Smart Grid Edge Analytics

Sponsored by the NSF Spoke Smart Grid Data Analytics

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SAS

Smart Grid Edge Analytics

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- Why does Smart Grid Edge Analytics Matter?
- Prioritized Areas of Analytic Application in Utilities
- Enterprise Analytics Lifecycle
- Smart Grid Edge Analytics
  - Examples
  - Key Drivers
  - What is being solved
  - Why are we solving
  - Global Customer Examples
- Artificial Intelligence(AI) and Machine Learning(ML) in Utilities
- Interesting Use Cases across industries
- Evolve Your Analytics Platform

  "Don't let your analytics environment limit the analytic processes you run"
  SAS EVP COO/CTO Oliver Schabenberger

SAS in the Utilities Industry

560 energy customers worldwide

100% of Fortune 500 US Utilities are SAS customers using SAS for an average of 30 years

80% of Global Fortune 500 Utilities are SAS customers

1976 SAS founded with 2 utilities among initial customers

Why do Smart Grid Edge Analytics Matter?

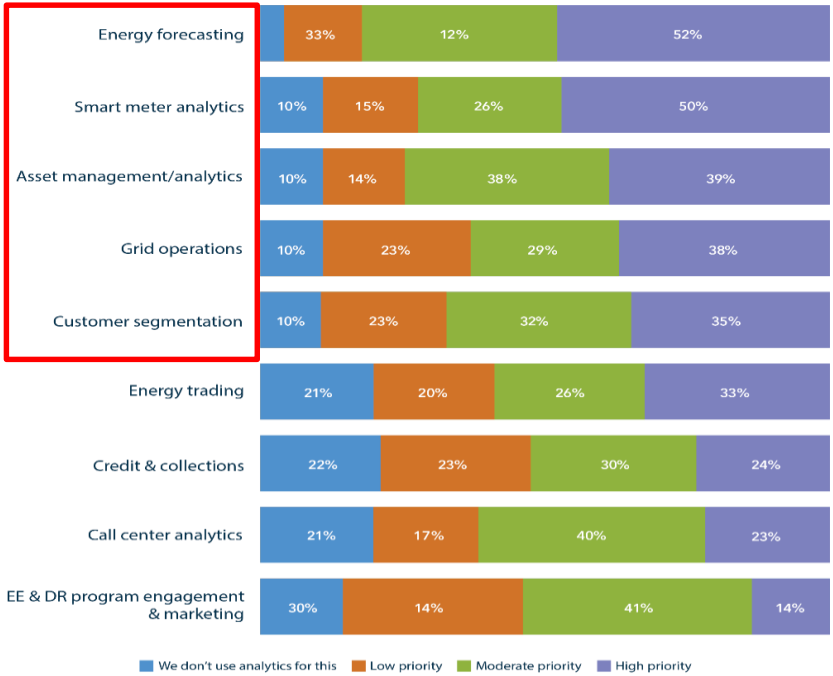
By 2019, at least 40% of IoT-created data will be stored, processed, analyzed and acted upon close to, or at the edge.

- Utilities are facing new operational challenges they have never seen before.
- Utility grid leaders are usually “hard-wired” to think operationally, not predictively.
- Expectations from regulators and customers are changing; the bar is being raised.
- Keeping the lights on will remain the #1 priority for utilities; they will need new tools to do this.
- The volumes, velocity, and complexity of smart grid/meter data will require a robust enterprise analytics platform.
- In addition, a streaming analytics engine will be required; this can be and should be deployed at the grid edge.

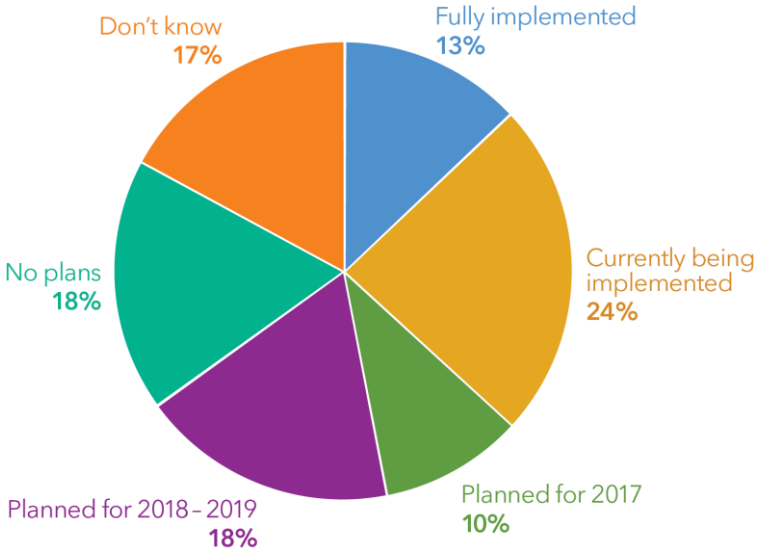
Edge AI will be critical as Edge Computing becomes mainstream.

