System Health Monitoring and Reactive Measures Activation

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- **Alert optimization**
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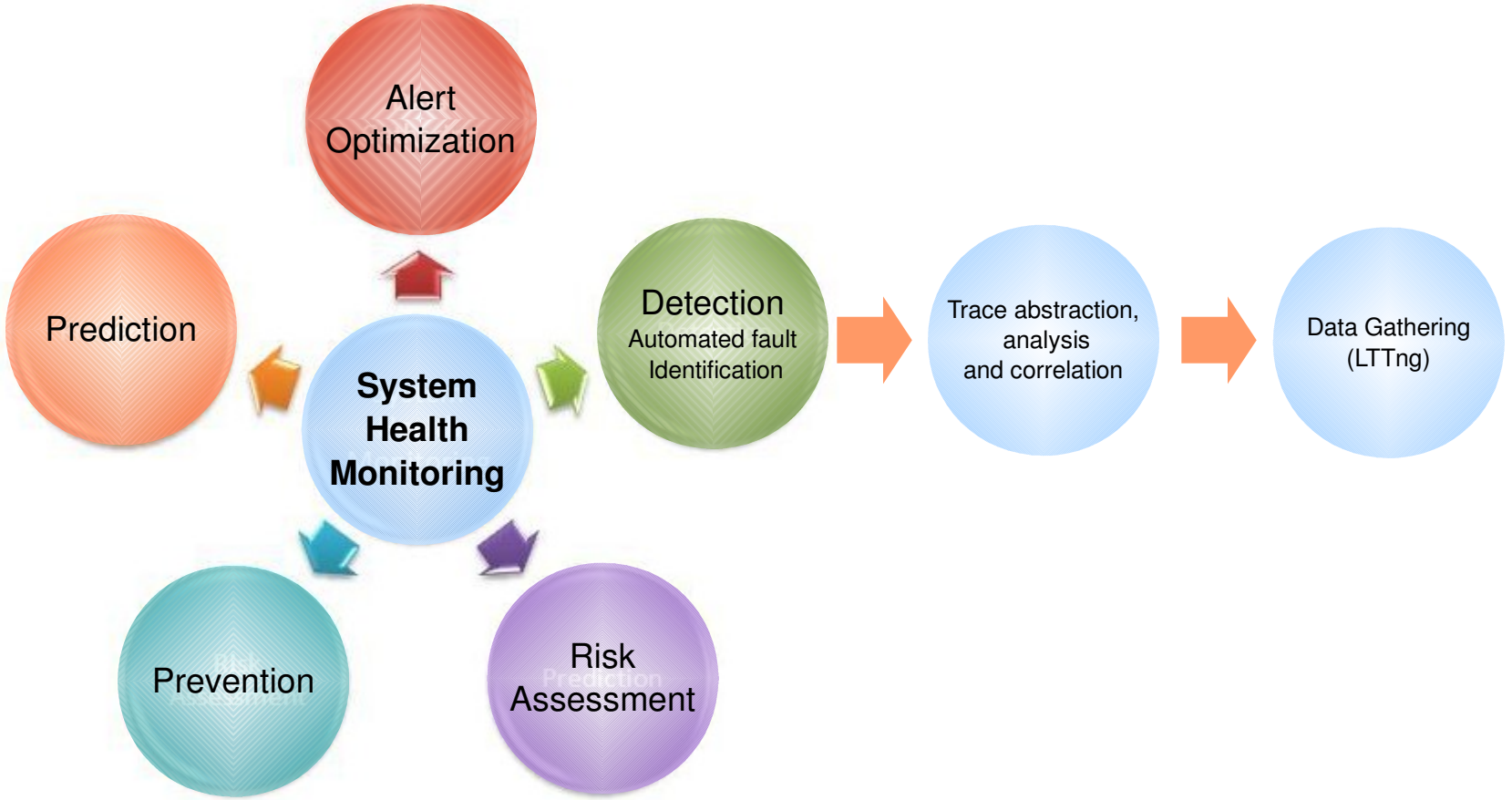
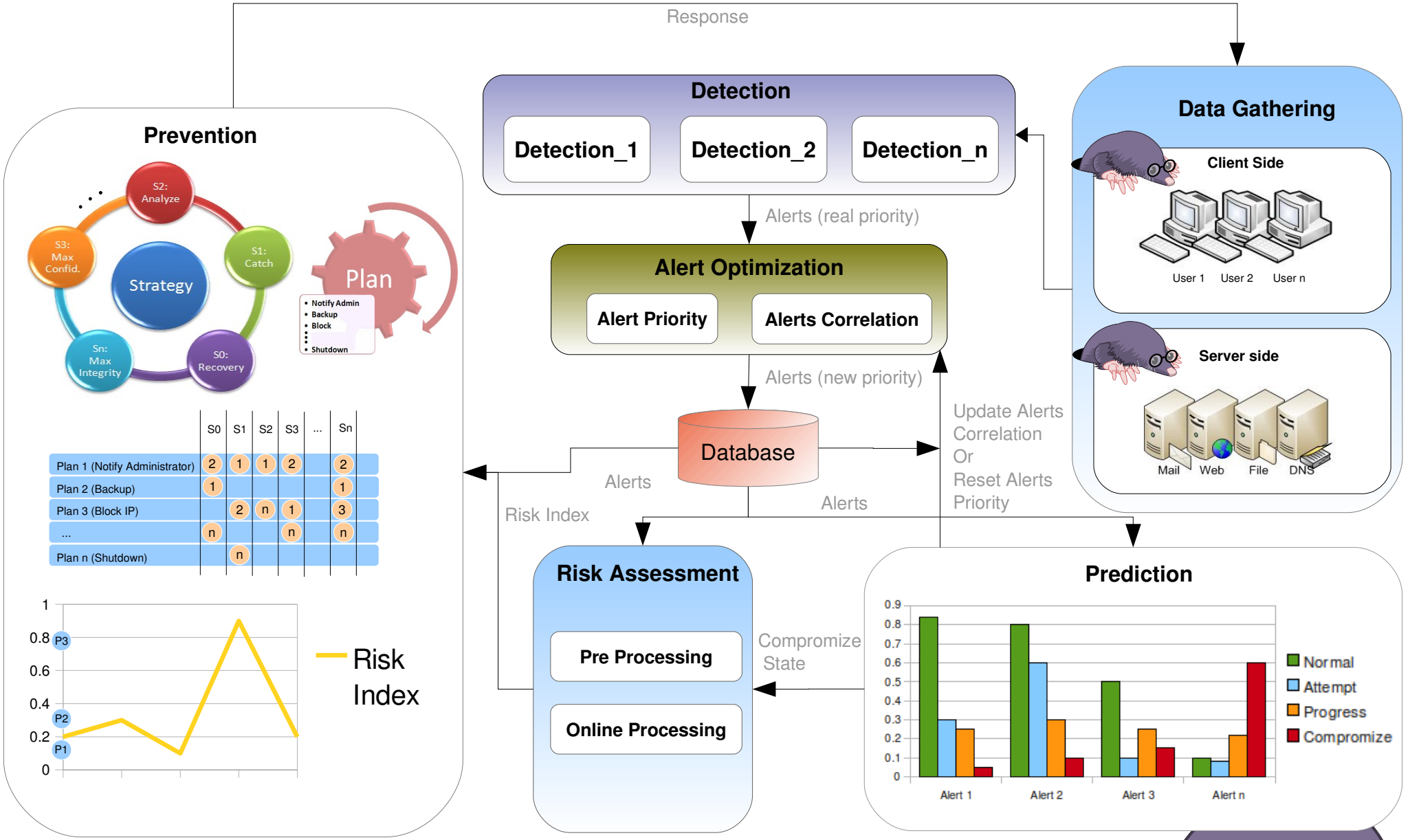
System Health Monitoring and Reactive Measures Activation

