

Arista AVA: The Power of Al-Driven Networking

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Introduction

Artificial intelligence (AI) has been all over the news especially as large language models like GPT-4 capture the imagination of even the average internet user, let alone the technophiles. These solutions have the potential to change the very definition of the enterprise, what it means to work, and lower the cost of doing business. In parallel, the world is producing data at a blistering pace. A World Economic Forum¹ study estimates that by 2025, we will create 463 exabytes of data daily. For context, that's 463, followed by 18 zeros! Or as the authors put it, "Forty times more bytes than there are stars in the observable universe." Of course, what isn't likely to happen in that same time frame is that humans will suddenly evolve to consider all of that available data, factor probabilities, and make optimal operational choices. That is not to suggest that humans are becoming expendable. Far from it, we have highly tuned abilities to recognize patterns², understand abstract relationships, and generalize. For instance, we don't need hundreds or thousands of training samples to know that a user being targeted by a phishing attempt is the CFO of the organization. We recognize the name right away and our instincts take over to drive remediation next steps. The task at hand then for the Al tools, is to surface just the right information that enables operators to make decisions which ultimately lead to the most favorable business outcomes.

When it comes to IT and security use cases, the network can be foundational to generating the decision support data operators and analysts need. But at the same time, as networks have expanded from campus to data center and cloud, the amount of data to be processed has grown exponentially. So how do you get to the Goldilocks balance of "just right" information? It comes down to two key capabilities:

- A system to efficiently and in real-time collect the ground truth data.
- Intelligence to extract the information and context buried within the raw data and present it to the operator.

Arista is uniquely positioned to deliver on both of these capabilities. Arista EOS® based on our network data lake (NetDL[™])³, provides a multi-modal, multi-tenant-capable data lake that offers real-time network telemetry to other Arista solutions as well as those from our partners. Arista Autonomous Virtual Assist (AVA) uses an Al-driven approach to anticipate operator questions, extract answers from NetDL and deliver the insights necessary for effective human decision-making. With this combination, Arista is providing networking for the data-driven enterprise.

In this paper, we will share how AVA uses cutting-edge AI models to solve real-world challenges for network and security operators and present specific case studies that illustrate the business value the approach can generate.

¹<u>https://www.weforum.org/agenda/2019/04/how-much-data-is-generated-each-day-cf4bddf29f/</u>

² https://arxiv.org/ftp/arxiv/papers/1801/1801.00631.pdf

³ https://www.arista.com/en/solutions/cloud-networking



AVA Architecture

Arista AVA is an Al-enabled decision support system that combines cloud scalability with the codified expertise of real-world network and security operations experts. Real-time, complete data, including application, in-band network telemetry, flow visibility, and complete control plane state incorporated into the Arista EOS and NetDL stack, constantly serve as the basis to train the AVA AI/ML models. These data originate from a wide range of sensors and devices, physical or virtual, or through direct integrations with network and cloud infrastructure components such as the Arista DANZ Monitoring Fabric (DMF) or span ports on Arista EOS platforms.

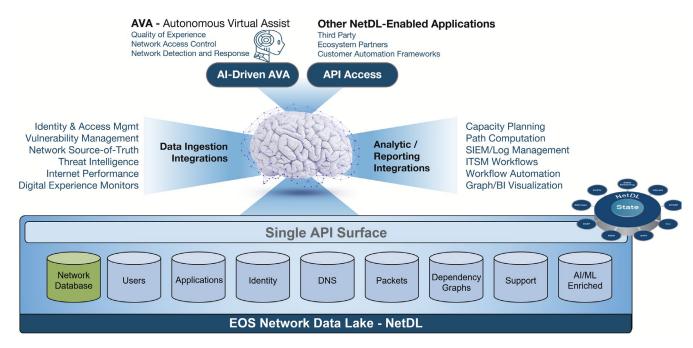


Figure 1: The Arista Data-Driven Cognitive Architecture

Based on the specific use case, AVA processes ground-truth data about the network devices' state and, if required, raw packets to pre-compute answers for questions a highly skilled analyst would ask. AVA thus surfaces the weak and early signals of a network issue, along with corroborating evidence to establish conviction. By that same token, AVA also eliminates those signals that cannot be corroborated so that human analysts avoid wasting valuable cycles. The net result is that the operations team is in a far better position to act—whether by proactively identifying connectivity issues or disrupting an adversary's objectives at the outset because AVA identified the initial warning signs of a ransomware attack. Our field results show that AVA frequently finds more incident-related activity than a senior human operator analyzing the same activity.

