# MACHINE LEARNING AND AI IN HIGH SPEED SYSTEM DESIGN


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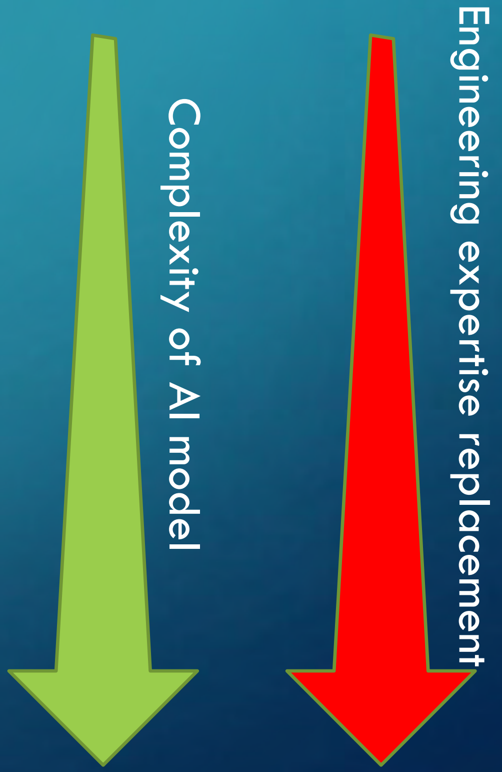
# WORK IN PROGRESS, THE JOURNEY CONTINUES….

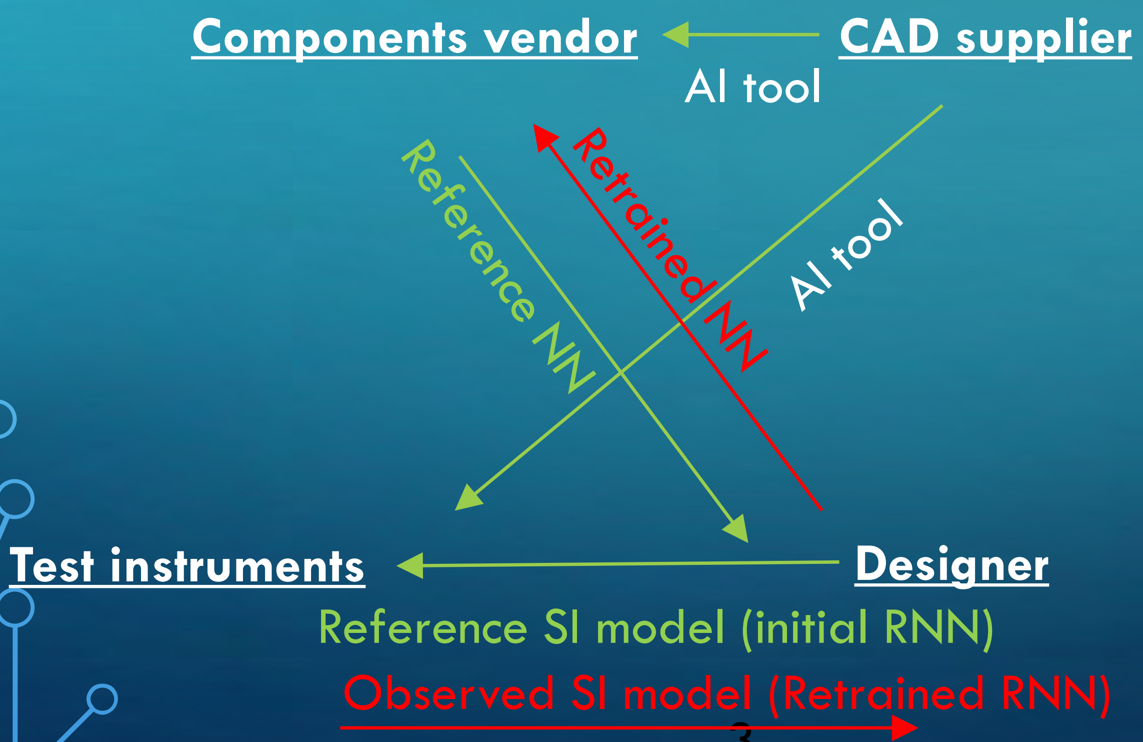
- Year one : Improving an existing process
  - Self correcting simulation models with neural network
- Year two : Speeding up and optimizing a design
  - Accelerating 56G PAM4 SerDes tuning with PCA vectors
- Year three : Digital Twins
  - Automatic channel condition detection and SerDes tuning using digital twins
- Year four : Deep learning of a design process
  - GAN modeling of SerDes

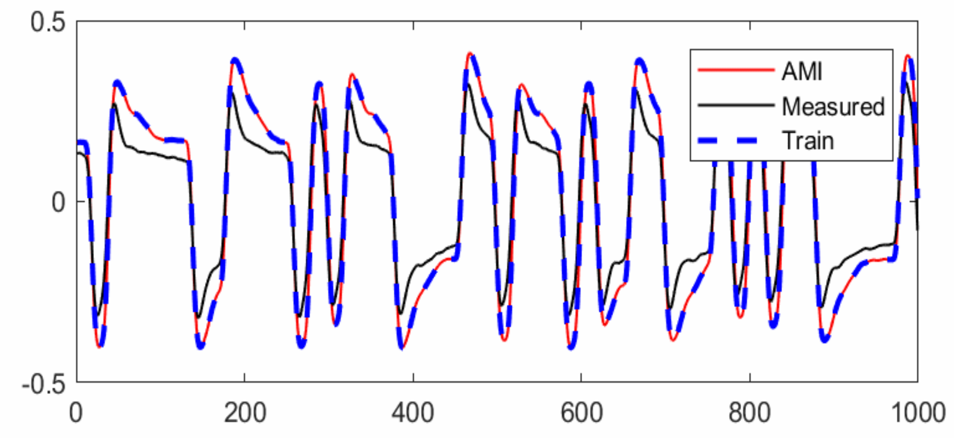


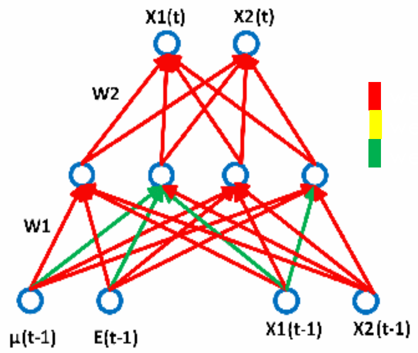
# Year 1 : Self correcting models

- Objective :