SHM continuously monitors the health of a multi-core distributed system so that system anomalies (bad behaviors and attacks) can be detected and handled appropriately

System Health Monitoring Components



System Health Monitoring Architecture



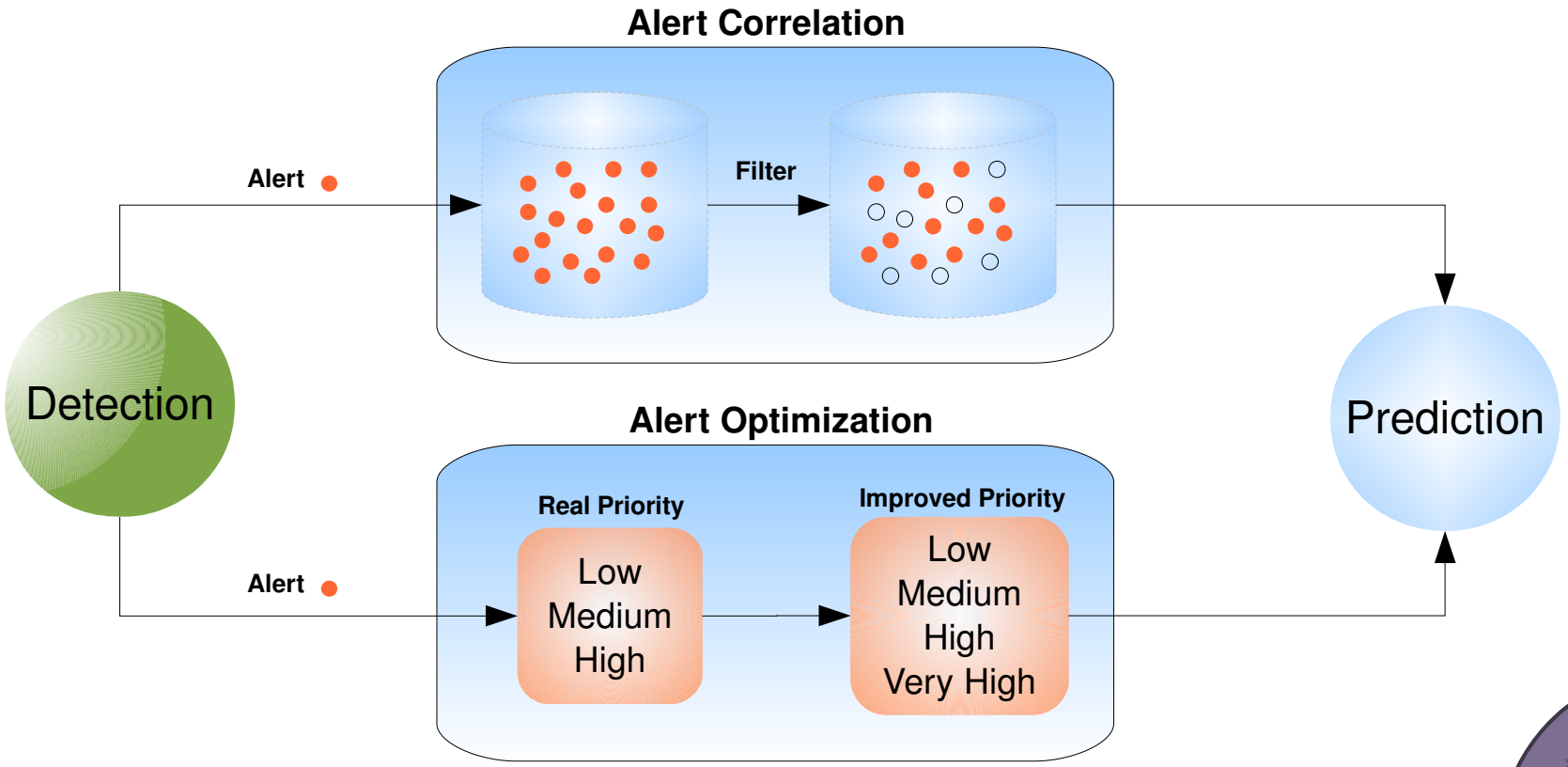
Alert Optimization

Alert Optimization (1)