The AVA Advantage

Legacy data science approaches run into some significant challenges given the scale and diversity of the modern network. Any Al model is only as effective as the labeled samples used to train it. However, volumes of data and the types of conditions on even the simplest of today's networks make effective labels scarce. In addition, given how aspects such as threats evolve rapidly, the labels themselves become obsolete quickly, requiring frequent retraining and operational costs entailed in that effort. Even if these challenges are overcome, the resulting models are often massive, monolithic, and opaque, making them less useful, as they are slow and not explainable. In other words, a human analyst seeing the result often has no idea why something is flagged as a network or security issue. Consequently, neither do they feel confident in the veracity of the information, nor do they know what they should do next (Figure 2).



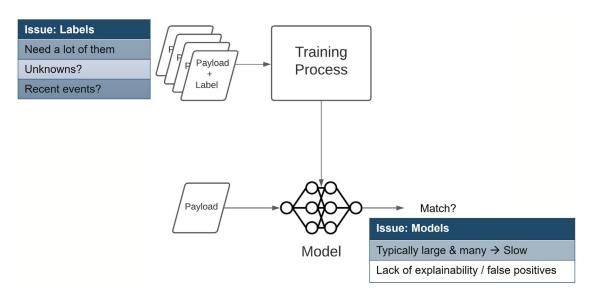


Figure 2: Challenges with legacy artificial intelligence approaches applied to network data

Even though one of the goals is to find the outliers and the anomalies, AVA doesn't approach this problem like legacy AI solutions. Instead, AVA starts by learning what is normal and, dare we say, mundane. In most networks, this includes traffic such as email, patching, and even department or workgroup-specific application usage. As you can imagine, there is an abundance of labels to train AVA's ML models to find these kinds of network behaviors. Unlike the approach described in Figure 2, which attempts to learn what "bad traffic" looks like, AVA works to eliminate much of the hay from the proverbial haystack of network data. This, in turn, leaves a significantly smaller consideration set within which AVA can then look for the needles.

Core to AVA's success with processing the voluminous data in NetDL is the knowledge graph. The data AVA consumes is first processed with techniques to discover the entities—people, devices, VLANs, applications, etc.—and the relationships between them. This forms the core of the knowledge graph. The graph can then be enhanced iteratively by knowledge from domain experts in the form of heuristics, as well as ongoing feedback from human operators. Given the size of the knowledge graph is significantly smaller than the raw features, additional AI approaches can be applied iteratively. This not only allows for better AI analysis but, unlike traditional ML models, with AVA, the algorithmic outputs are captured as real-world entities and their properties. The human-readable and understandable outputs deliver explainable AI with clearly defined next steps for the analyst.

AVA Delivers Solutions

The data-driven architecture, coupled with artificial intelligence, enables several network and security operations use cases. This section will provide a few examples of how AVA is optimizing workflows, speeding mean time to resolution, and improving security outcomes.

Case Study 1 – Proactive Network Operations

AVA enables network reachability modeling to deliver proactive notifications when a specific network service or application is experiencing reachability issues. Using dynamic anomaly detection, AVA identifies anomalies based on deviations from a learned reachability/latency baseline. The historical bounds and anomaly scores adapt to normal variations as time goes on. Access to NetDL's historical data supports both real-time and forensic troubleshooting of any issues identified.



