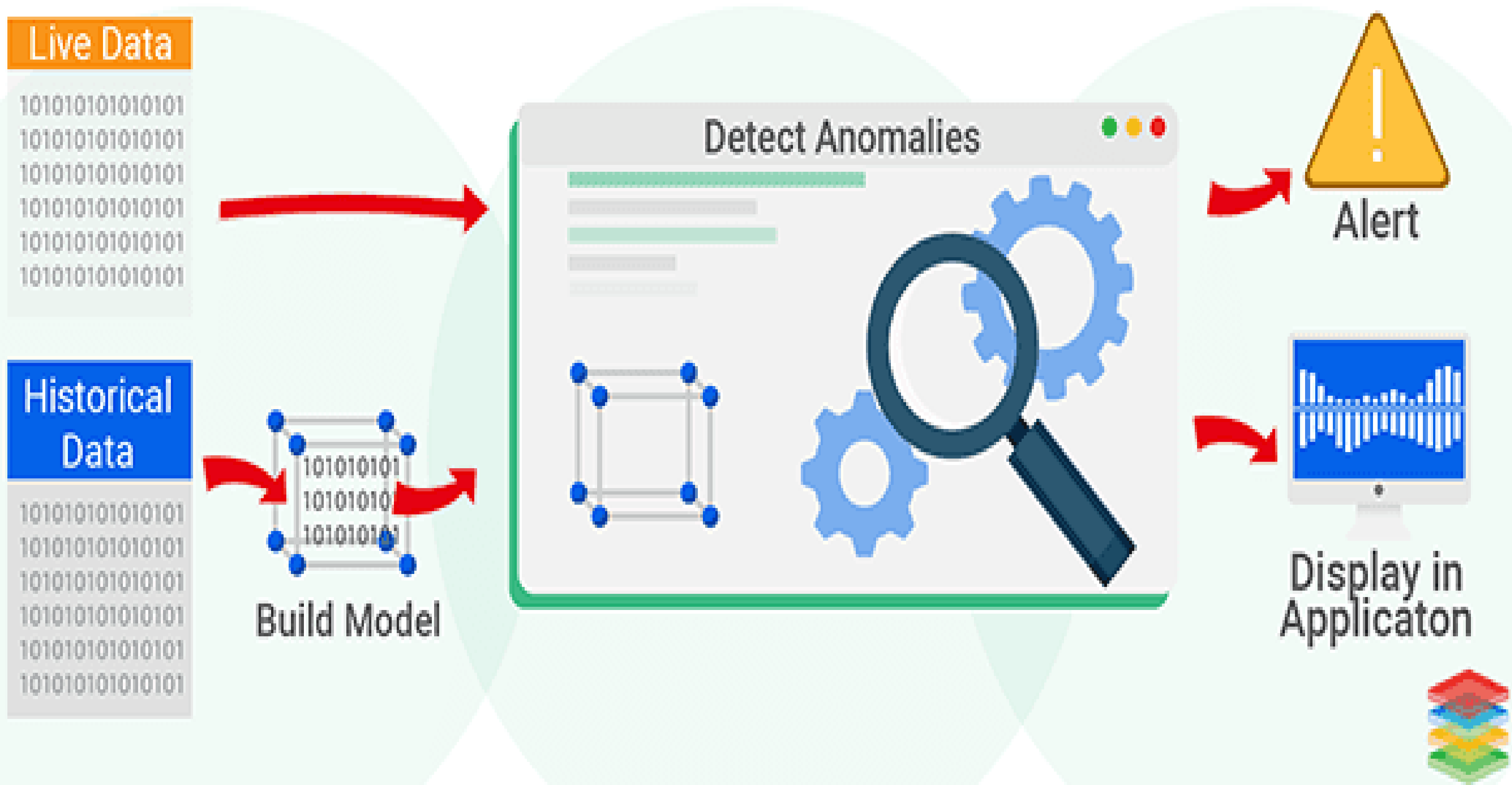
Anomaly Detection



Unsupervised Learning



Real Time Anomaly Detection

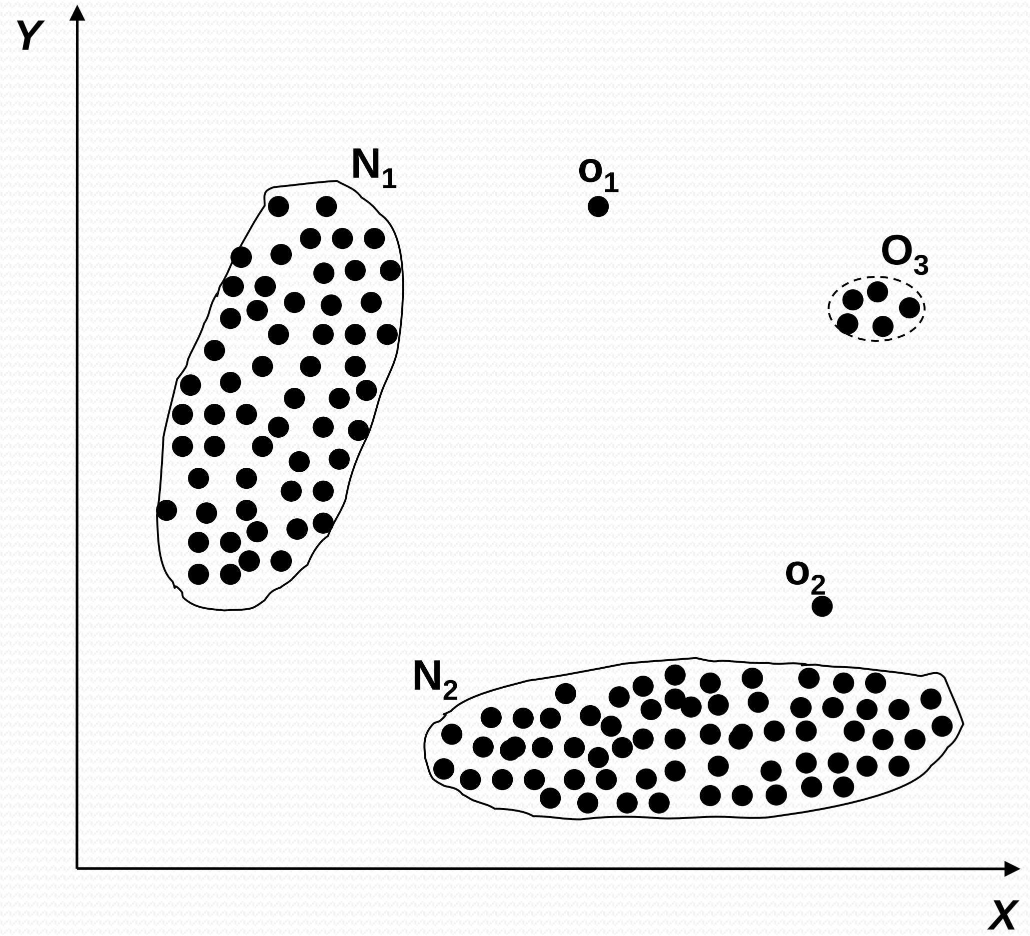


What are Anomalies?

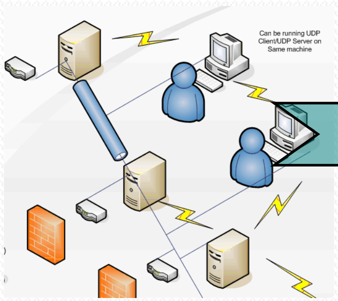
- Anomaly is a pattern in the data that does not conform to the expected behavior
- Also referred to as outliers, exceptions, peculiarities, surprise, etc.
- Anomalies translate to significant (often critical) real life entities
  - Cyber intrusions
  - Credit card fraud

Simple Example

- N_1 and N_2 are regions of normal behavior
- Points o_1 and o_2 are anomalies
- Points in region O_3 are anomalies



Using Clustering for Intrusion Detection



A Set of Unlabeled Data

Unsupervised Anomaly Detection Algorithm

Detected Intrusion Clusters

Connection Comparison with Detected Clusters

Detected malicious attacks

<u>Assumptions for unsupervised anomaly detection algorithm:</u>

1. The intrusions are rare with respect to normal network traffic.

2. The intrusions are different from normal network traffic.

<u>As a Result</u>:

The intrusions will appear as outliers in the data.

Using Clustering for Intrusion Detection

Once data is clustered, all of the instances that appear in small clusters are labeled as anomalies because;

- The normal instances should form large clusters compared to the intrusions,
- Malicious intrusions and normal instances are qualitatively different, so they do not fall into the same cluster.