Machine learning as an alternative for existing solution



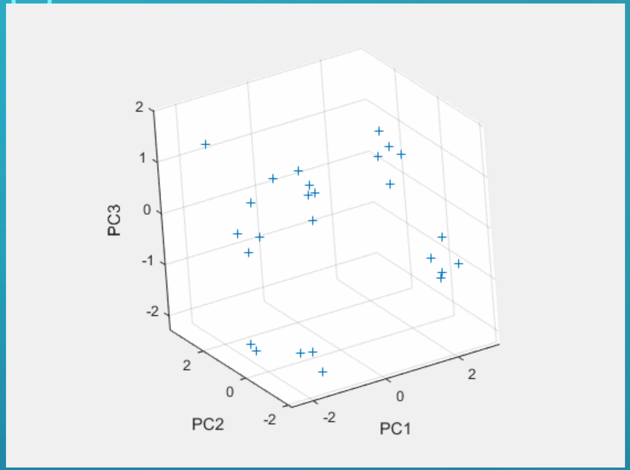



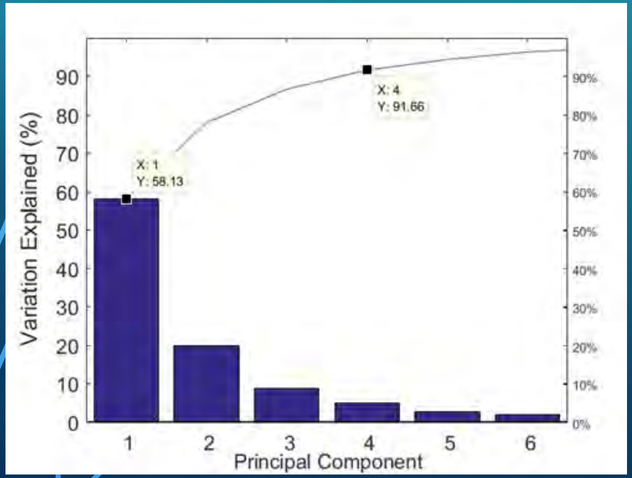



# YEAR 2 : ACCELERATING 56G PAM4 SERDES TUNING

- Objective :

Using Machine learning to accelerate optimizing a design

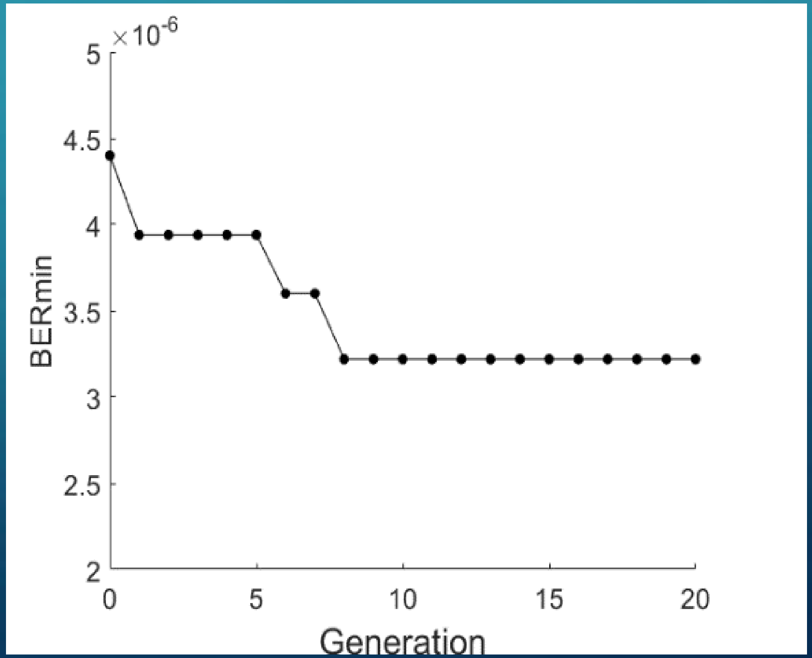


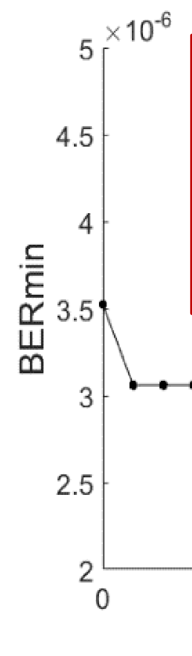

Zhu et al, DesignCon 2019

Best fitness function versus generation.