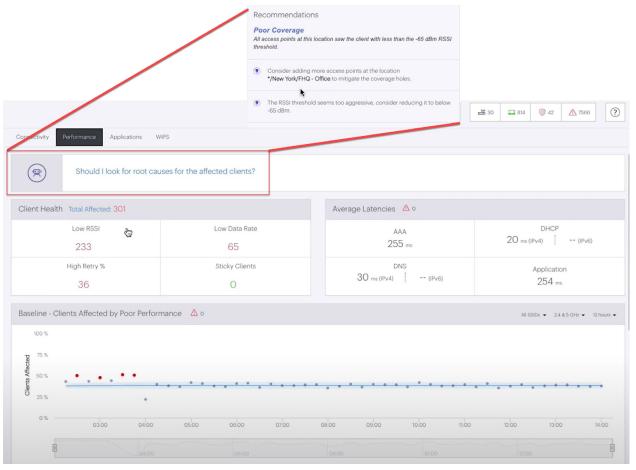


Figure 3: AVA proactively identifies network and application reachability issues

AVA also assists with another common network operation challenge: switch table overflow, resulting in a network outage. With the myriad chipset implementations and associated hardware table capacities, it is difficult for operators to monitor, track and extrapolate utilization trends manually. Instead, AVA models hardware resource utilization growth trends, enabling predictive assessments and notification ahead of exceeding capacity. Customers use these notifications to take preventive measures and avert a crisis.

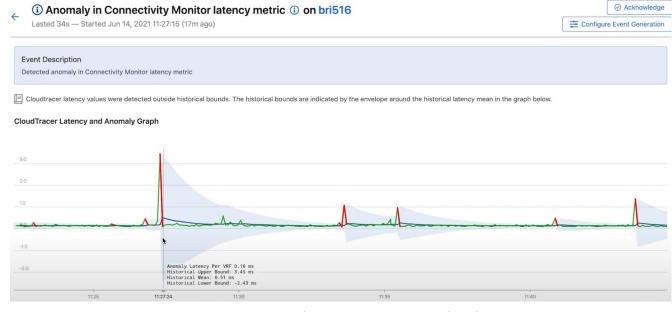


Figure 4: Detecting anomalies from a baseline enable AVA to identify grey failures

Case Study 2 – AlOps for Network Access Control

Deploying and managing network access control (NAC) solutions have historically been cumbersome and error-prone, requiring expensive and hard-to-find human experts. Arista CloudVision AGNI innovates in this area by automating and optimizing key workflows, including providing a conversational AI capability called Ask AVA for configurations, troubleshooting, and simulations.

Ask AVA uses various AI techniques including a generative pre-trained transformer (GPT)-based approach for training purposes. AGNI has two sets of models: one based on classic machine learning uses support vector machines while the other uses ChatGPT's large language models via OpenAI APIs. Ask AVA uses a chat-like interface and natural language processing (NLP) to aid even a junior analyst with tasks such as configuring, troubleshooting, and analyzing policy configurations. From the NLP queries, AVA autonomously identifies the analyst's intent and assists in configuration, provides contextual output to troubleshoot problems, and analyzes the correctness of network and security policies. The net effect is a simpler and more secure NAC deployment.

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MONITORING Dashboard Sessions	Ask AVA Chat to explore and troubleshoot			
ACCESS CONTROL Vetworks Li= Segments	B why is bob not able to connect ?			
ACLS IDENTITY ACLS Identity Provider	I found 2 users in the organization matching bob. Which one are you looking for? Bob Miller bob@antaraaiqa.onmicrosoft.com			
🛍 User 🔶 🗸	B Bob Marley			
CONFIGURATION Access Devices ~ Certificates ~	I found the user Bob Marley in the organization. Bob Marley has 2 onboarded devices. Bob Marley was last active on the network 3 hours back.			
Administration CONCOURSE Explore	Some of Bob Mariey's devices have faced difficulty in connecting to the network over the past week. These clients seem to be affected by below errors Incorrect PSK			
😳 Installed Apps	Bob Marley bobmarley@antaraalqa.onmicrosoft.com			
	The client(s) referenced are, 10:61:b4:72:84:0a Bob Marley's iPhone			
« Collapse Sidebar	B Write your query here		A	Send

Figure 5: AVA streamlines operations and reduces errors in network access control workflows using conversational AI

Case Study 3 – Autonomous Network Detection and Response

Like the network operations use cases above, AVA can also deliver day 0 value to the security operations team. For instance, AVA uses unsupervised machine learning to identify and track users, devices, applications, and other entities over time. AVA can also use this information to cluster similar entities. This presents a significant enhancement from legacy approaches that rely on unsupervised learning to spot anomalies from "normal" baselines for individual IP addresses rather than entities. Attributing behaviors to an IP address leads to high false positives and negatives, which translates to operational burdens on analysts.

Similarly, AVA uses supervised machine learning to identify patterns of activity that relate to attacker tactics, techniques, and procedures. For instance, AVA can classify remote access tools, reverse shells, unauthorized applications used for command and control, etc., without the need for decrypting the underlying data. This encrypted traffic analysis eliminates the privacy, policy, and technology challenges of decrypting data for analysis.