Prioritized Areas of Analytic Application in Utilities

Smart Grid Edge Analytics Impact all of these areas directly



What is your utility's current status regarding implementation of an enterprise analytics platform?

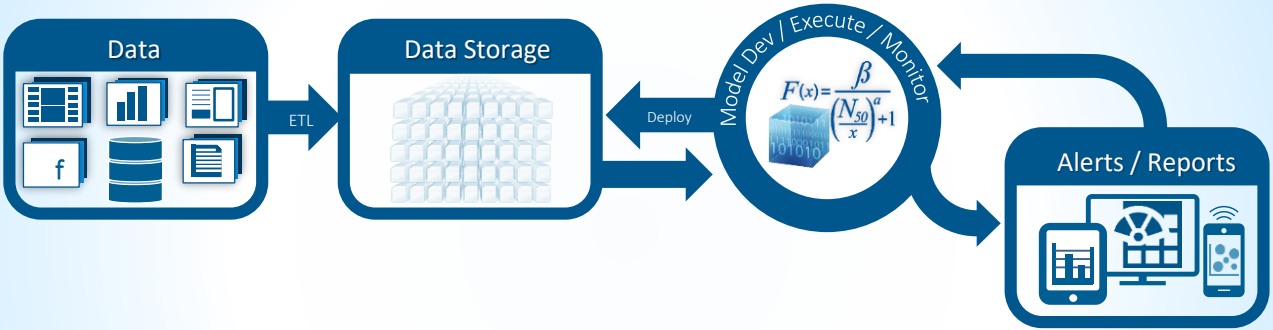


Source: https://www.sas.com/utility-analytics-2017

Enterprise Analytics Lifecycle

TRADITIONAL ANALYTICS LIFECYCLE APPROACH:

ACCESS - STORE - ANALYZE

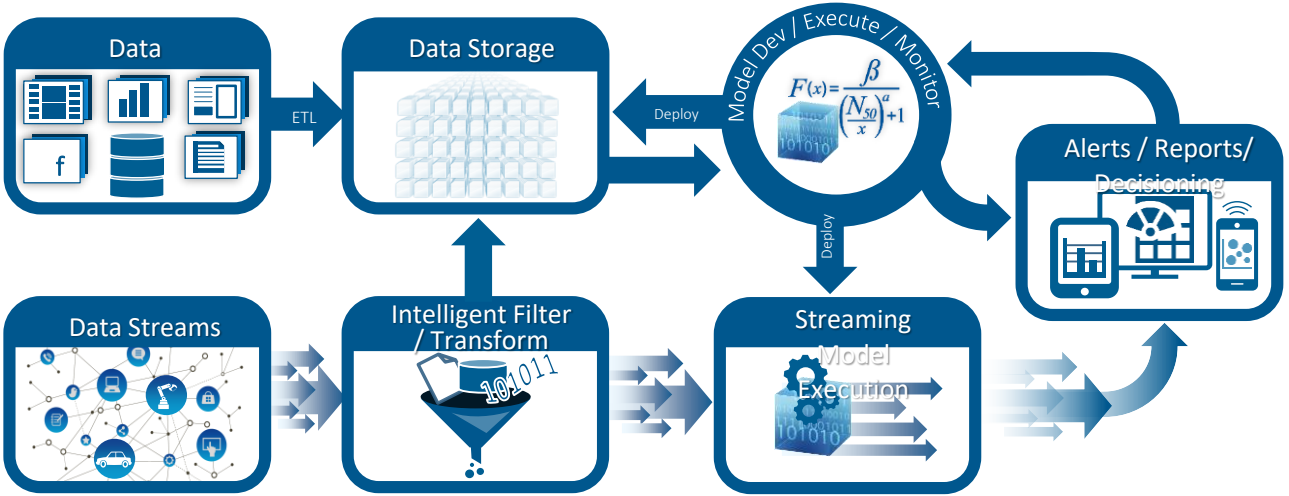


Traditional Approach

Enterprise Analytics Lifecycle

STREAM IT, FILTER IT, SCORE IT, STORE IT

SENSE - UNDERSTAND - ACT



Smart Grid Edge Analytics Approach
Or Recommended IoT Analytical Lifecycle Approach

Streaming Analytics Ecosystem

Edge Analytics

Network Systems, Surveillance

Monitor equipment on the platform for failures and safety issues, and take action.

In-Motion Analytics

Transactions, Logs, Clickstreams

Identify fraudulent transactions and be alerted in real-time.