(a) GA

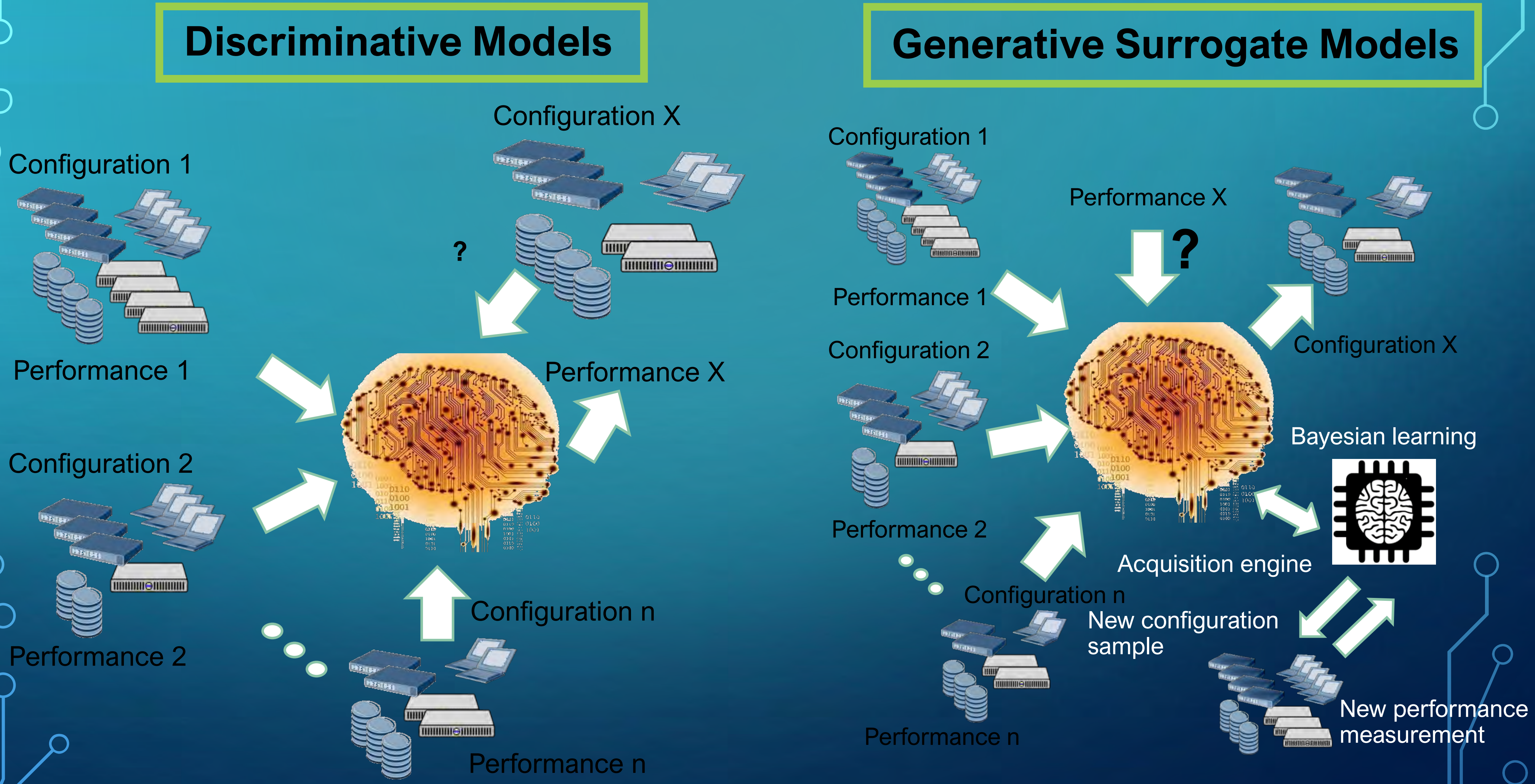



(b) GA-PCA

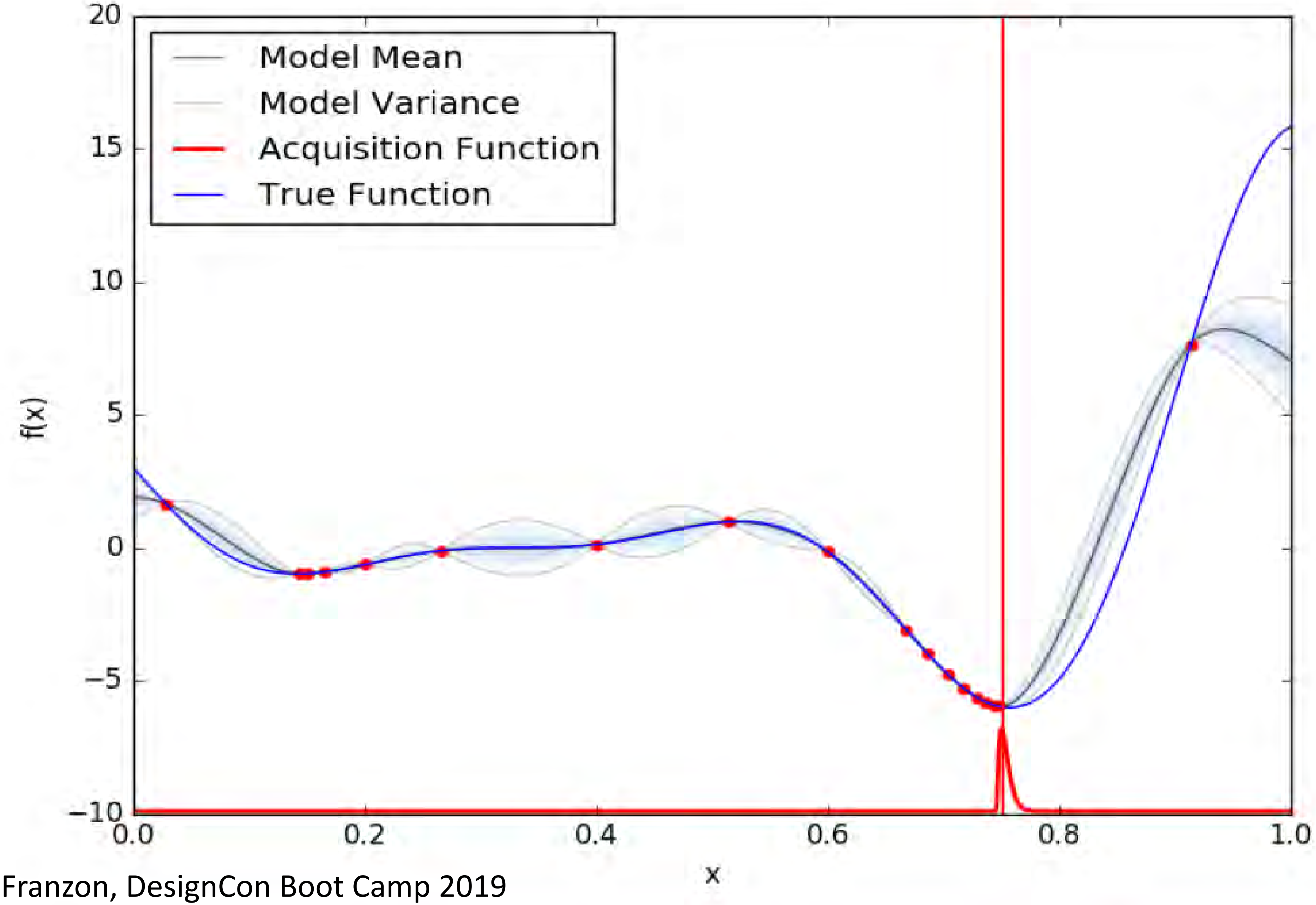



PCA based GA algorithm converged with fewer generations, more quickly than the general GA algorithm.