By 1.5KB 1000B 1000B 1000B	03:38:19.478	03:38	19.480 03:38:19.48	2 03:38:19.484		
Туре 🖗	Start Time 🖗		Duration 👻	Details 🛛 🚍		
Unencrypted	03:38:19.476 Jun 24, 2021		1ms	Source: 4 packets, 1,485 payload bytes Destination: 3 packets, 1,473 payload bytes		
Unclassified	03:38:19.477 Jun 24, 2021		465us	Source: 4 packets, 1,920 payload bytes Destination: 3 packets, 700 payload bytes		
Auth Success	03:38:19.478 Jun 24, 2021		Single packet	Source: 0 packets, 0 payload bytes Destination: 1 packet, 36 payload bytes		
Unclassified	03:38:19.478 Jun 24, 2021		418us	Source: 3 packets, 700 payload bytes Destination: 7 packets, 1,076 payload bytes		
Remote Control	03:38:19.478 Jun 24, 2021		Single packet	Source: 1 packet, 36 payload bytes Destination: 0 packets, 0 payload bytes		
Keystroke	03:38:19.478 Jun 24, 2021		Single packet	Source: 1 packet, 36 payload bytes Destination: 0 packets, 0 payload bytes		
Packet Type A user is typing one character via their keyb		eket Count	Server 0	Data Volume (Bytes) Client 36B Server 0B		
Remote Control	03:38:19.478 Jun 24, 2021		100us	Source: 2 packets, 72 payload bytes Destination: 3 packets, 172 payload bytes		

Figure 6: AVA flushes out the entire scope of an attack, enabling a decisive and rapid response

Another instance of AVA driving value for the security team is the ability to autonomously pull open-source and threat intelligence and thus, contextualize a potential threat uncovered in the environment. For example, when confronted with a suspect domain or IP address, much like an experienced security expert would, AVA pre-computes answers to questions such as:

- What other domains or destinations first showed up on the network at approximately the same time as the initial suspect domain?
- Did other devices attempt to connect to any of the same domains?
- Was there any trace of lateral movement activity beyond the initial victim?

Answering questions like these requires analyses of both internal data sources and external information via search engines, threat, and vulnerability databases, etc. AVA analyzes these results using natural language processing techniques such as entity extraction and topic modeling. For the operator, the benefit is that AVA helps uncover all potential victims within the organization and different parts of the attacker infrastructure, e.g., multiple command and control domains and Ips, all on a single screen.



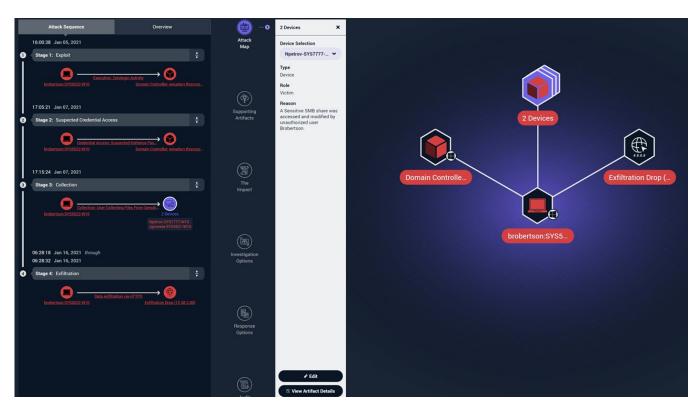


Figure 7: AVA flushes out the entire scope of an attack, enabling decisive and rapid response

Case Study 4 – Quality of Experience (QoE)

AVA helps provide the network operator with a clear view of the root causes of poor user experience and what remedial actions can be taken to improve that experience. This day 0 capability analyzes real-time data with the benefit of lab-trained models

that understand the causes of network QoE issues, their interaction, and their effects. As a specific example, AVA employs a support vector machine (SVM) classifier to determine the performance of voice and video collaboration applications. The model is trained using a vast library of voice and video call flows labeled as a good or bad experience.