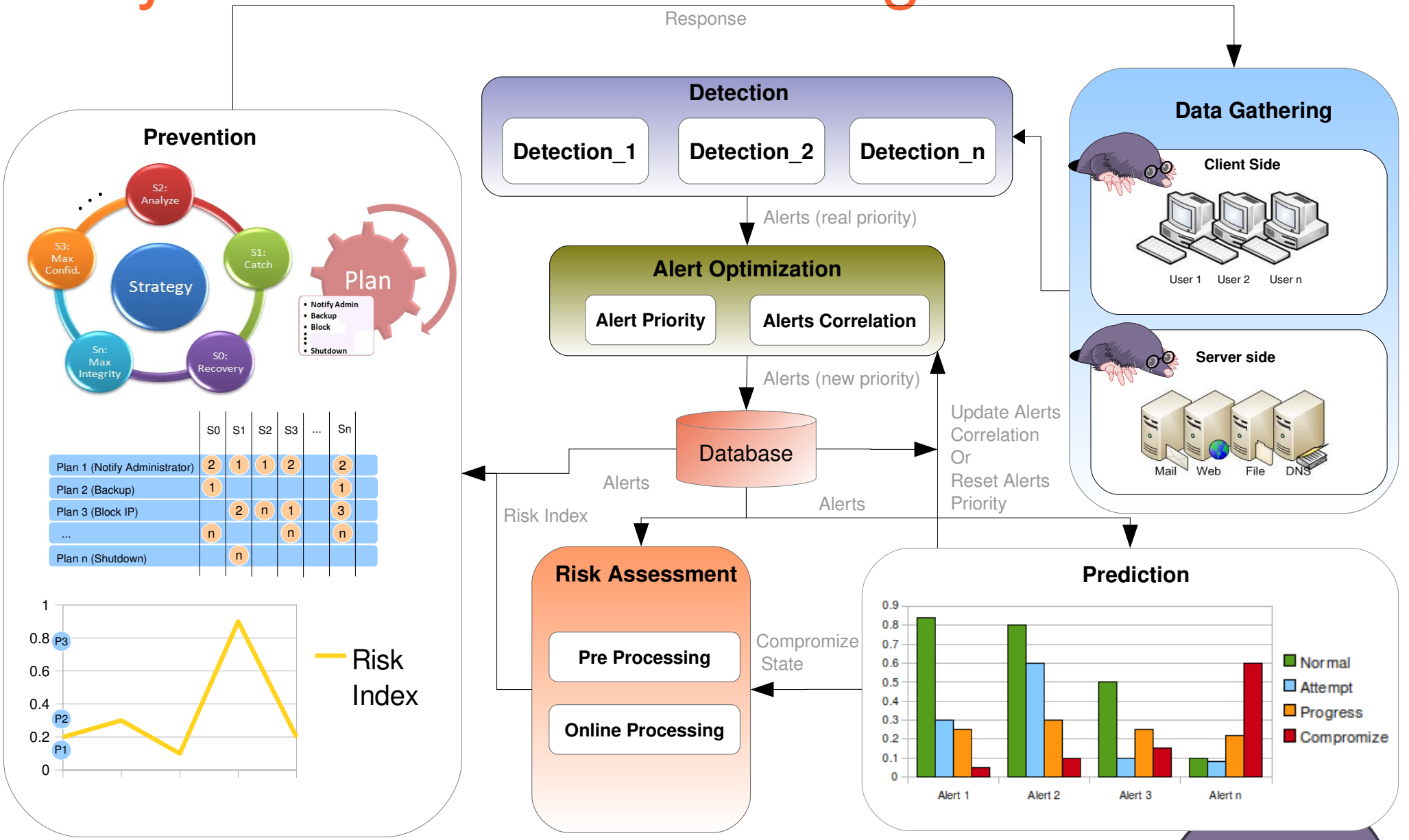
- Alert correlation means to extract true alerts from alerts generated by detection component (filter view)
- In this project, we have taken a different view comparing to the filter view
- Multi steps attack's actions are unknown but may be partially detected by detection component and reported as alerts

Alert Optimization (2)

- Alert optimization component **increases alert priority with correlation concepts**



System Health Monitoring Architecture



Alert Optimization (3)

- Alerts Correlation
  - Alerts correlation shows correlation weights between any two alerts
  - It plays an important role in attack prediction
  - It is defined by expert persons
  - It will be updated by receiving hints from prediction component. It happens whenever the probability of progress state is more than 90%

	Alert 1	**Alert 2**	**Alert 3**	**Alert n**
Alert 1	W11	W12	W13	W1n
Alert 2	W21	W22	W23	W2n
Alert 3	W31	W32	W33	W3n
Alert n	Wn1	Wn2	Wn3	Wnn

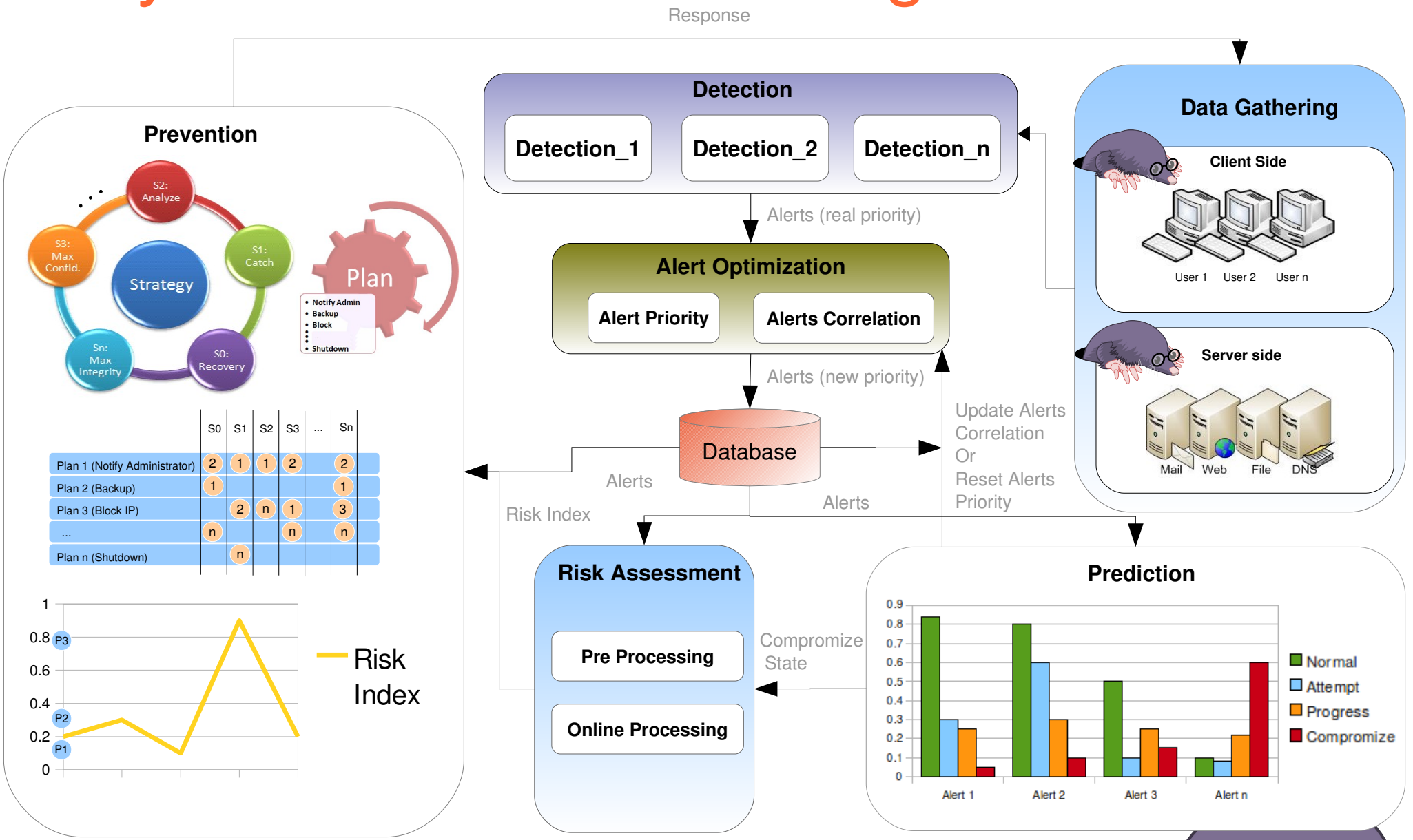
Alert Correlatiom Matrix (ACM)