# YEAR 3 : GENERATIVE MODELS AS DIGITAL TWIN



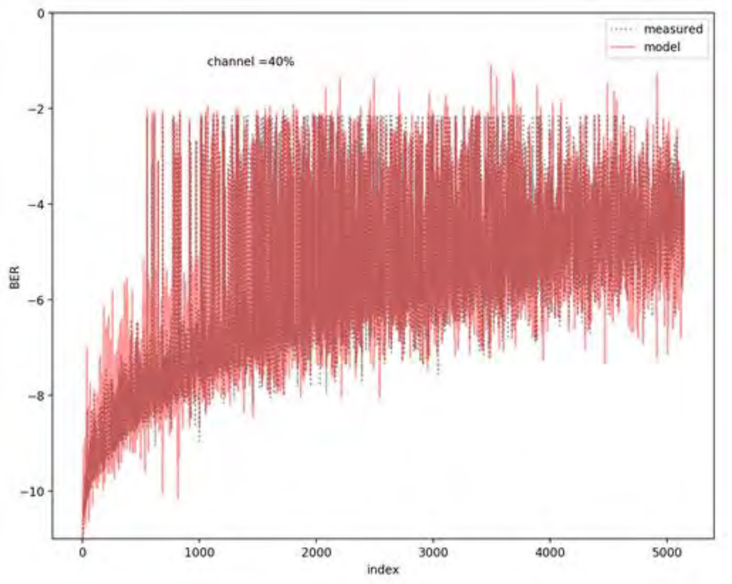
# BAYESIAN LEARNING 1D DEMO



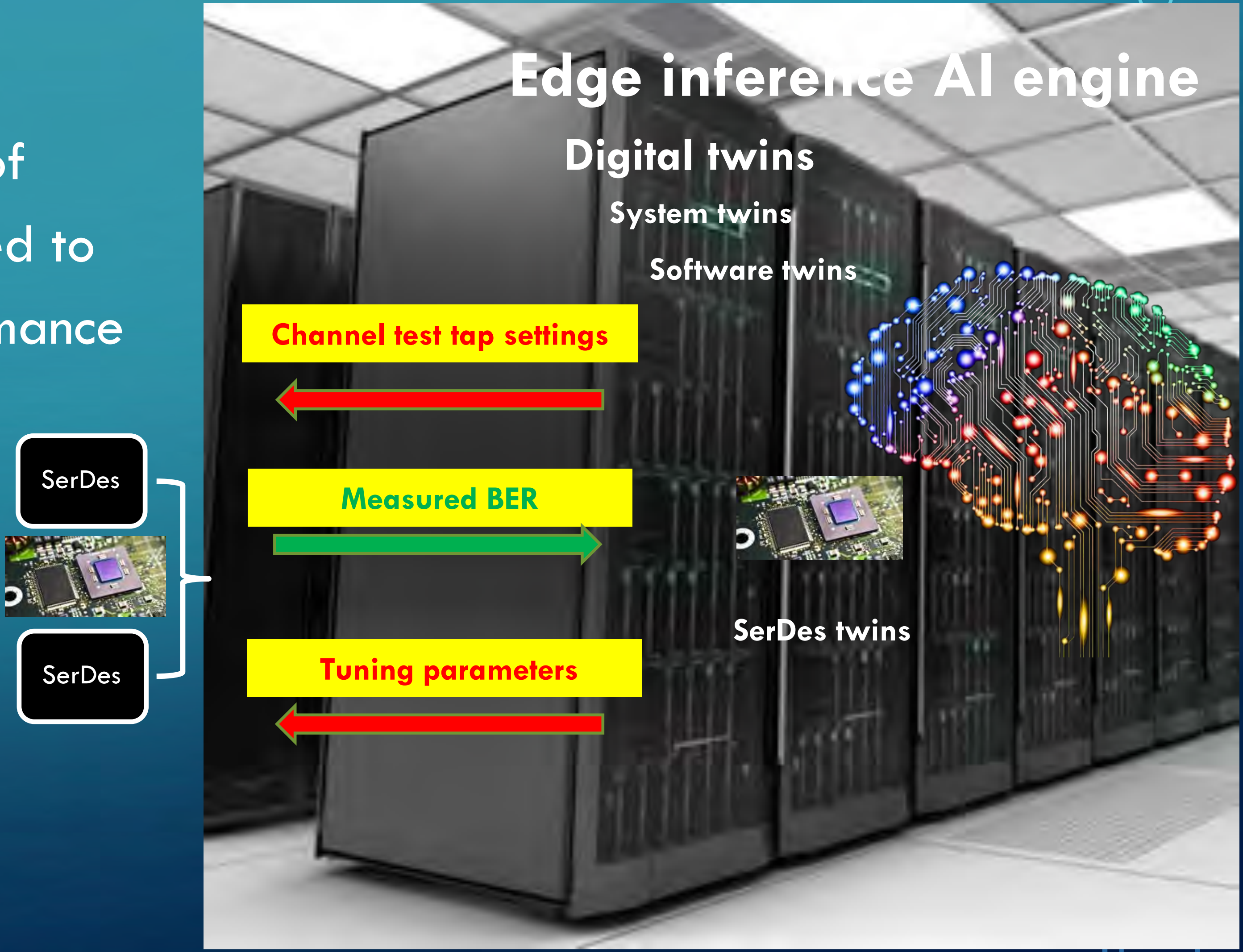

Franzon, DesignCon Boot Camp 2019

# DIGITAL TWINS FOR INTELLIGENT EDGE COMPUTING

- Next generation platforms will have build-in AI engine to perform inference at the edge
- Digital twins are surrogate models of system performance and can be used to dynamically tune the system performance