At-Rest Analytics

Strategic Data Integration

Intelligently integrate customer information with real-time streaming data

Key Drivers

Smart Grid Edge Analytics

Reactive Monitoring & Control		Proactive Operations
Central Station Generation		Distributed Generation
Time-Based Maintenance		Predictive Maintenance
Siloed Customer Operations		Customer/Grid Nexus

Key Drivers

Smart Grid Edge Analytics

Reactive Monitoring & Control	→	Proactive Operations
Central Station Generation	→	Distributed Generation
Time-Based Maintenance	→	Predictive Maintenance
Siloed Customer Operations	→	Customer/Grid Nexus

…And do it all in Real to Near Real-Time!!!

Photo by Filip Mroz on Unsplash

Smart Grid Edge Analytics Examples

- Edge Analytics – through the use of event stream processing
- Asset Analytics – preventive vs reactive
- Power Quality – analysis done more often and further down into smaller subsections of the grid
- Use of PMUs – helping with reliability and fine tuning operations
- Renewables & Microgrid Optimization – requires different and/or more load forecasting to be done

Photo by Nikola Johnny Mirkovic on Unsplash

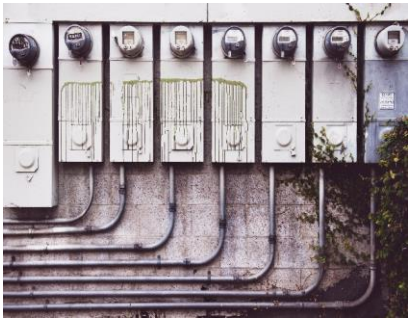


Photo by Tim Mossholder on Unsplash

Photo by RawFilm on Unsplash

What Are We Solving

Smart Grid Edge Analytics

- Electric power distribution circuits provide power to end users through a network of cables, transformers, switches, and other devices
- Circuit loading is limited by the physical capacity of devices
- When load exceeds limits, the circuit is shut down or damaged or becomes susceptible to future failure
- Necessary to identify transformers, switches, devices etc that are of higher risk to avoid interrupting power supplies to end users

What Are We Solving

Smart Grid Edge Analytics

- **Line distribution transformers:**
  - Not monitored by any automated processes
    - Distribution service transformers typically do not have sensors, instrument transformers, and other equipment to monitor its health.
  - Issues are captured on these devices when customers call in with a problem or outage is identified
    - Investigation that follows shows a transformer overload problem
- **Substation transformers:**
  - Annual analysis utilizing SCADA and load forecasting (Five year out) to plan for substation transformers
    - Some substation transformers may include monitoring systems such as sensors
- **Preventive Maintenance:**
  - All types of equipment on both the generation and transmission sides of the grid

Why are we solving

Smart Grid Edge Analytics

- **Costs**
  - Cost of distribution service transformer ranges from ~$1000 to more than $100,000+ based on its size
  - The power transformer costs can easily exceed $1 million
- **Business Needs**
  - Increase proactive prediction of pending transformer failures
  - Failure factor assessment to reduce transformer maintenance cost (O&M) and increase system reliability
  - Streamline planning and coordination required for transformer placement and maintenance
- **Business Opportunity**
  - Leverage smart meter (AMI) data and big data platform to monitor and proactively manage distribution transformer overloading

Why are we solving

Smart Grid Edge Analytics

Value of Predictive Maintenance

Independent reports* indicate the following industrial average savings resultant from the initiation of a functional predictive maintenance program:

- Return on investment: 10 times
- Reduction in maintenance costs: 25% - 30%
- Elimination of breakdowns: 70% - 75%
- Reduction in downtime: 35% - 45%
- Increase in production: 20% - 25%

*Source: Operations and Maintenance Best Practices Guide. US Department of Energy

Global customer examples

PG&E
Enterprise platform for analytics; smart meter analytics identify past and future cost savings

Eversource
Predict customer payment trends; drive corporate performance reporting

ScottishPower
Minimize debt across 5M customers by improving credit risk modeling

SCE
Improve forecasting efficiency with SAS; streamline the load and price forecasting process

Southern Company
Established predictive model for payment behavior to improve collections

British Gas
Optimize marketing campaigns to strengthen customer interactions and improve asset lifecycles

ENEL
Analyze smart meter data to determine trends and seasonal behaviors as well as simulate business scenarios