Alert Optimization (4)

- Alert Priority
  - Alert priority is computed by an exponential formula
  - At the beginning, it is equal to the real priority of alert
  - The equation for each alert is : $f_{\text{priority}} = e^{E*N/(K*A-E*N)}$
    - E (Effect of Alert): It is extracted from the Alert Correlation Matrix and is varied if ACM is updated
    - N (Frequency of each Alert)
    - A (Acceptable number of alert per day)
    - K (Empirical constant): Function has good results with K=200
  - *f* is reset when prediction component sent a message that an intrusion will be happend

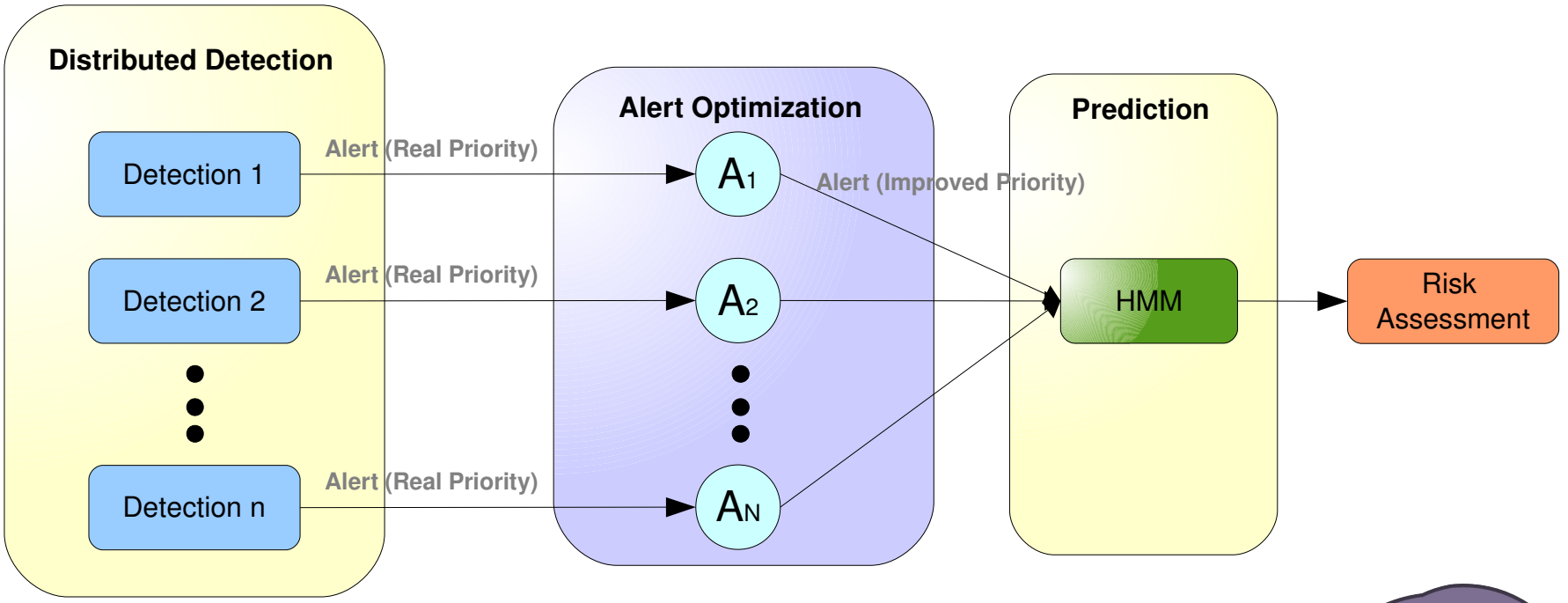
Prediction

System Health Monitoring Architecture