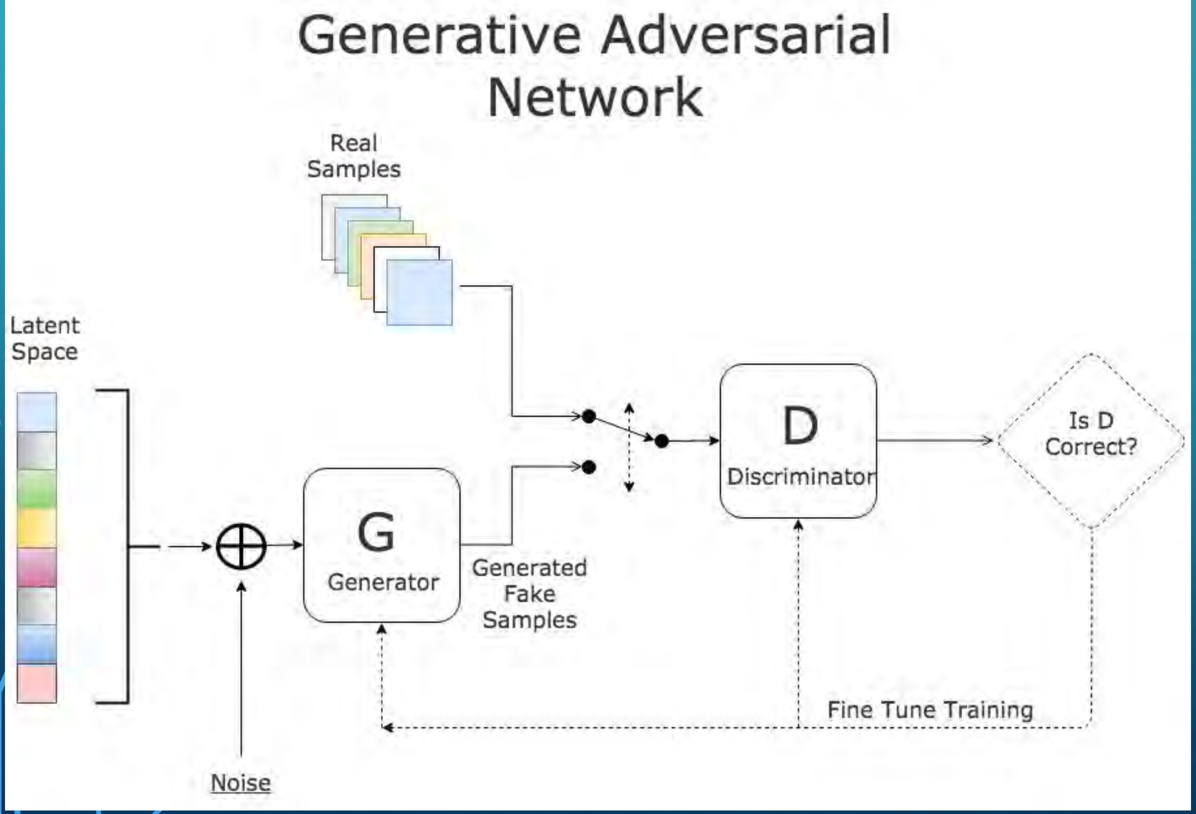

Choi et al, DesignCon 2020

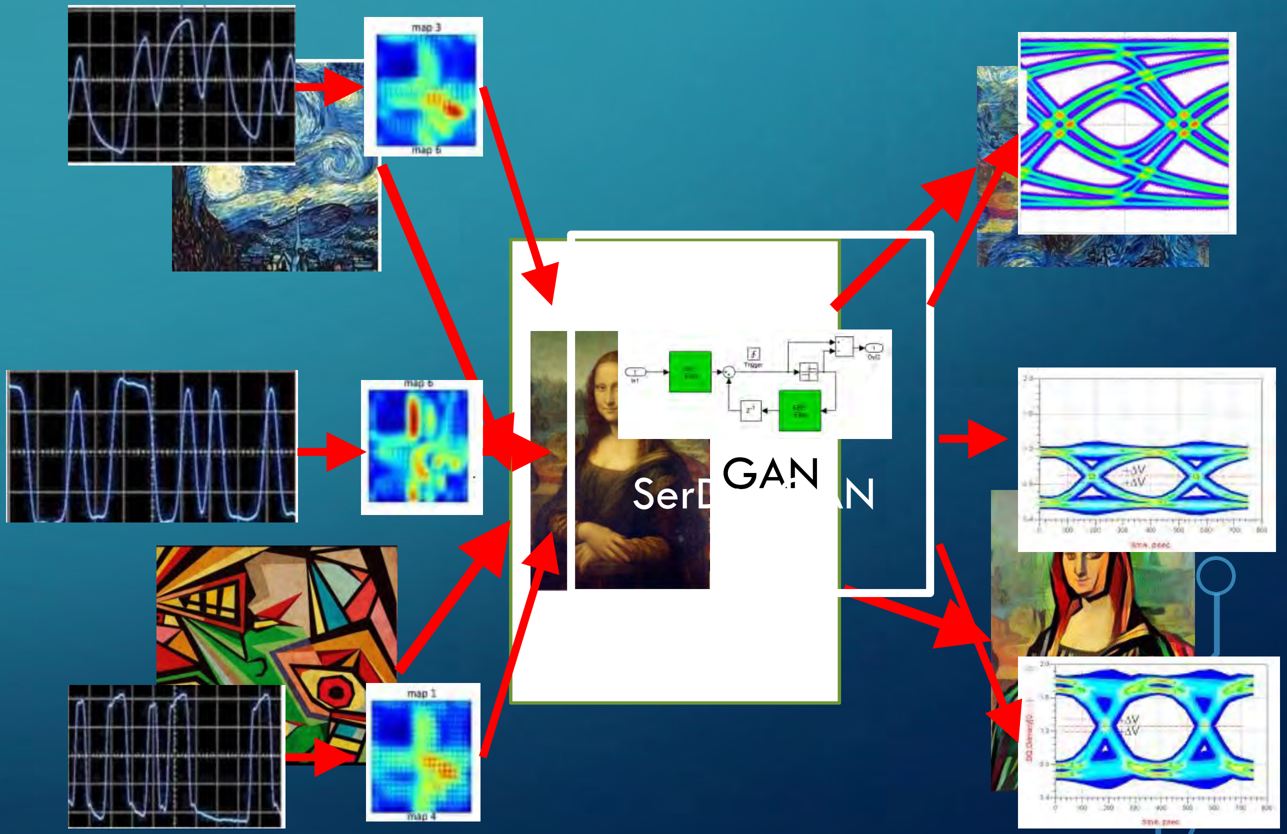


# YEAR 4 : DEEP LEARNING OF DESIGN PROCESS

- Objective

Deep learning of SerDes modeling using Generative Adversarial Networks

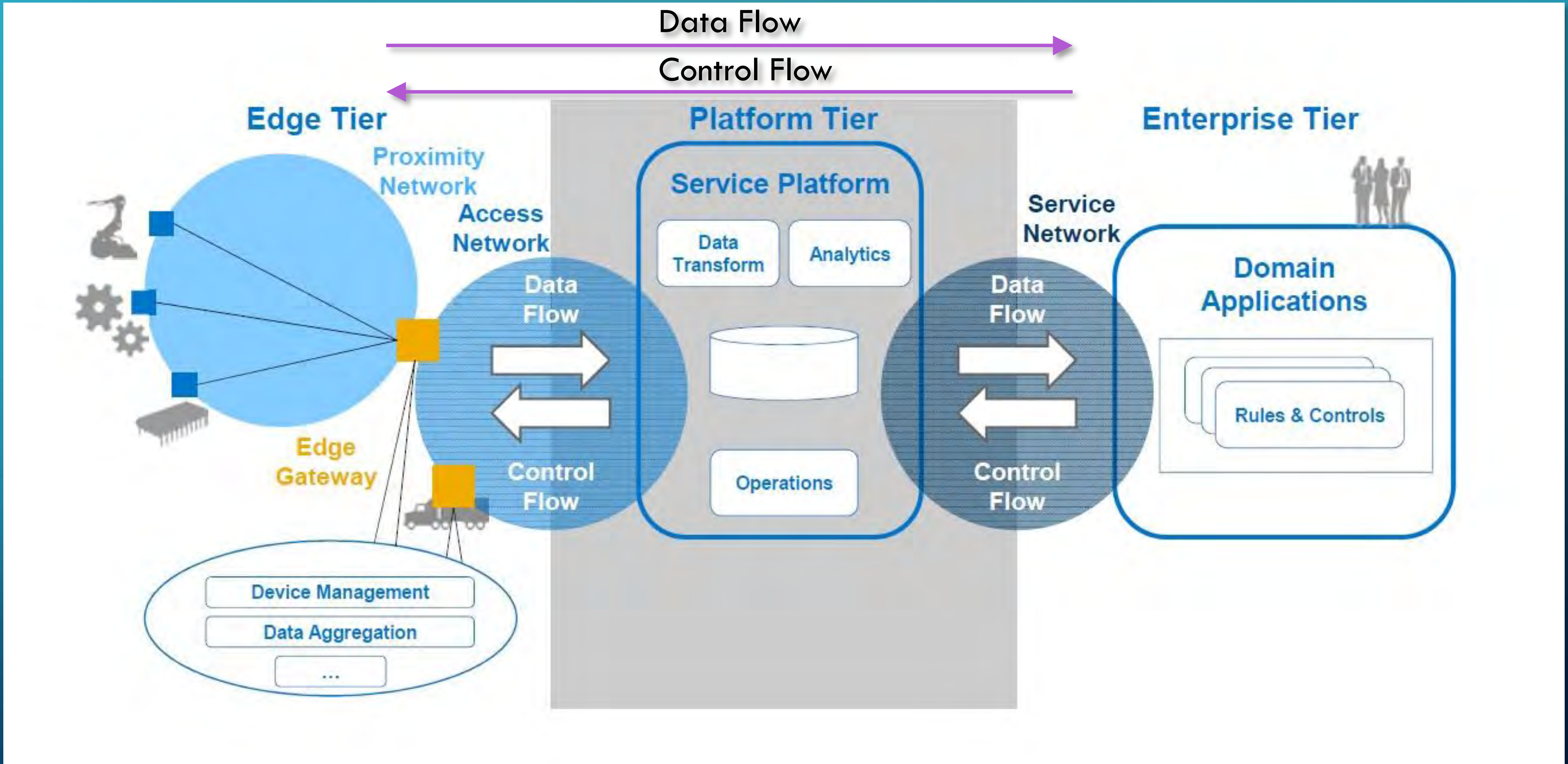


# INTELLIGENT EDGE FOR THE 5G/IOT GENERATION

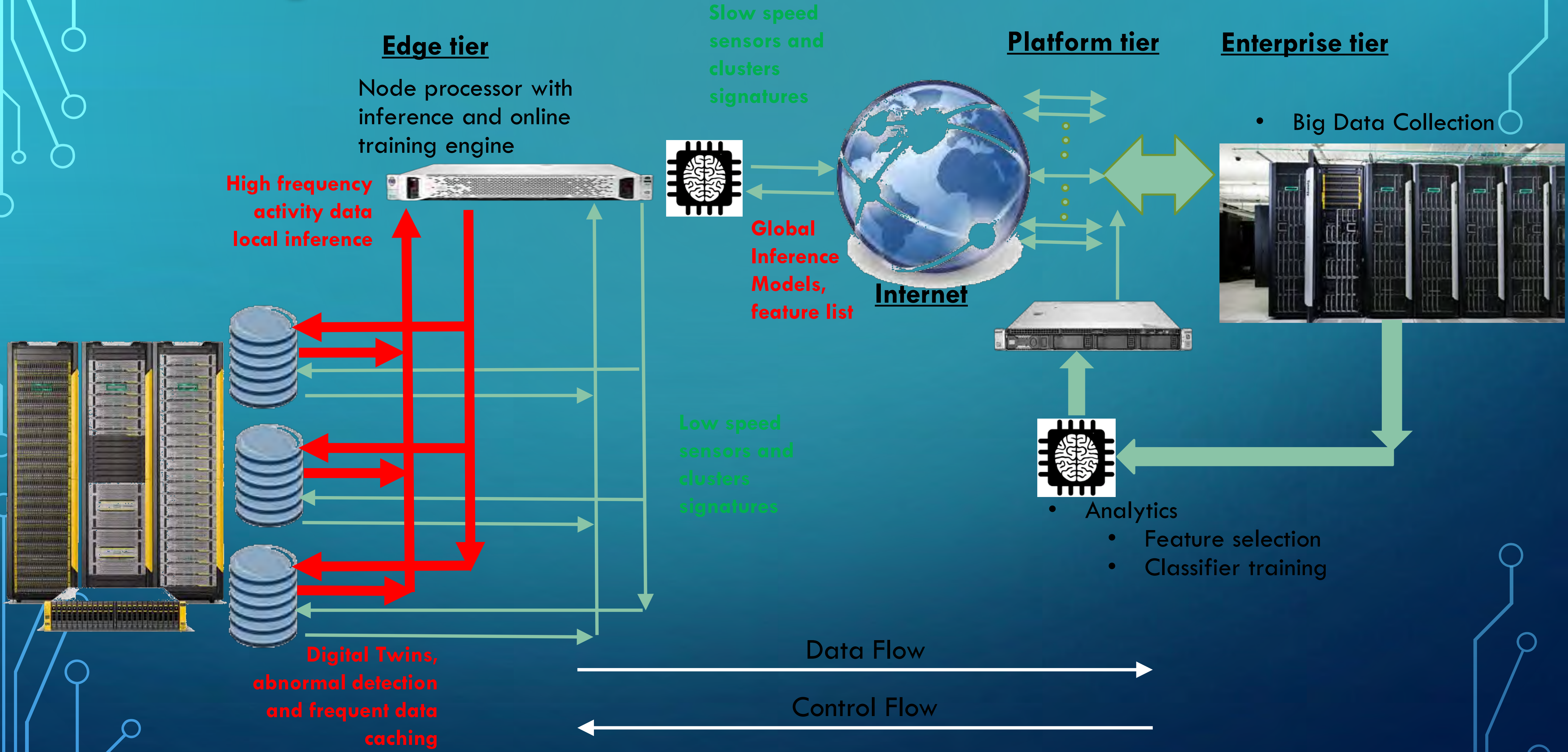
AI FOR INTELLIGENT EDGE MANAGEMENT AND SECURITY

# IoT management model




IEC IoT white paper

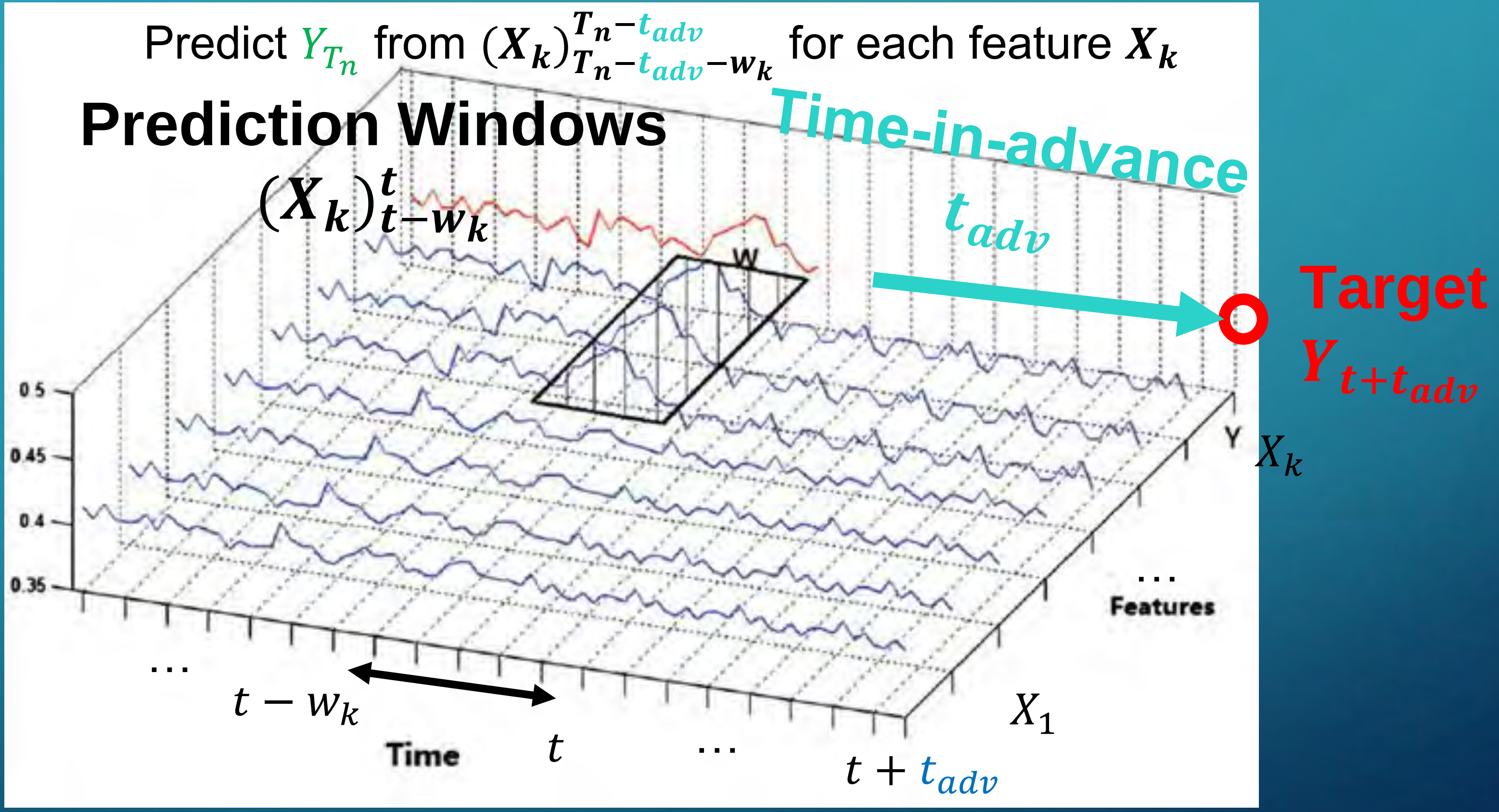
# Edge inference



# 3 Types of IoT and hardware management models

| | Feature size (number of variables or complexity) | Prediction throughput | Prediction interval | Machine learning engine | Examples |
|---|---|---|---|---|---|
| Big data Small learning | Less than 100 | A few thousands to millions of predictions per sec | Variable from days to ms | Ensemble classifier | Hardware failure prediction<br>Software failure prediction<br>Automatic application detection<br>Storage security applications (ransomware detection)<br>System abnormally detection |
| Big data Medium learning | Between 100 to 500 | A few hundred predictions per secs | A few secs | Generative performance surrogate model with Bayesian learning | Digital Twins for dynamic system performance optimization |
| Big data Deep learning | 100s to 1000s | 1000's of predictions in an hours | 5-15 mins | Deep Markovian Models<br>Deep learning neural networks | High dimensional time series for resource demand prediction |