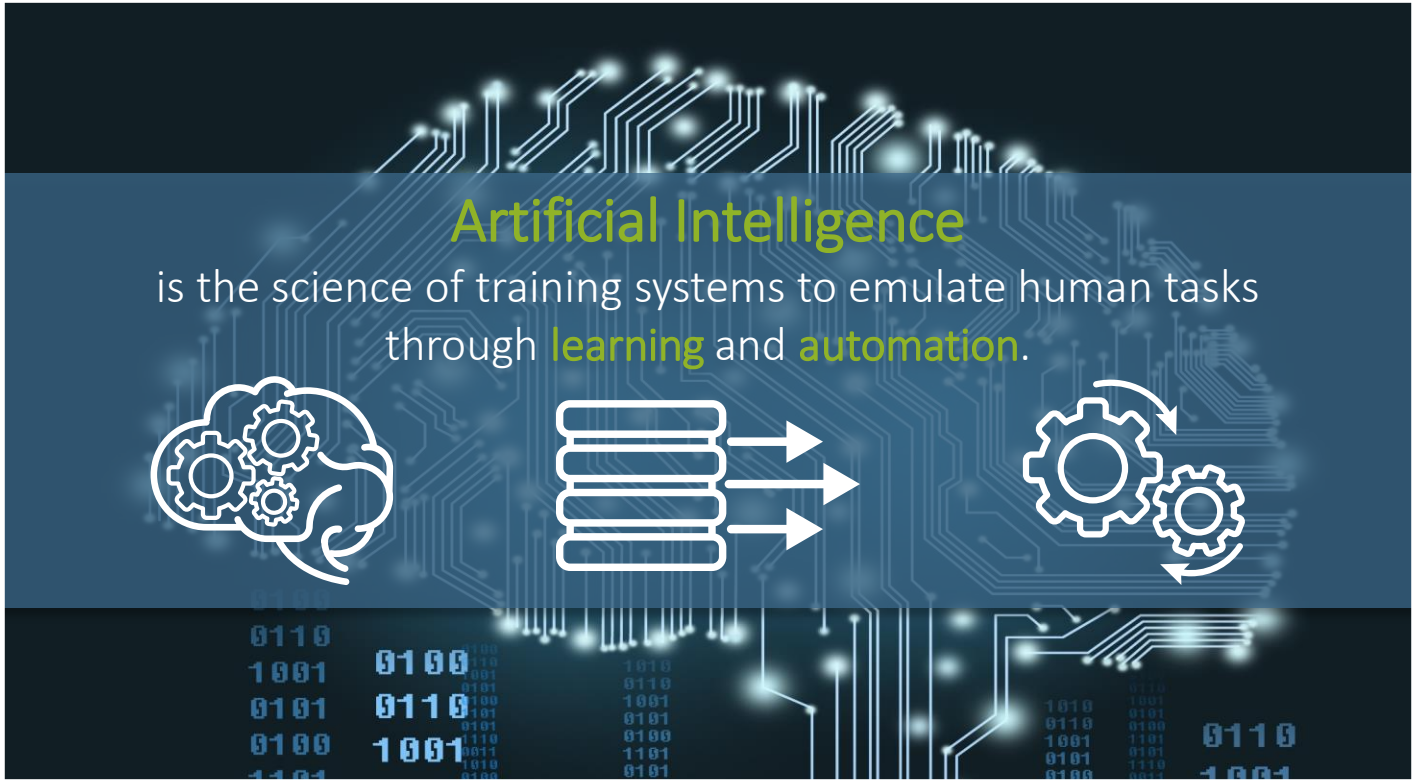
SRP
SAS Analytics provides insights on managing load and optimizing trades

RWE nPower
Improve short term demand forecasting for volatile and competitive market

Origin Energy
Improve demand planning, leading to more efficient generation and trading operations

EDF Energy
SAS data analytics improve modeling of churn and propensity for new products and services

Ausgrid
Integrate data for a single customer view; provide network performance analytics; improve reporting efficiency



