Applications of AIML in Sync Networks

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Agenda

- Introduction
- AIML for clock Selections.
- Predictive PTP Offset computes.
- Real-Time Holdover forecasting.
- AI-powered Sync Anamoly detections.
- Clustering for SyncTraffic Steering.
- Conclusions

1. ELEVATING PRECISION & RESILIENCE

2. PROACTIVE NETWORK MANAGEMENT

3. UNLOCKING OPERATIONAL EFFICIENCY

4. REVOLUTIONIZING SYNC ACROSS THE NETWORK

Clock Selection using ML Recommendation Systems

- ML-Powered Decision Making using Content-Based Similarity(recommendation systems).
- Quantify similarity by comparing and calculating distance.
- Calculate and Rank Master from Reference Master Proximity.
- Dynamic Master Selection with least distance.

Lab Results

Source	P1	clock class	Accuracy	Variance	P2	Weighted Euclidean	Weighted Cosine	Weighted Jaccard	BMCA
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	a0:00:00:00:00:01	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
b0:00:00:00:00:04	128	7	22	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01
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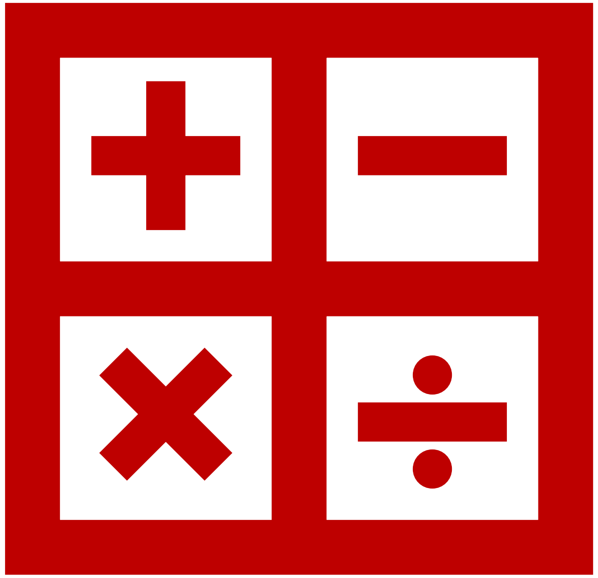
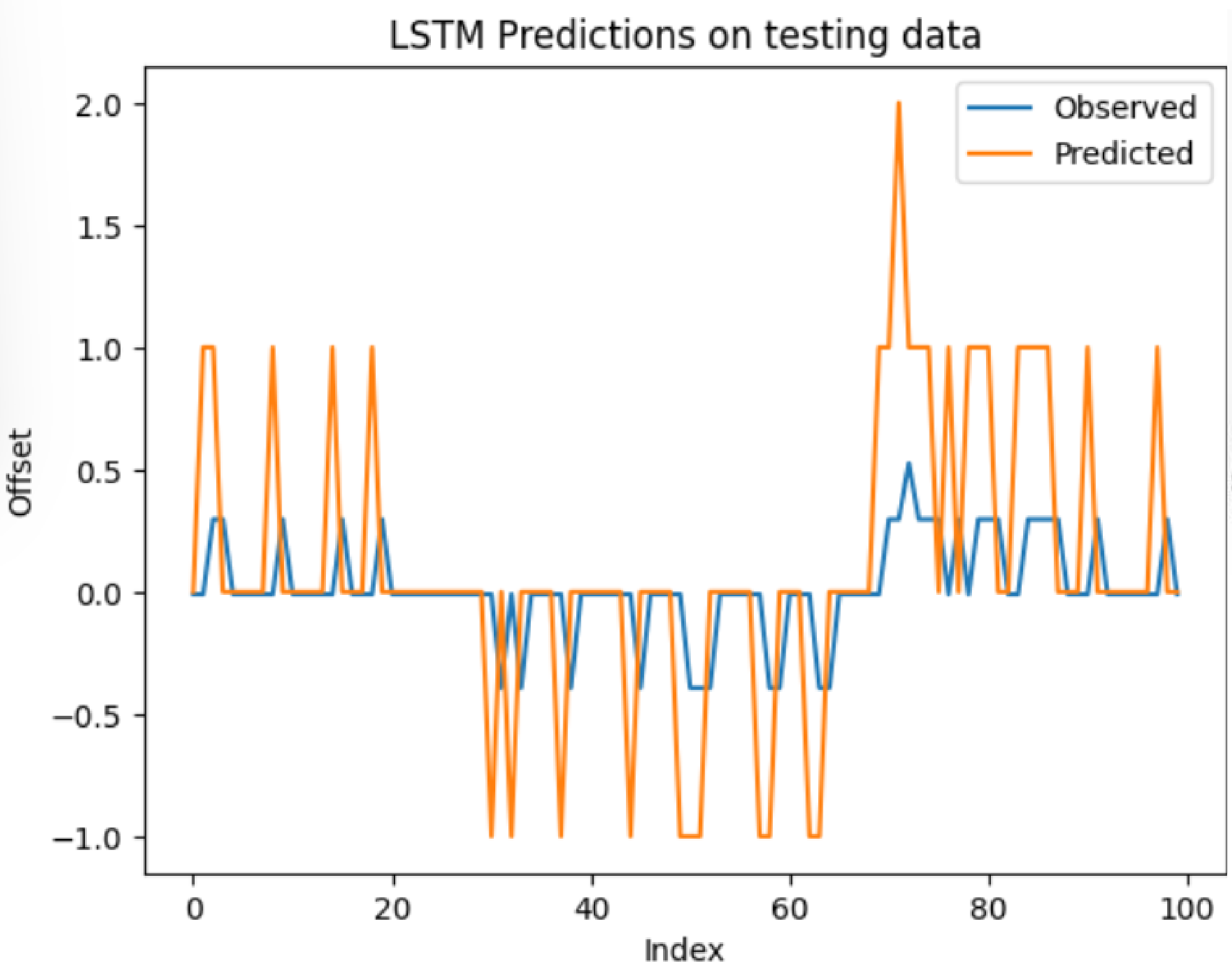
a0:00:00:00:00:01	128	6	21	19250	128	a0:00:00:00:00:01	b0:00:00:00:00:04	a0:00:00:00:00:01	a0:00:00:00:00:01