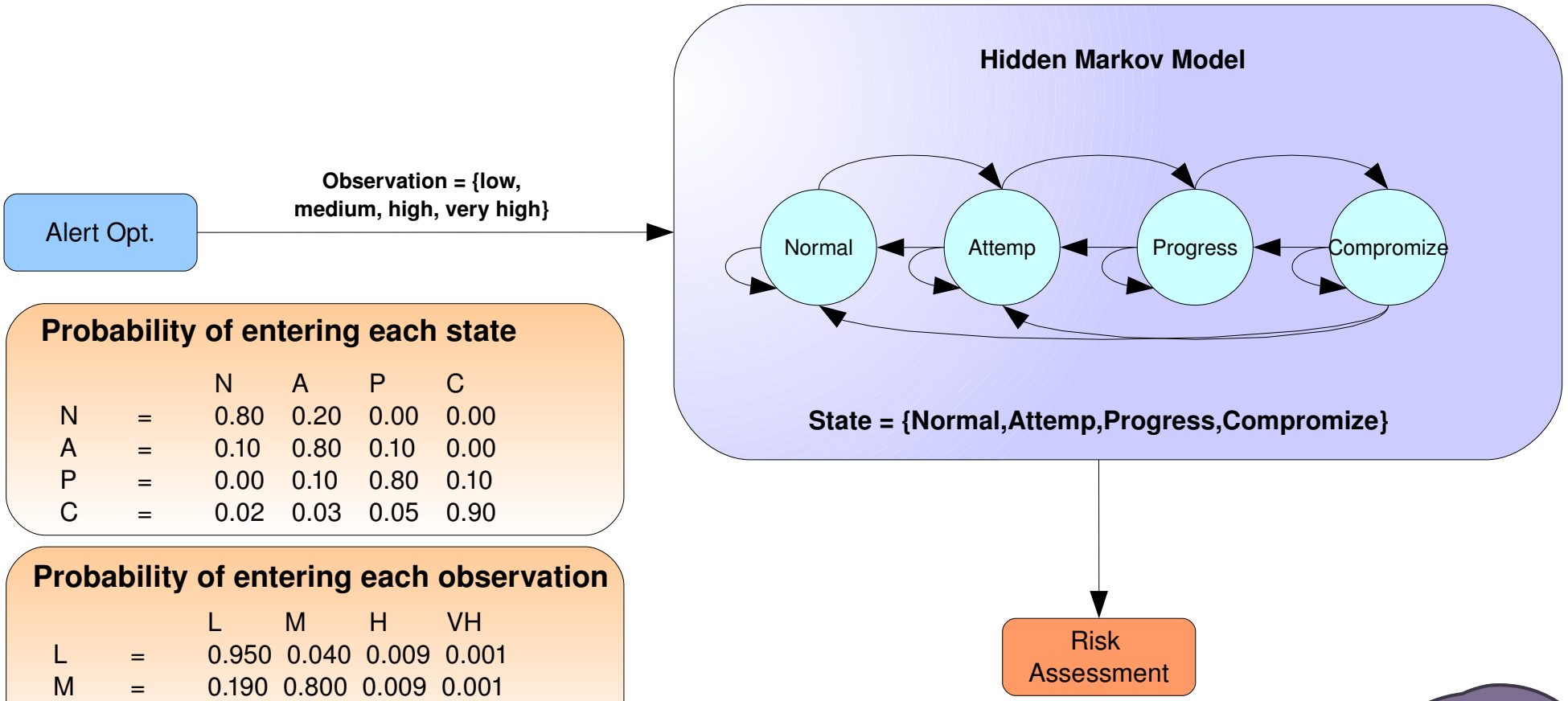


Prediction Structure

- The prediction component will attempt to make a prediction of a possible future problem
- A model is needed to capture the interaction between the attacker and the distributed network



Prediction Algorithms-HMM



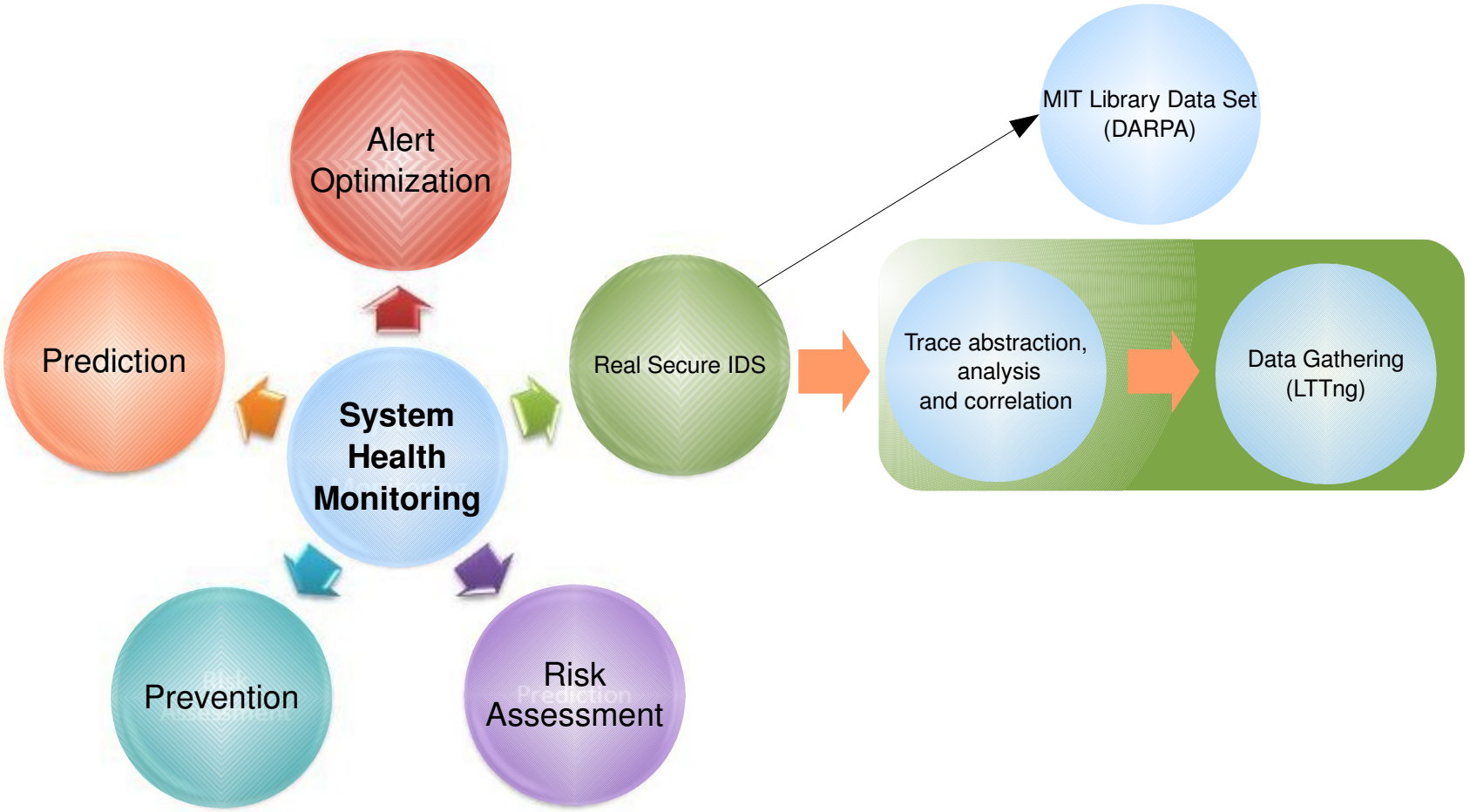
Probability of entering each state

		N	A	P	C
N	=	0.80	0.20	0.00	0.00
A	=	0.10	0.80	0.10	0.00
P	=	0.00	0.10	0.80	0.10
C	=	0.02	0.03	0.05	0.90

Probability of entering each observation

		L	M	H	VH
L	=	0.950	0.040	0.009	0.001
M	=	0.190	0.800	0.009	0.001
H	=	0.010	0.190	0.700	0.100
VH	=	0.010	0.040	0.200	0.750

Prediction Results (1)



Prediction Results (2)