AI/ML

WHAT YOUR FRIENDS AND FAMILIES THINK YOU DO AS A DATA SCIENTIST

Photo by Joshua Earle on Unsplash

AI/ML

WHAT YOU SPEND MOST OF YOUR TIME DOING AS A DATA SCIENTIST

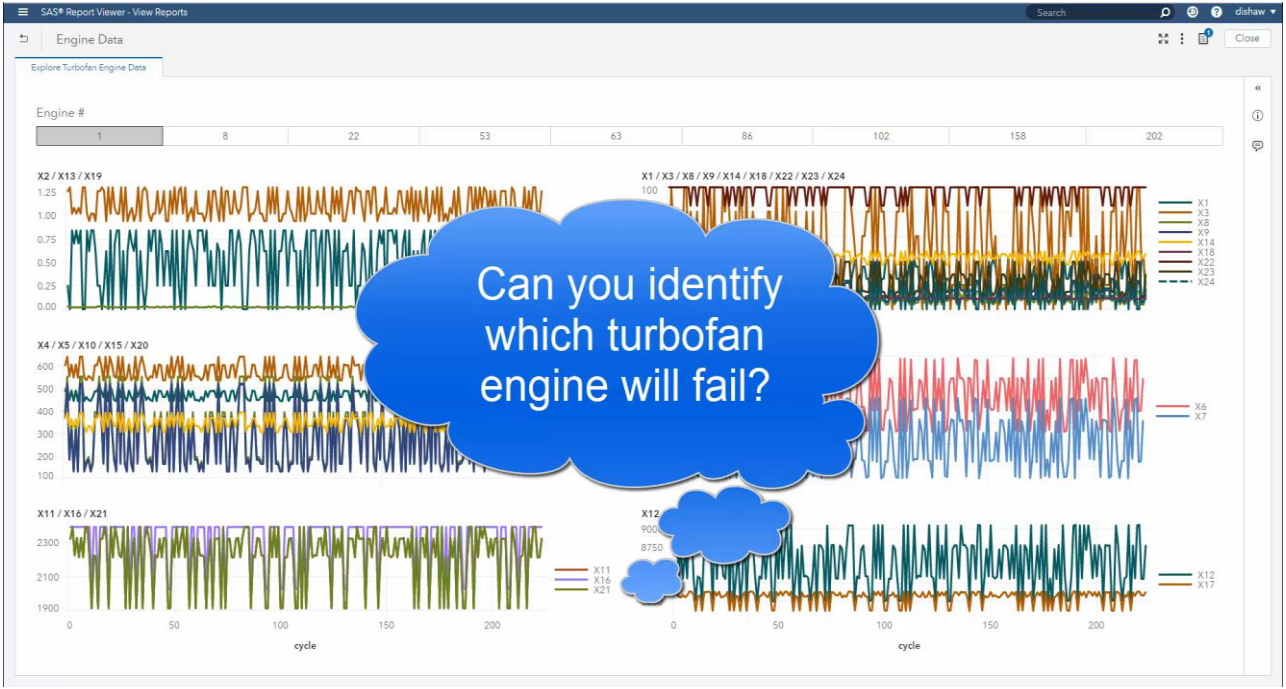
Photo by JESHOOTS.COM on Unsplash

AI in Utilities

Grid Reliability