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GoToMeeting		Slack	Google Hango	uts W	lebEx	Skype	
faced poor app experience 27% of the time.	Users	had an excellent application experience.	Users had an excellent application	n experience. Users had an excel	nt application experience.	Users had an excellent application experience.	
	-					1-5 of 7 Show	v All
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Figure 8: AVA proactively surfaces application quality of experience issues and recommends fixes



Case Study 5 - IoT Observability and Security

Detecting unknown IoT devices on the network offers a great example of how AVA automates human expertise.

A human expert intuitively describes an IoT device as one that most often doesn't have a browser, doesn't use enterprise protocols like SMB and Kerberos, and typically communicates with a small set of destinations. Using the information in NetDL, AVA can infer and index properties like these for the devices on the network, thereby easily highlighting the IoT devices. AVA then goes further by using recommendation systems algorithms to tag other IoT devices that are not captured by the originally encoded human intuition. This iterative approach is both quick and comprehensive at the task of eliminating an important blind spot for customers dealing with an explosion of devices on the network.

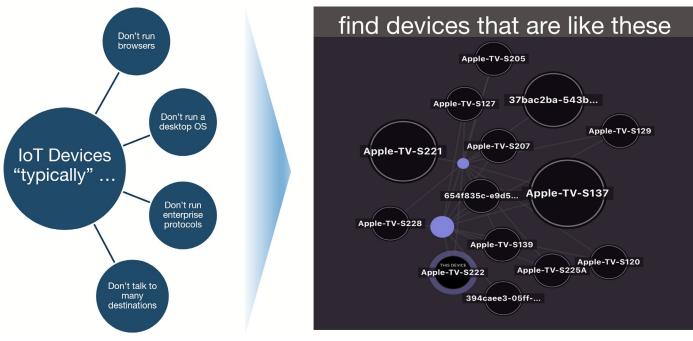


Figure 9: AVA encodes human intuition to discover IoT devices on the network

Consider the following real-world customer example which illustrates the benefits of this IoT observability. An IoT device plugged into a critical device's USB port was being used to intercept keystrokes between the keyboard and the computer. Detecting this threat first required identifying the shadow IoT device. As Figure 9 shows, the device had been sending encrypted emails and a custom UDP stream to locations in Germany and Malaysia. These "weak signals" added further conviction, allowing AVA to trigger a device quarantine via CloudVision AGNI, Arista's NAC solution.



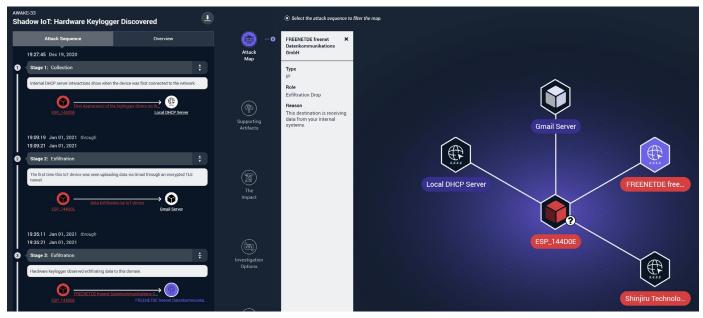


Figure 9: Discovering and remediating rogue IoT devices on the network

Case Study 6 – Enriching the Ecosystem with AVA Insights

AVA insights can also be used to enrich other parts of the customers' IT and security ecosystem. For example, with one click, analysts using log aggregation and SIEM tools such as Splunk or Azure Sentinel can pivot from a meaningless IP address in those tools to an AVA-enriched profile that includes the name of the device, its primary user, applications running on it and other similar devices, as well as a forensic timeline of device activities. In addition, the analyst has a detailed timeline of that device's activities and can therefore make appropriate risk management decisions.

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	Network			GoDaddy.com. LLC				
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	DNS		Adversaria	Il Model - Privilege Escalation: Remote Desktop & Admin Access F	om Non-Admin Device			
	TLS							

Figure 11: Enriching Splunk with AVA context



Summary: Data-Driven Networking Made Possible

The combination of Arista AVA and EOS NetDL provides predictive and prescriptive intelligence for data-driven networks. AI/ ML enrichment and analytics in combination with a broad ecosystem of vendors/partners, deliver market and customer-specific security, application, and network performance analysis, feeding continuous awareness and assurance. This provides a single source of truth and a decision-support architecture for Arista customers that ultimately delivers better business outcomes.

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