# Casual Inference for feature selection

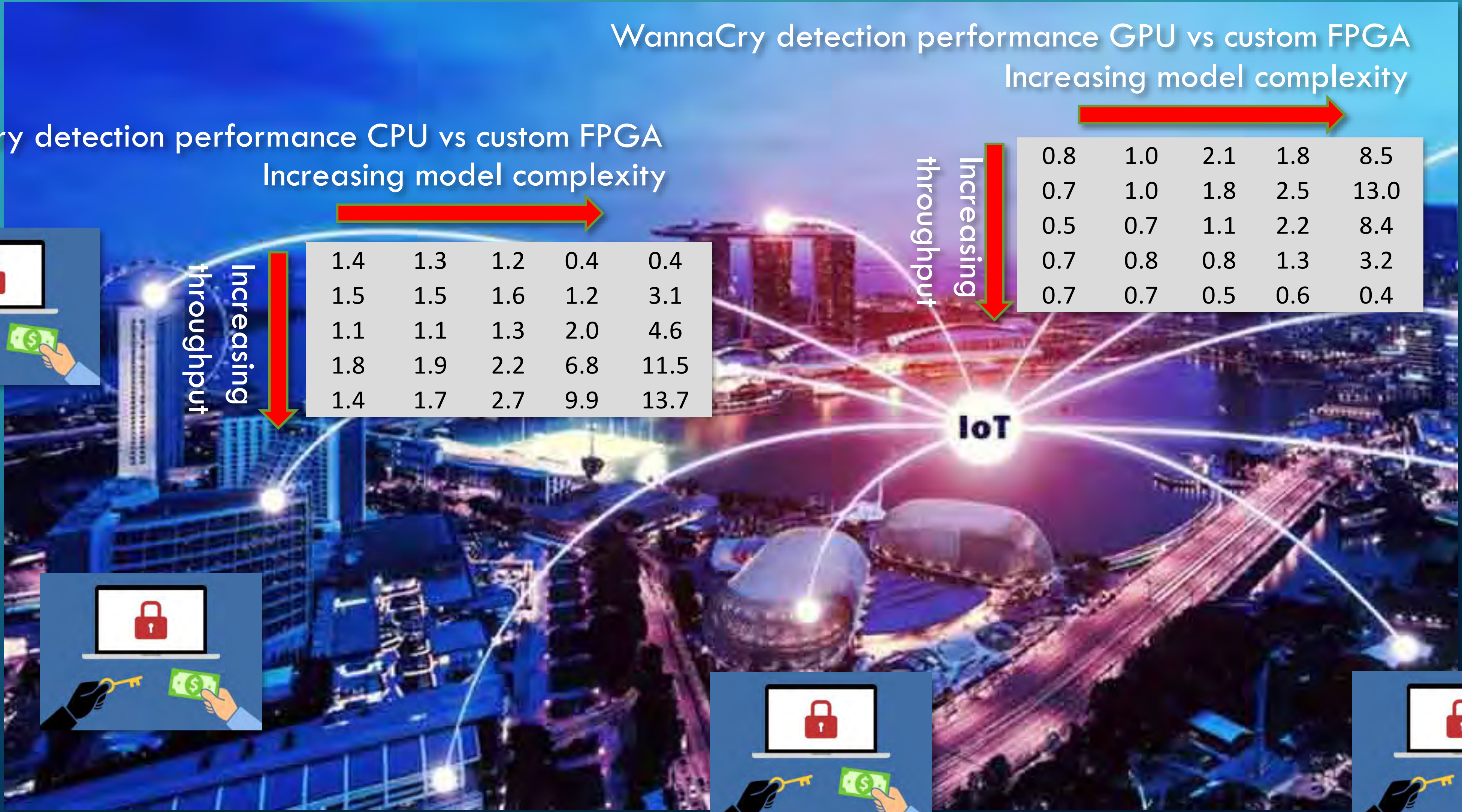



- 30% features reduction
- 15% accuracy improvement

CAEML research

# SECURING THE EDGE : RANSOMWARE DETECTION

- Machine learning has been shown to be effective in detecting day zero attacks
- Latency and throughput are both important




WannaCry detection performance CPU vs custom FPGA

Increasing model complexity →

Increasing throughput ↓

| | | | | |
|---|---|---|---|---|
| 1.4 | 1.3 | 1.2 | 0.4 | 0.4 |
| 1.5 | 1.5 | 1.6 | 1.2 | 3.1 |
| 1.1 | 1.1 | 1.3 | 2.0 | 4.6 |
| 1.8 | 1.9 | 2.2 | 6.8 | 11.5 |
| 1.4 | 1.7 | 2.7 | 9.9 | 13.7 |

WannaCry detection performance GPU vs custom FPGA

Increasing model complexity →

Increasing throughput ↓

| | | | | |
|---|---|---|---|---|
| 0.8 | 1.0 | 2.1 | 1.8 | 8.5 |
| 0.7 | 1.0 | 1.8 | 2.5 | 13.0 |
| 0.5 | 0.7 | 1.1 | 2.2 | 8.4 |
| 0.7 | 0.8 | 0.8 | 1.3 | 3.2 |
| 0.7 | 0.7 | 0.5 | 0.6 | 0.4 |

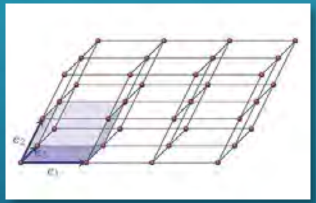
# SECURING THE EDGE : POST-QUANTUM SIDE CHANNEL ATTACH

Quantum computers is expected to be able to crack factor-based encryptions such as RSA

Homomorphic encryption

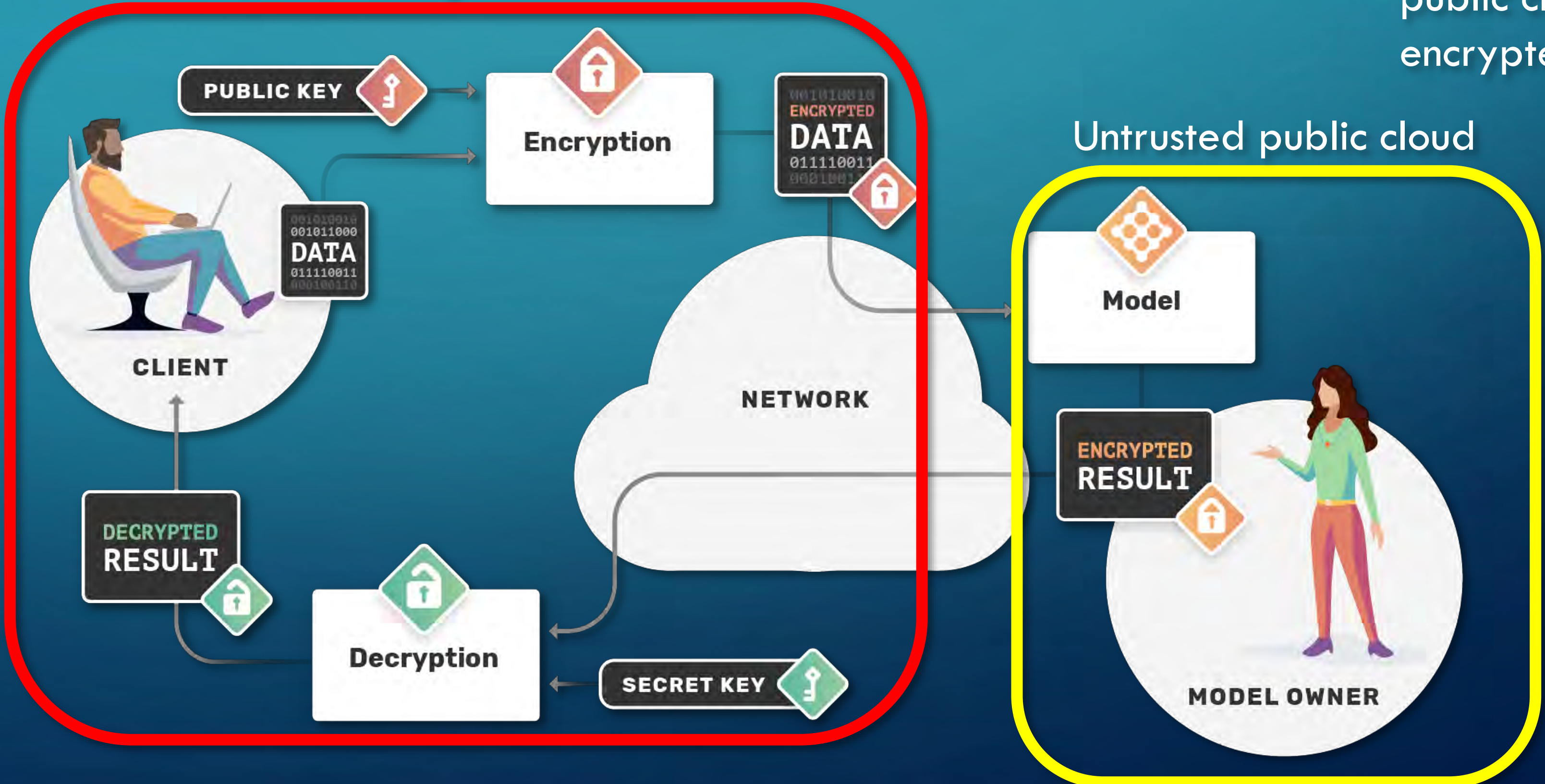
- Compute and operations done in public cloud with encrypted data

