



# Enabling Predictive Maintenance using **NLP**

—  
CASE STUDY : MIST

# Background

## CLIENT

Mist Systems, Inc.

## INDUSTRY

Wireless Network

## HEADQUARTERS

San Francisco, USA

## FOUNDERS

Bob Friday, Brett Galloway  
& Sujai Hajela

## FOUNDED

2014

## ACQUIRED BY

Juniper Networks in 2019

<https://www.mist.com>



**Mist Systems** is the world's first intelligent wireless network products developer that leverages machine learning. It builds innovative products to improve the user experience for wireless network users and helps enterprises with proactive network management.

# Challenges

Mist Systems aimed to automate predictive maintenance for early fault detection, diagnosis, and prevention of the loss of service. This implementation required detecting anomalies from the kernel logs in wireless access points to identify the root cause. But the implementation involved some key challenges:



## Volume of logs

Kernel logs size was 2-3GB data and ~100,000 log entries per day.



## Variations for a fault

The same type of fault had different logs across different access points.



## Types of faults

It should detect several types of faults, including critical ones.

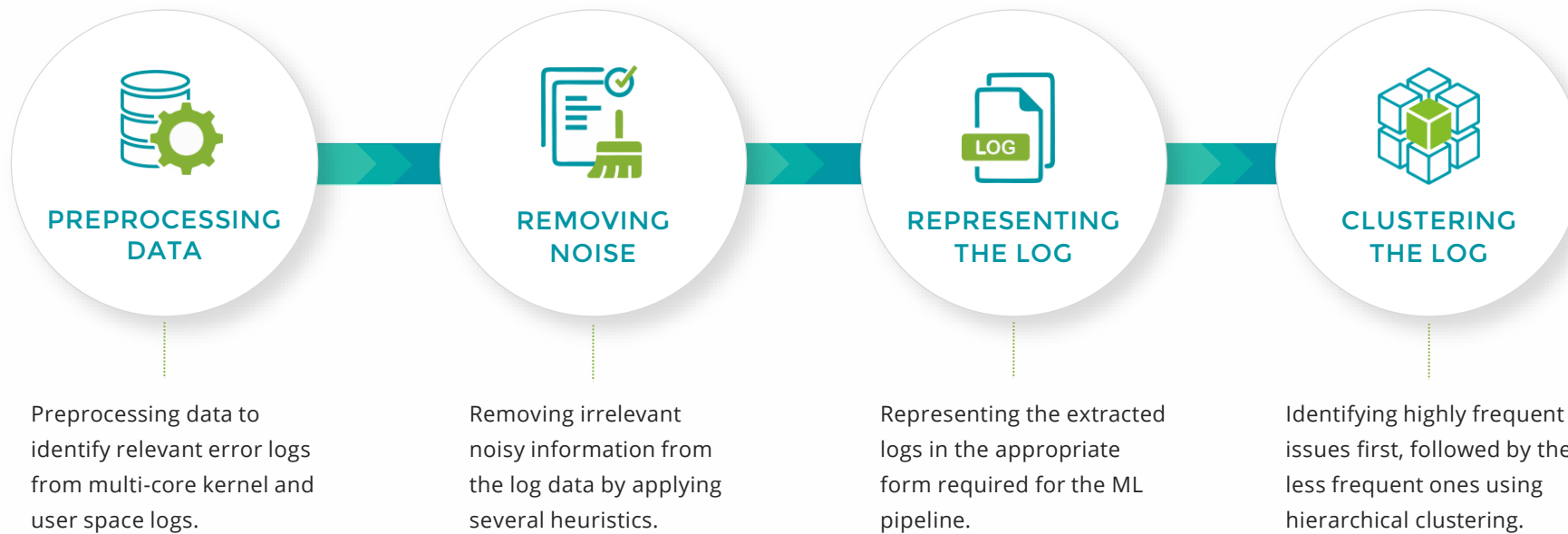


## Continuous monitoring

The implementation should continuously monitor and report potential faults.

## Solution

We could not use readily available solutions either because they are too customized or are meant for a specific set of application logs. We decided to build the solution on both Google Cloud Platform (GCP) and Amazon Web Services (AWS) considering the platforms used by existing customers.



## Solution

Clustering could identify issue-specific clusters with direct indicators. But the clusters with indicators for various generic issues required a different solution.



### DIFFERENTIATING ISSUES

Intra- and inter-cluster quality measures were identified to differentiate the specific problems from generic ones.



### INTRODUCING AUTOMATED PIPELINE

Our automated pipeline ensured that we always identify new issues and create Jira IDs accordingly instead of re-creating old issues.

## Results

**Clusters** at different hierarchies had different performances. **Top-level clusters** had high log quantity but were less in numbers. **Lower-level clusters** were high in number but had fewer logs, thereby resulting in more cluster similarity. A firmware team manually evaluated our clusters.



### Better Coverage

**80-85%** of the known and unknown issues were covered in 2 levels of hierarchical clustering.



### Higher Accuracy

The combined accuracy of clusters from the first two hierarchies was around **80%**.

*The percentage is extremely high considering variations in logs for the same issues and over 70% irrelevant loglines in each file.*



### Faster Turnout Time

Our system design ensured a turnout time of fewer than **2 hours**, implying an issue can be identified as early as 2 hours of its occurrence if it is seen in many devices.



[www.talentica.com](http://www.talentica.com)

---

## Let's Disrupt Together!

SUITE 300, 6200 STONERIDGE MALL  
ROAD, PLEASANTON, CA 94588

---

B-7/8, ANMOL PRIDE, BANER,  
PUNE, INDIA - 411045  
+91 20 4660 4000  
[info@talentica.com](mailto:info@talentica.com)