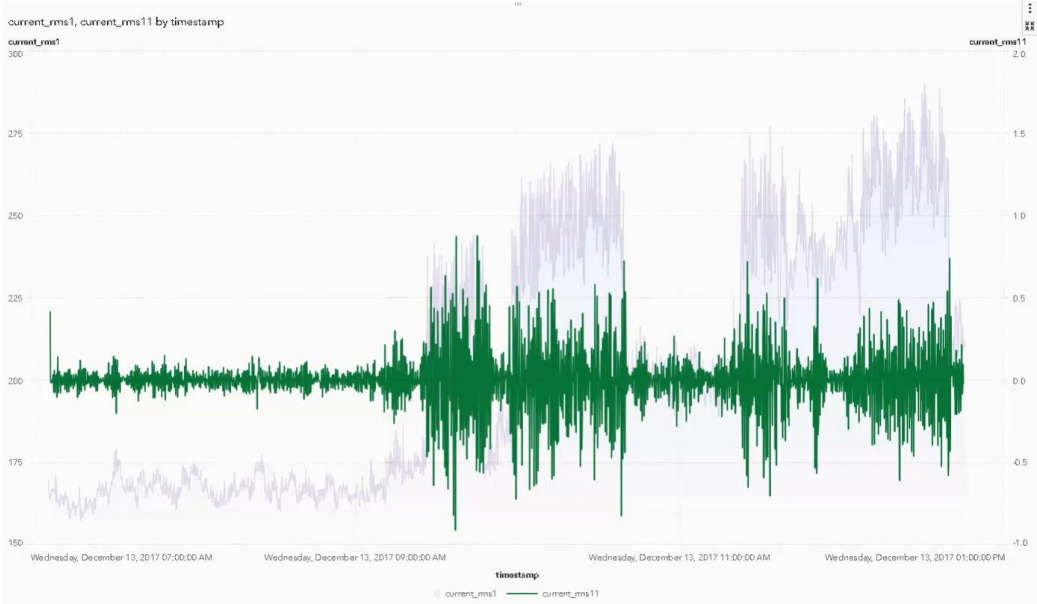
Customer Experience

Energy Forecasting



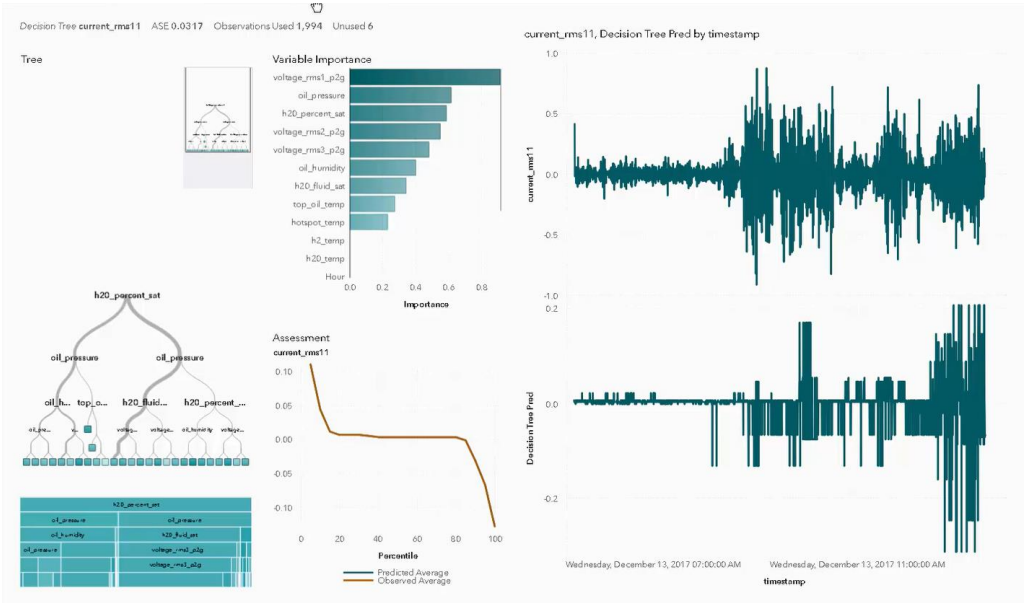
Transformer Behavior Over Time

HISTORICAL DATA USED AS A TARGET FOR PREDICTIVE MODELS



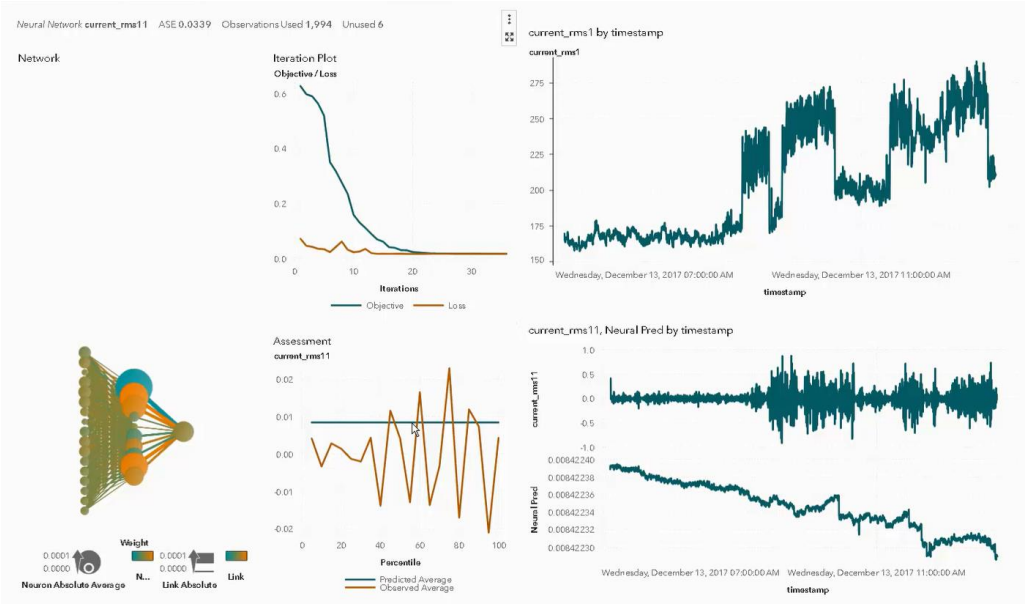
Target EKG Transformer Signal vs. Decision Tree Model