Lattice based
Post quantum
Homomorphic encryption

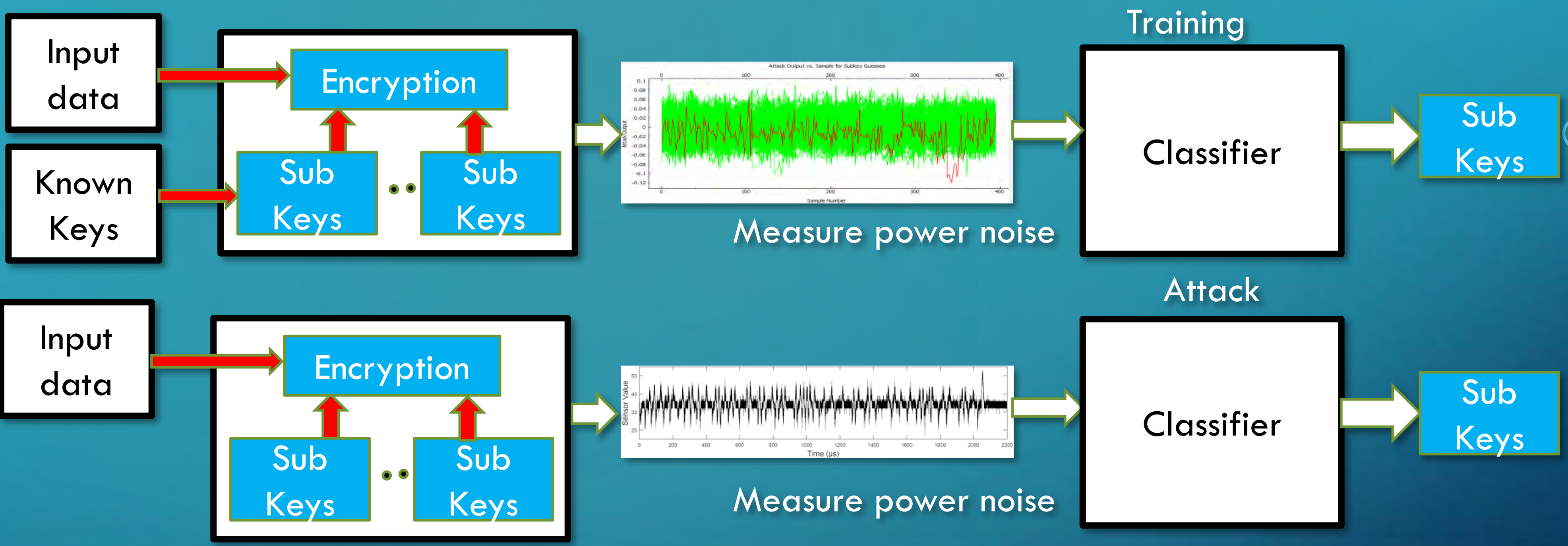


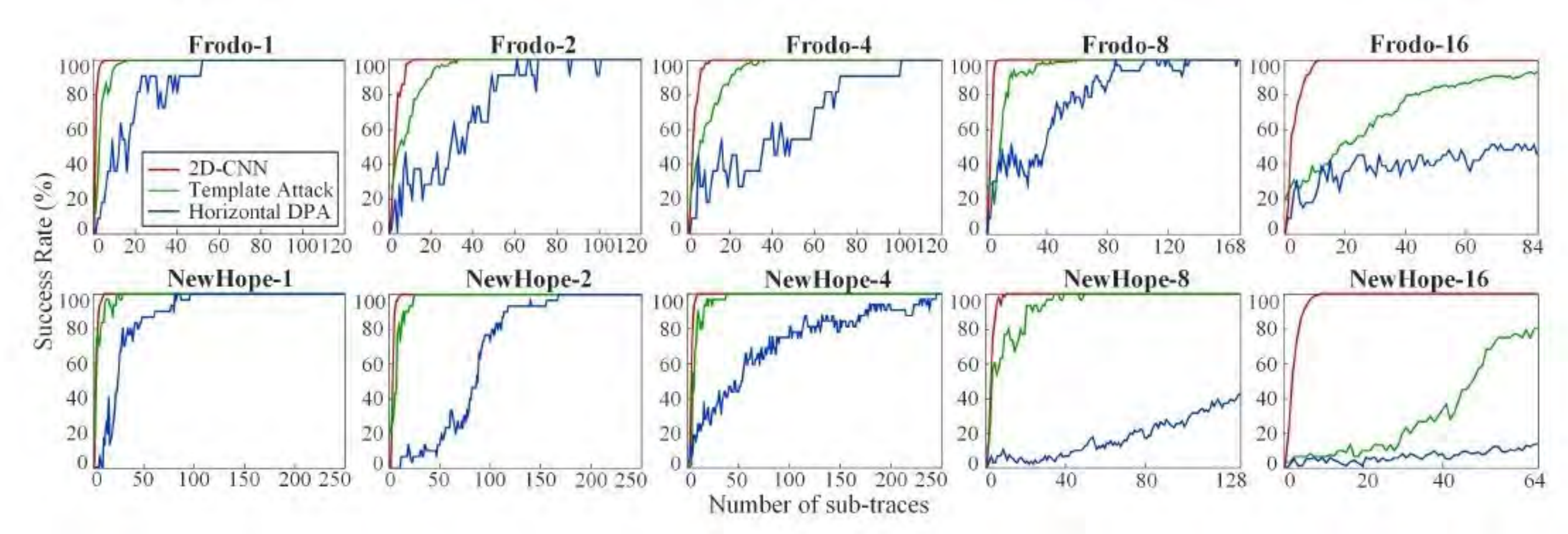
Secured edge device

Untrusted public cloud



# SIDE CHANNEL ATTACK POWER ANALYSIS




Aydin et al, SAMOS 2020

# FINAL THOUGHTS

- The learning continues but..
- Real world applications of ML/AI for SI/PI are here and many more to come
- Set up your own goals of using ML/AI and search for readily available solutions first
- Be prepare to spend 80-90% of your development time in data preparation, extract translate load (ETL)
- Enjoy the journey !