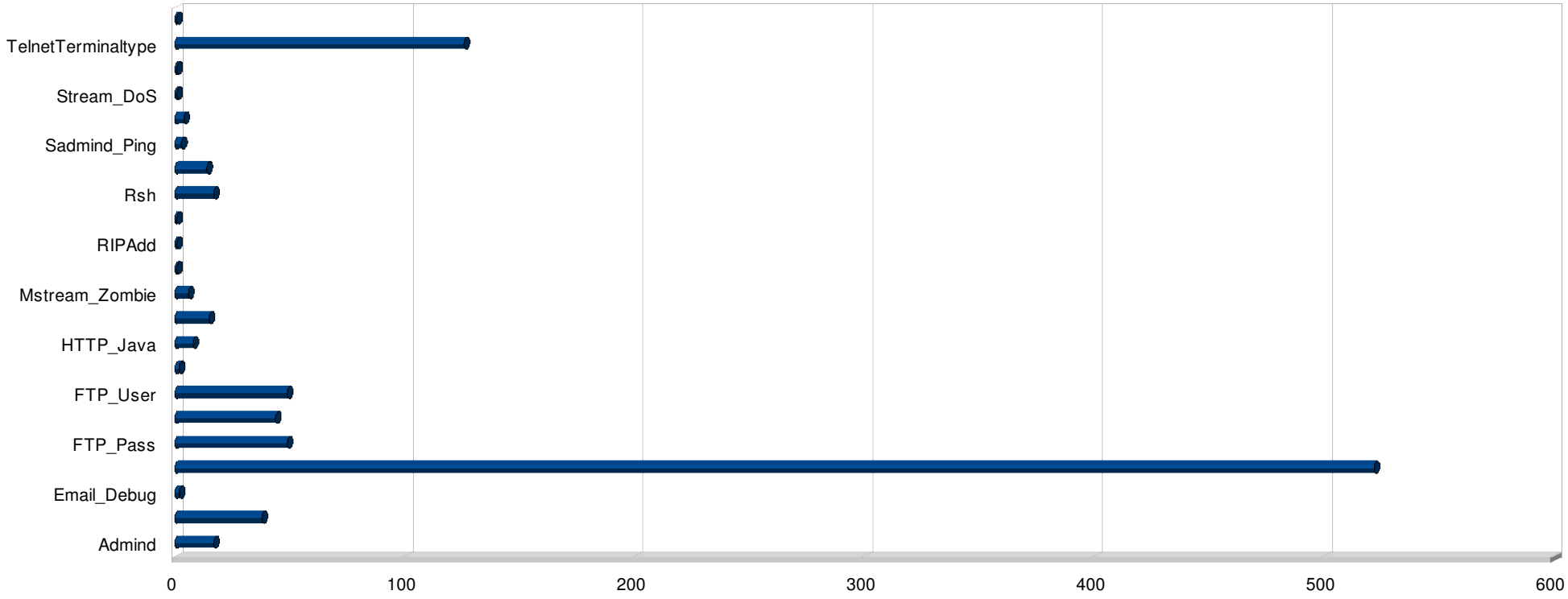
- Lincoln Laboratory 2000 data set (DARPA)
- The data set contains more than 3 hours of intrusion detection data
- The data set contains an attack in 5 phases
- Finally, 3 hosts are attacked and compromised

Prediction Results (3)

Phase	Name	Time	Goal
1	IP sweep	9:45 to 09:52	The attacker sends ICMP echo-requests in this sweep and listens for ICMP echo-replies to determine which hosts are "up"
2	Sadmind Ping	10:08 to 10:18	The hosts discovered in the previous phase are probed to determine which hosts are running the "sadmind" remote administration tool. This tells the attacker which hosts might be vulnerable to the exploit that he/she has
3	Break into	10:33 to 10:34	The attacker then tries to break into the hosts found to be running the sadmind service in the previous phase. Breakins via the sadmind vulnerability
4	Installation	10:50	Installation of the trojan mstream DDoS software on three hosts
5	Launch	11:27	Launching the DDoS

Prediction Results (4)

- RealSecure generates 922 alerts based on DDOS1.0

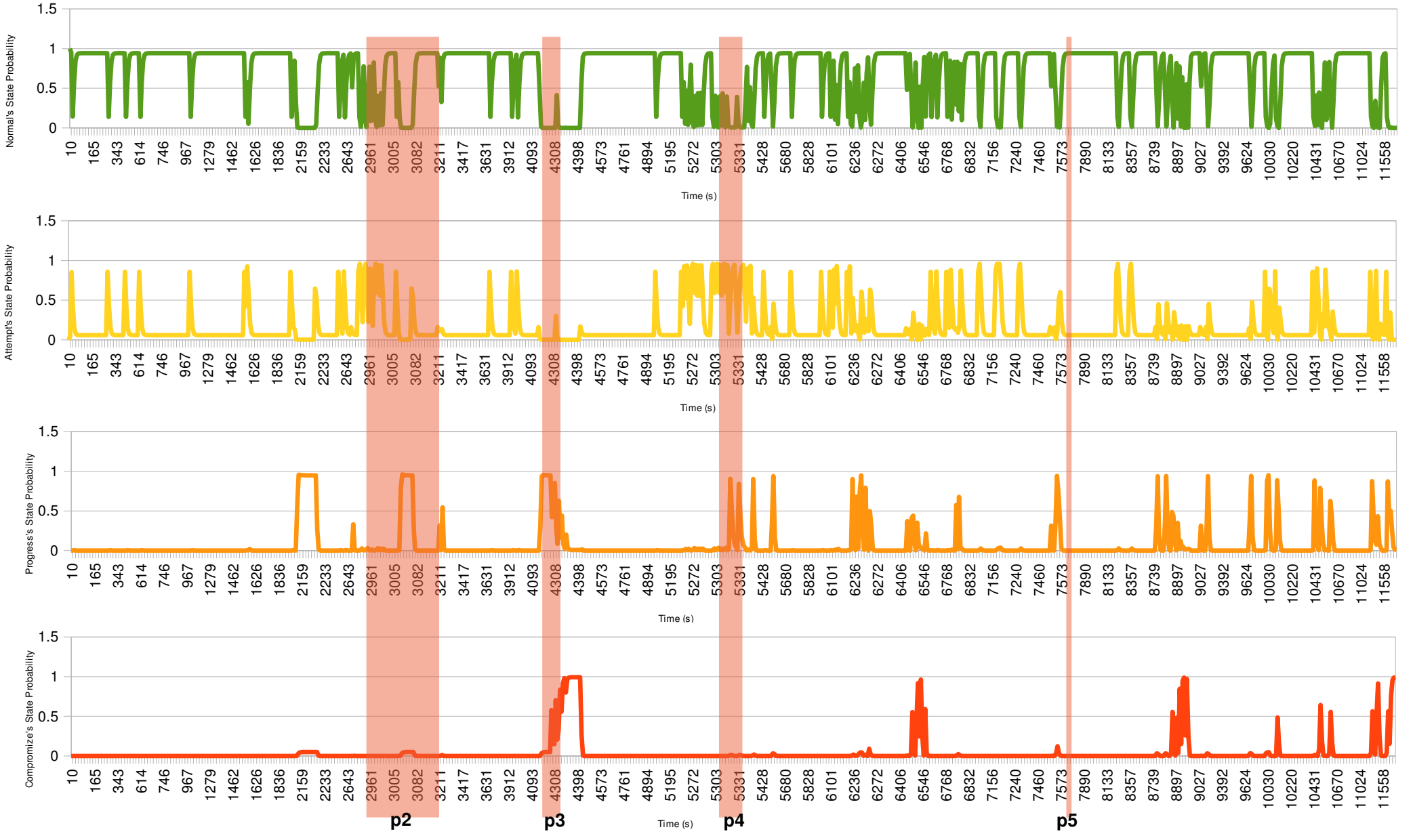


Prediction Results (5)