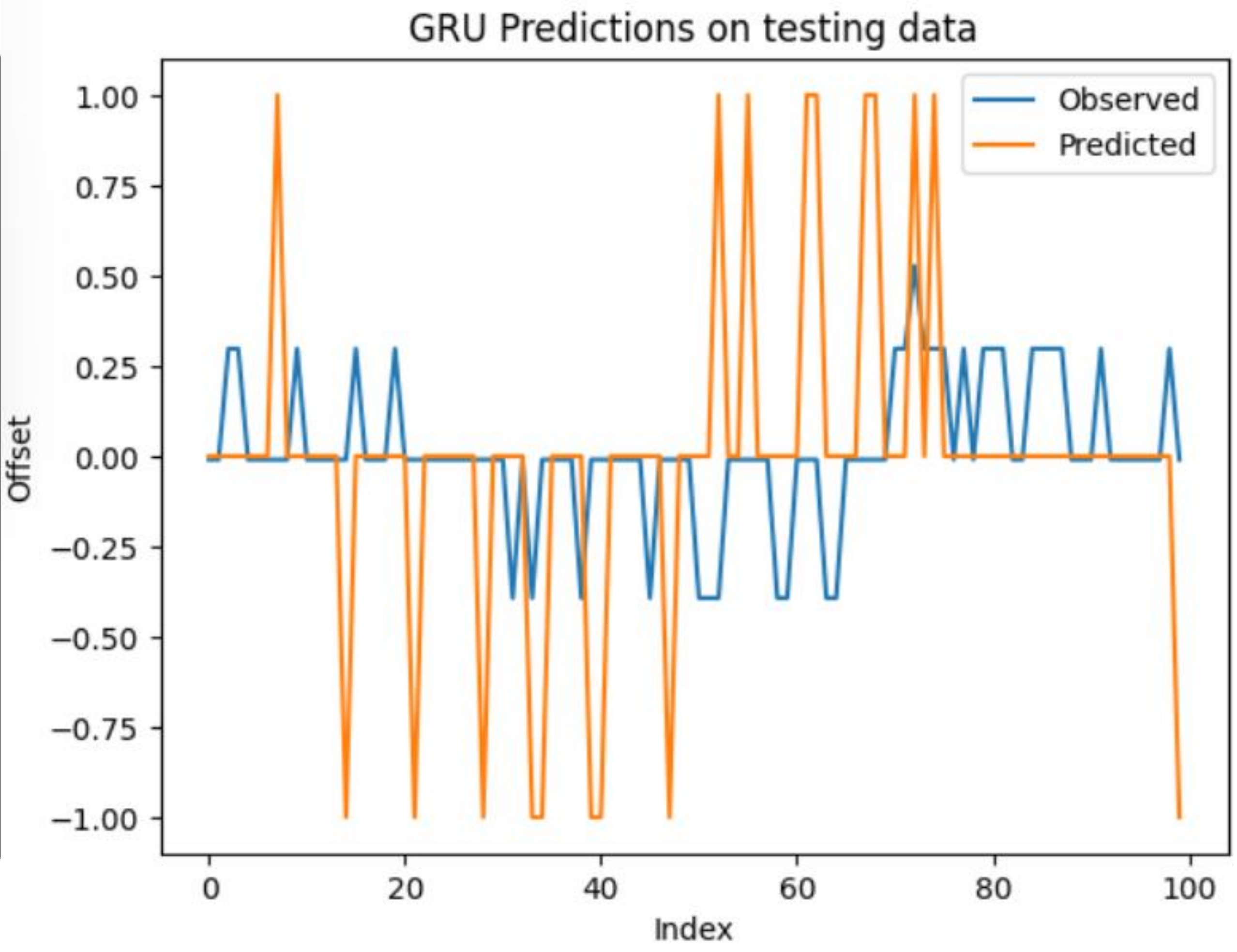
PTP Offset Computes using DL

- Due to Dynamic nature of OFM, influenced by network latency, jitter, and clock drift, traditional methods struggle with its non-linear and time-dependent nature.
- Use Deep Learning for PTP Offset computes.
- Predicts future PTP offset, allowing for feed-forward compensation and pre-emptive clock adjustments.