VARIABLE IMPORTANCE INFORMS US WHICH VARIABLES ARE THE MOST IMPORTANT FOR THIS MODEL

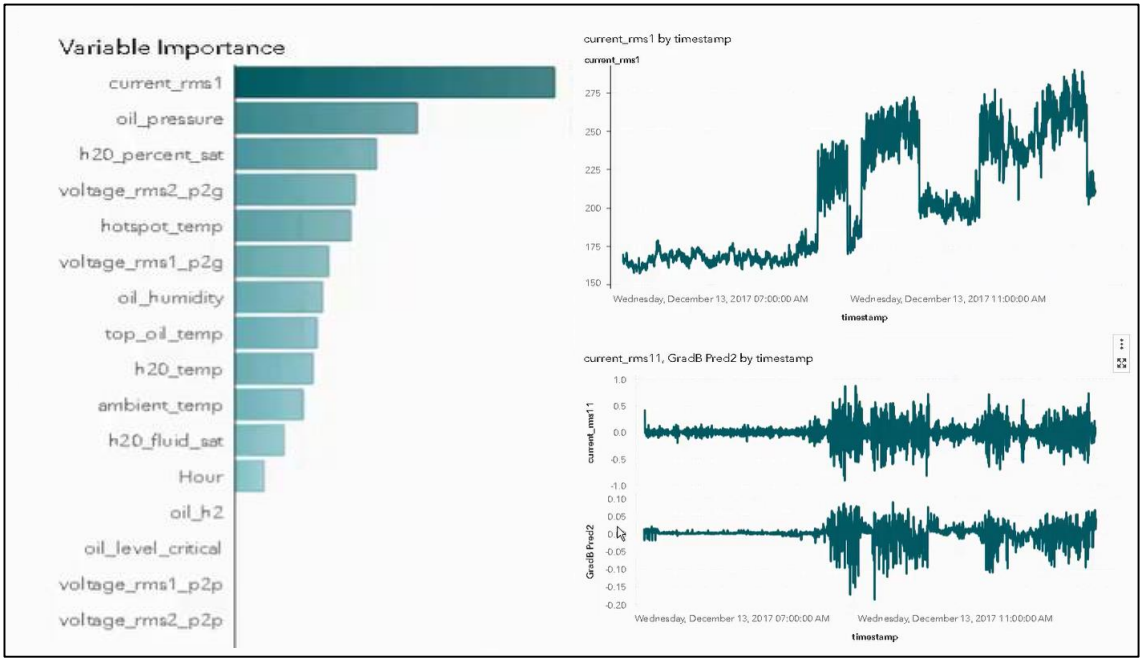


Target EKG Transformer Signal vs. Neural Network Model

IN THIS CASE A NEURAL NETWORK MODEL DOES NOT DO A GOOD JOB IN PREDICTING THIS TYPE OF DATA.