- RealSecure generates this alerts for each phases

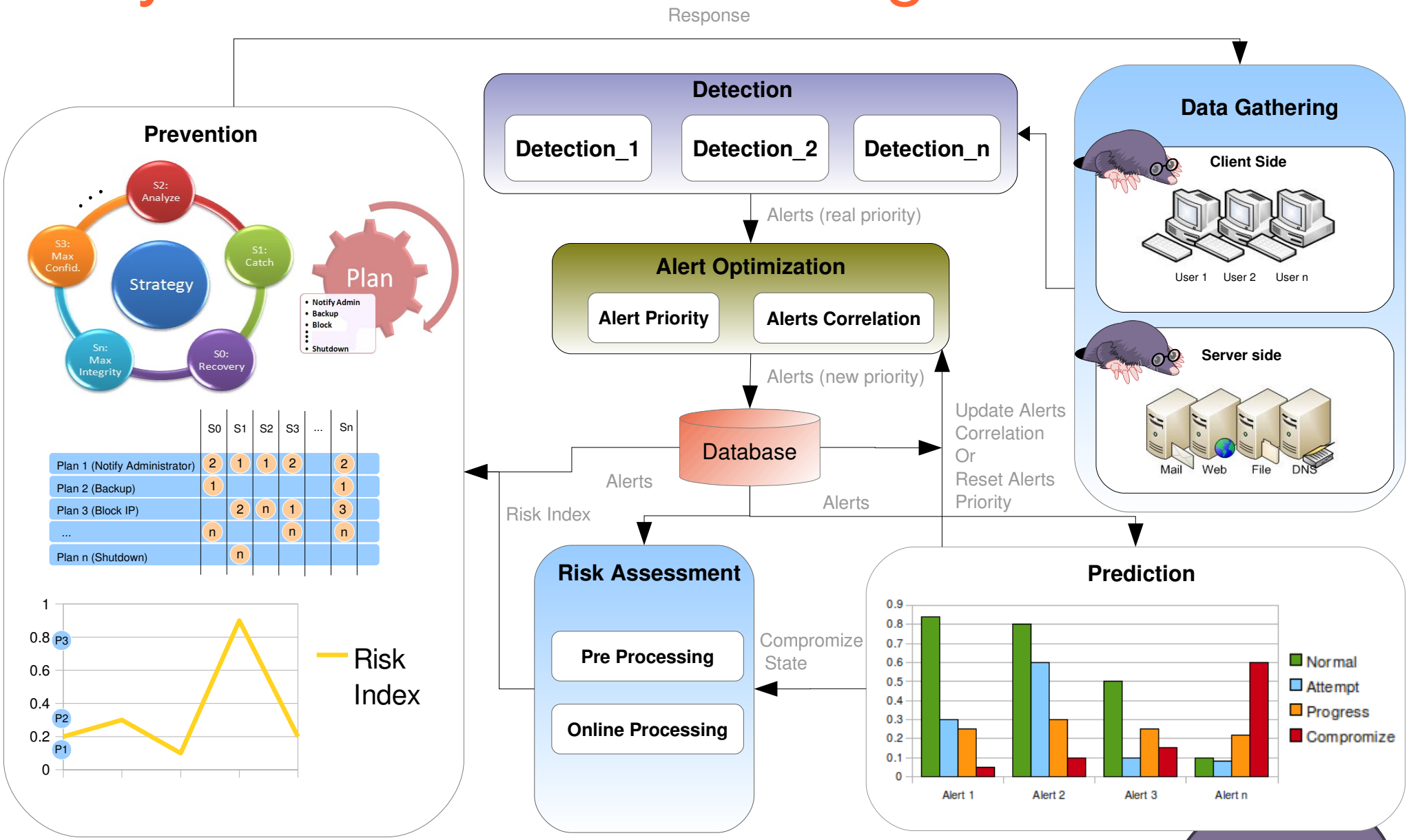
Phase	Name	Alerts
1	IP sweep	No alert is generated for this phase
2	Sadmind Ping	Sadmind_ping
3	Break into	Sadmind_Amslverify_Overflow, Admind
4	Installation	Rsh, MStream_Zombie
5	Launch	Stream_DOS

Prediction Results (7)