Testing Results





Need for AI powered real-time holdover estimations

DYNAMIC HOLDOVER DURATION MANAGEMENT

PROACTIVE FAILOVER TO REDUNDANT SOURCES

ADAPTIVE NETWORK CONFIGURATION

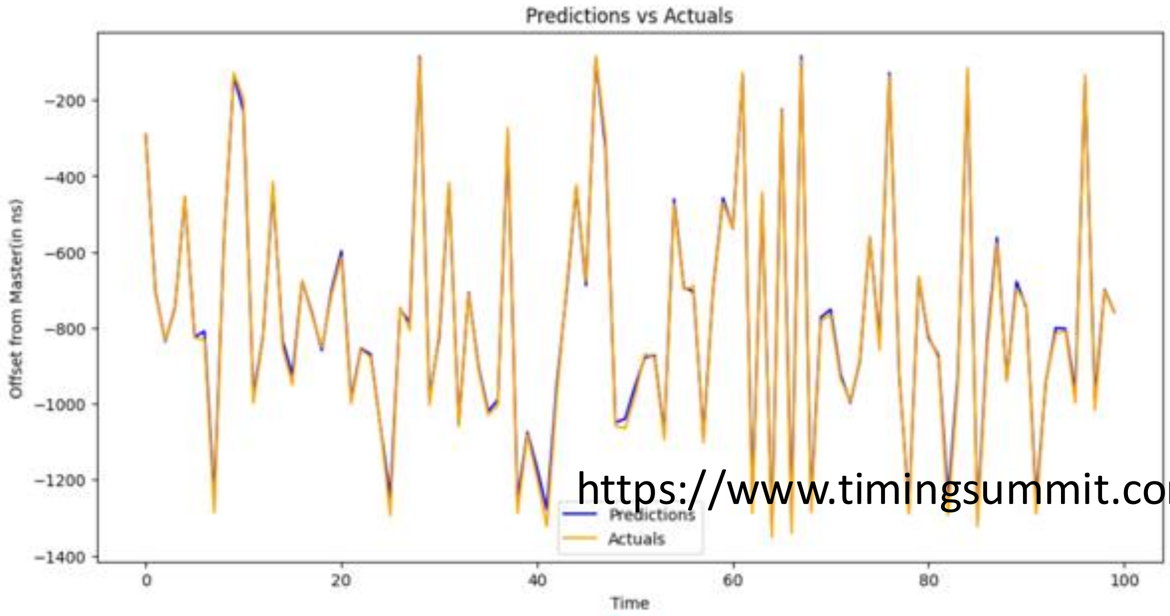
OPTIMIZED ALERTING AND ESCALATION

AIML Regression Models and their results

	Model	R-squared (Train)	MSE (Train)	RMSE (Train)	R-squared (Test)	MSE (Test)	RMSE (Test)
0	GradientBoostingRegressor	0.998128482	169.934879517	13.035907315	0.998124181	170.189446433	13.045667727
1	LinearRegression	0.566163390	39392.606232972	198.475706909	0.566429937	39336.975862640	198.335513367
2	DecisionTreeRegressor	0.998721518	116.086843992	10.774360491	0.998717216	116.384528323	10.788166124
3	XGBRegressor	0.997618388	216.251699834	14.705498966	0.997607720	217.046973423	14.732514158
4	Sequential_Conv1D_RELU	0.998531206	133.374628606	11.548793383	0.998533514	133.014129875	11.533175186
5	Sequential_Conv1D_SELU	0.998089812	173.455640709	13.170255909	0.998087373	173.480356833	13.171194207
6	LSTM	0.996858942	285.225375334	16.888616738	0.996856470	285.126473146	16.885688412
7	GRU	0.980488032	1771.794331511	42.092687388	0.980484163	1770.138043080	42.073008486

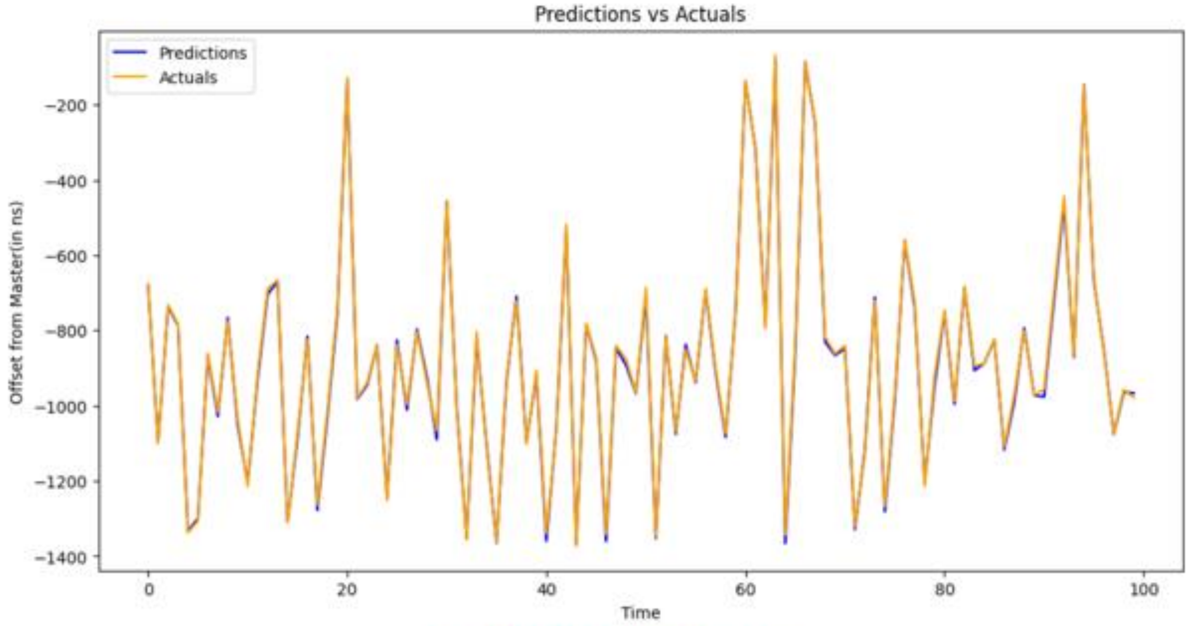
Testing Results

LSTM

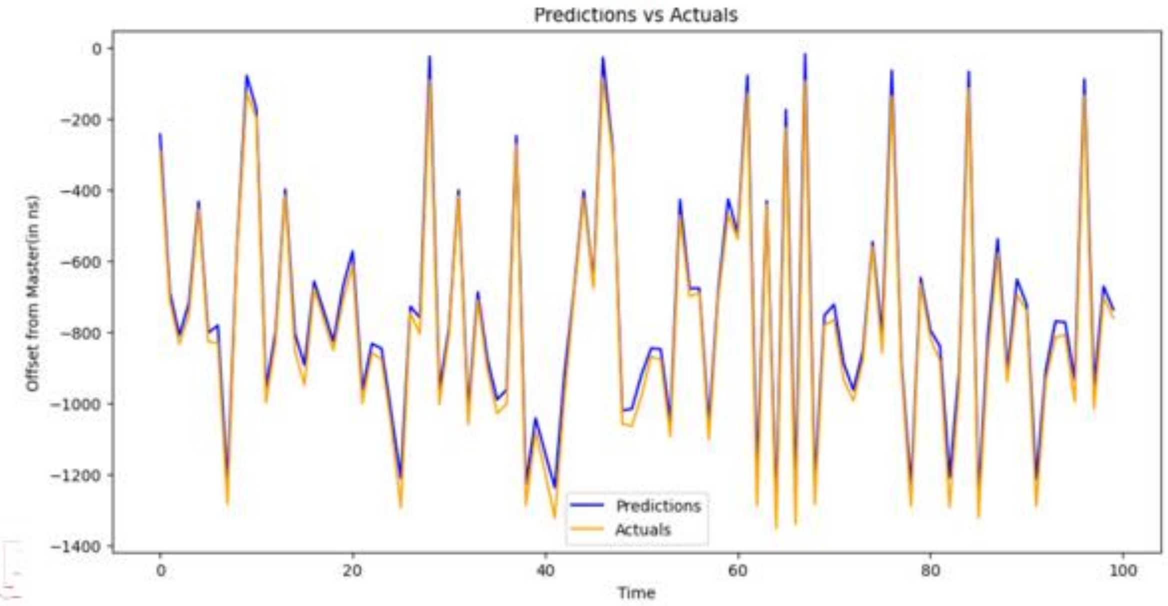


https://www.timingsummit.com/

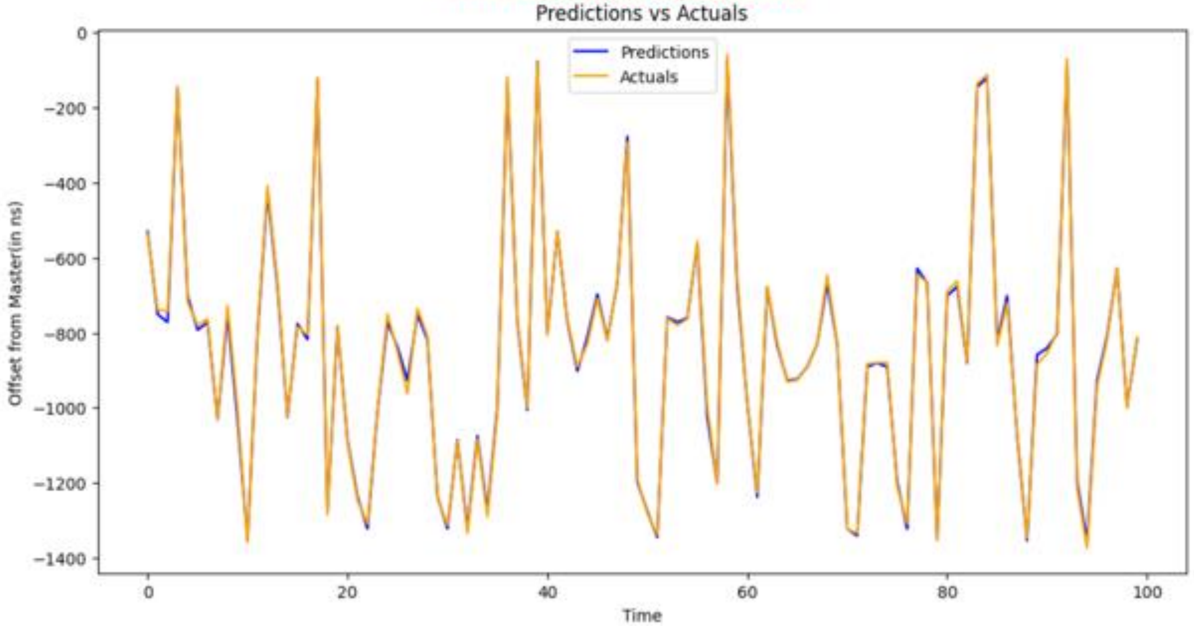
Sequential_Conv1D_RELU



GRU



GradientBoostingRegressor



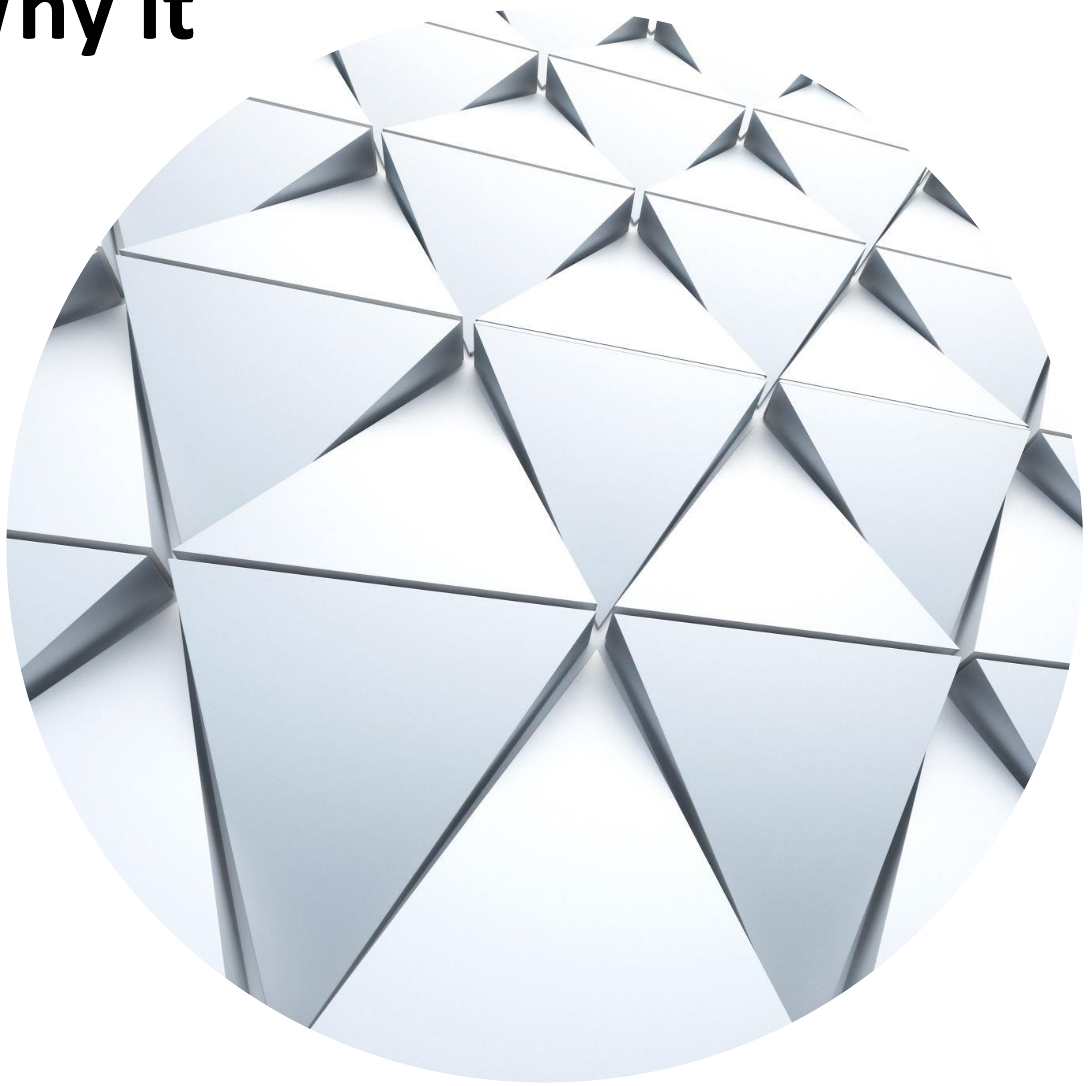
Sync Anamoly Detections:Why it Matters?

AI/ML transforms sync monitoring from reactive to predictive, ensuring the unwavering reliability of our critical network timing.

Traditional monitoring struggles to keep pace with network complexity and the subtle, evolving threats to synchronization integrity.

Need Next-Gen Defense Against Sync Disruptions

Implement AI-driven monitoring for identifying synchronization anomalies, outliers, and network vulnerabilities.



Conclusions

Urgent Need for Standardization - To fully unlock the potential of these AI/ML applications, we must collectively work towards integrating AI/ML considerations into timing standards.

Call to Action - Actively contribute to ITU-T and IEEE 1588 specifications to define best practices, data models, and interoperability frameworks for AI/ML-driven timing solutions.

Collective Innovation - This collaborative effort is vital to ensure that AI/ML truly revolutionizes sync across the network, fostering innovation, ensuring interoperability, and safeguarding the pulse of our critical infrastructure for years to come.

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Questions?

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