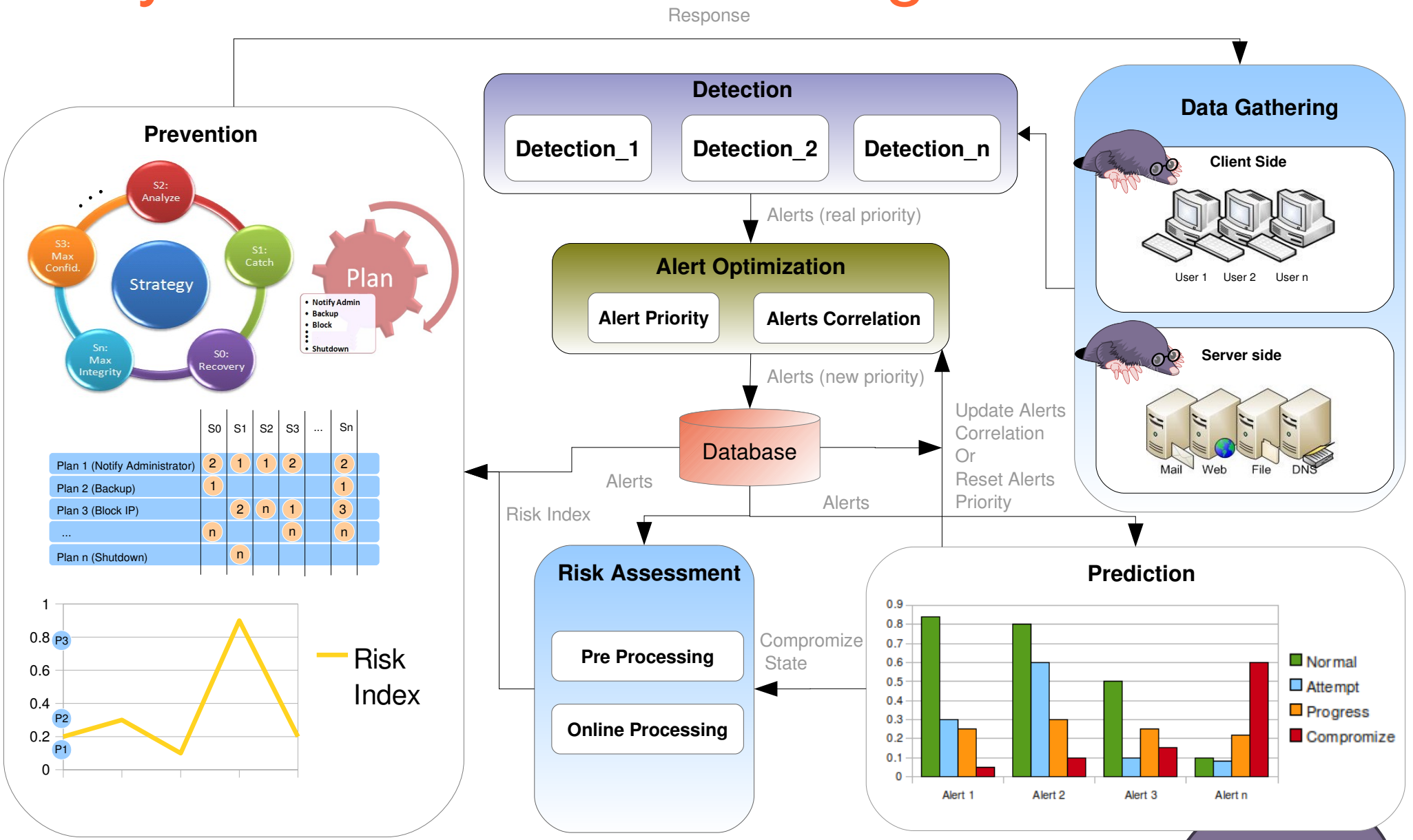
Risk Assessment

System Health Monitoring Architecture



Prevention

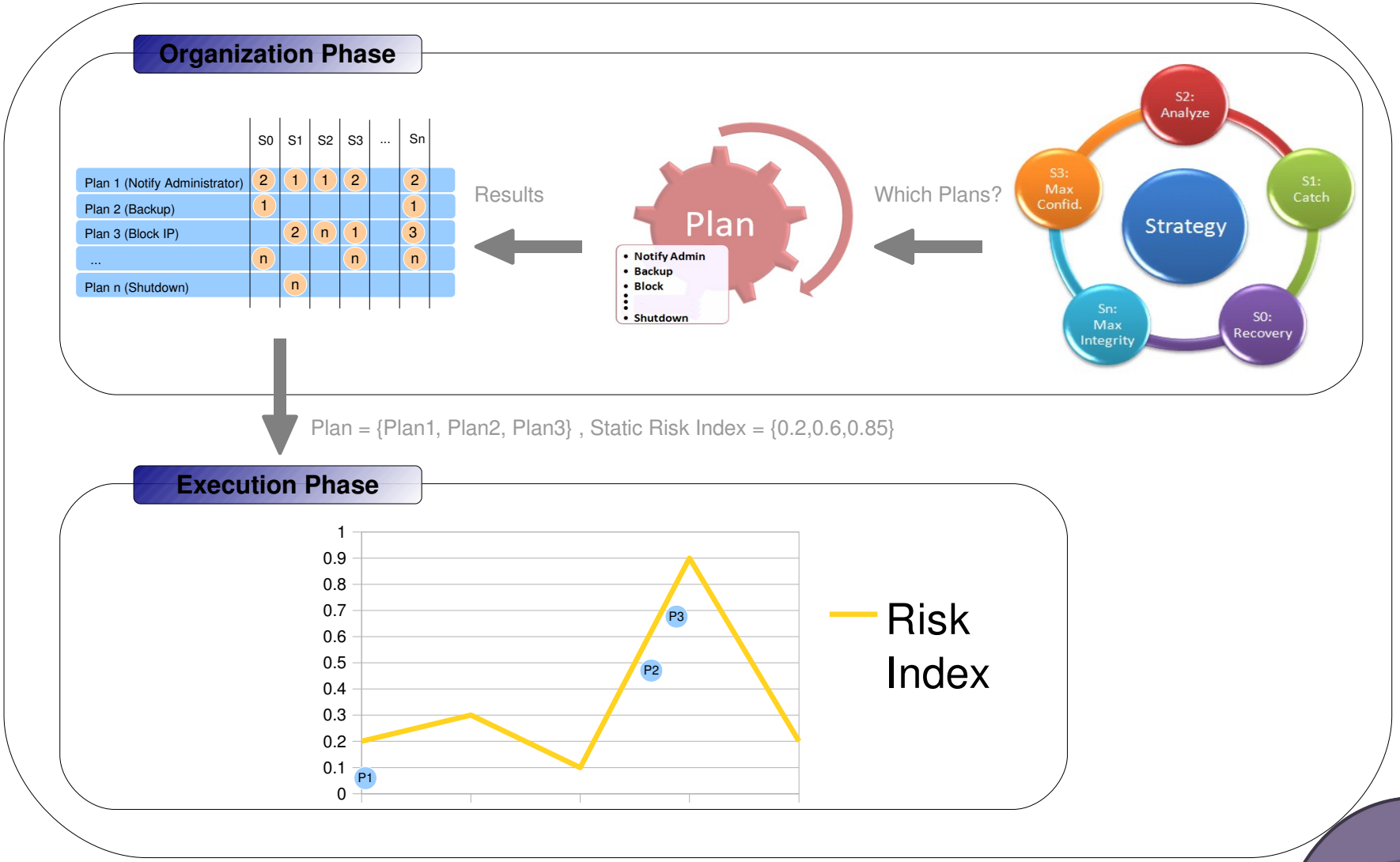
System Health Monitoring Architecture



Prevention

- Prevention component will try to run good strategies for trigger reactive measures with the objective of:
  - Preventing the problem growth
  - Returning system to the healthy mode

Prevention Structure



Prevention - Plan

- IP Blocking
- Dropping Packets
- Killing Process
- Reboot
- Shutdown
- TCP Reset
- Delete files
- Run Virus Check
- Turn off the services
- Applying Patch

- Change All Passwords
- Format the Hard Disk
- ...
-

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Thank you