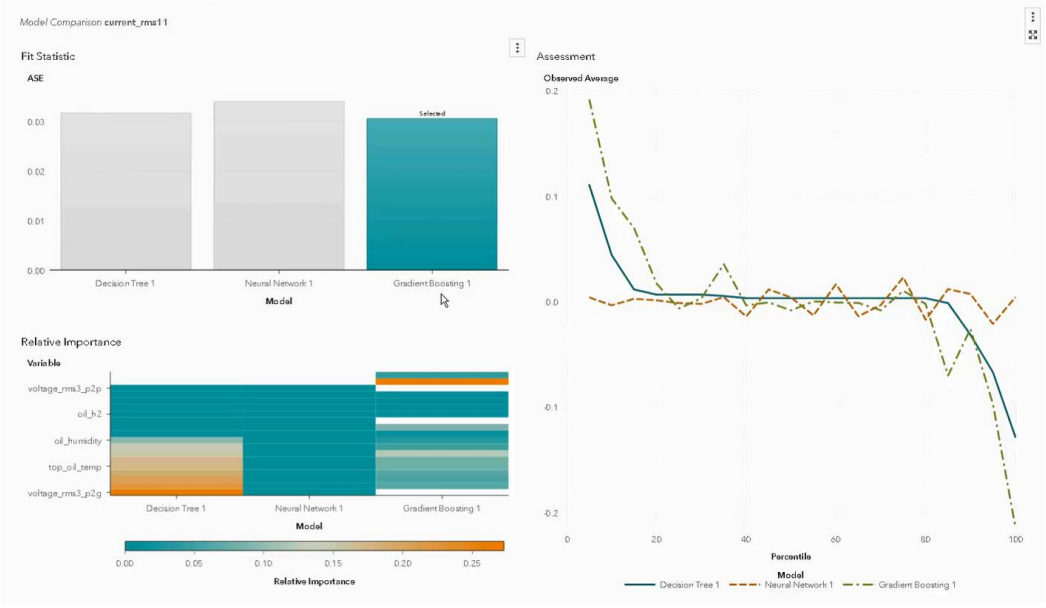


Target EKG Transformer Signal vs. Gradient Boost Model

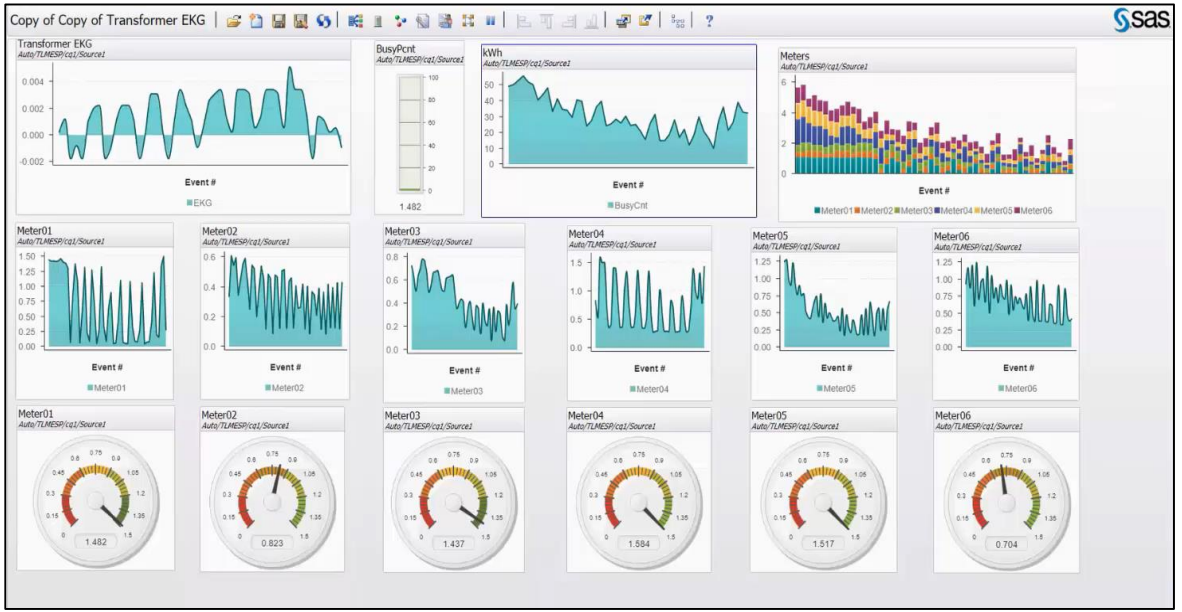


Automatic Model Comparison: Showing Gradient Boost as the Best

EVEN THOUGH IN THIS CASE IT WAS OBVIOUS THE BEST MODEL IT IS NICE TO HAVE DATA TO BACK US UP.



Transfer Model Deployed for Real-Time Monitoring



US Utility PMU Scenario

Key Challenges

- Phasor Measurement Units (PMUs) take measurements of the power transmission grid at a much higher speed and fidelity than previous systems provided
- PMUs take measurements on the power frequency (i.e. 60hz), voltage, current, and phasor angle (i.e. where you are on the power sine wave).
- These units take readings at a speed of 30 measurements/second, while the previous systems just took readings every 3-4 seconds.
- This more frequent interval provides a much more detailed view of the power grid and allows detection of sub-second changes that were completely missed before.
- To analyze data and learn about the whole grid, we need to synchronize the measurements taken at these locations.
- Big data is typically a large amount of data that has been captured and stored for analysis. Streaming data is constantly coming in a high rate of speed and must be analyzed as it is being received.
- One of the many interesting things about this project is that is involves both big data and streaming data.

How SAS® supported the process

Expected Results

- The main purpose of this project is to detect and understand events that are affecting the power grid, with the objective of keeping the grid stable
- We have learned there are a number of time-series techniques that are needed for the different aspects of providing the needed answers..
- The analysis flow breaks down into three areas: event detection (did something happen?), event identification (what happened?), and event quantification (how bad was it?).
- For event detection, the task at hand is streaming data analysis. 99.99% of the time there is not event in the streaming data and as such time series model can be used to detect when there is a deviation.
- Event identification is the next order of business. Some events are random, like a lightning strike or a tree hitting a power line. Others represent some type of equipment failure. As a result we found these types of events generate similar signatures in the data and through time series similarity and time series clustering you can identify what type of event has just happen and ignore those that are non-consequential.
- Finally there is event qualification. For some events its not that it is taking place, but the magnitude which may make it concerning. For example oscillation which are small in size and decreasing vs ones that are larger or increasing in size.
- If there is a need to automatically identify and categorize system events based on any type of streaming data patterns, or filter out events that are non-consequential, then these techniques will be helpful regardless of the industry.

Powered by

SAS®

Large US Utility
Customer Success

Key Challenges

- Distribution grid was under stress from integrating renewable energy resources, electric vehicles, and other new technologies.
- Disruptive technologies had potential to create or extend outages, impacting customer satisfaction.
- Needed to understand when installed assets are forecasted to exceed design limits because of forecasted changes in load and generation.

How SAS® supported the process

Expected Results

- Use analytics to drive long term asset planning.
- Implement data-driven predictive maintenance programs on distribution system.
- Improve reliability and customer satisfaction, thereby mitigating risk of grid defection.
- Significant improvements in forecasting accuracy and speed of performance.

Powered by

SAS® Energy Forecasting

Volvo Trucks and Mack Trucks
Customer Success

Key Challenges

Volvo Trucks and Mack Trucks are both subsidiaries of the Swedish Manufacturer AB Volvo.

- Enhance remote diagnostics and monitoring of critical engine, transmission and after-treatment trouble codes.
- Minimize unplanned downtime - which creates a tremendous toll on fleet operators and their customers who depend on timely deliveries.
- Improve vehicle efficiency and uptime to keep trucks running – or ensure the least disturbance to the business if something happens on the road.

How SAS® supported the process

Expected Results

- 175,000 trucks are supported with remote diagnostics.
- Millions of records are processed instantaneously - reducing diagnostic time by 70% and repair time 25%.
- Thousands of sensors on each truck collect streaming IoT data in real-time to provide the context needed for more accurate diagnosis.
- SAS enables Volvo and Mack to maximize vehicle uptime and minimize the costs of service disruptions by servicing connected vehicles more efficiently, accurately and proactively.
- Able to help customers recover from problems faster while preventing problems from arising in the first place.

Powered by

SAS® Advanced Analytics and AI

"With SAS, we're working smarter – we're seeing things that exist in our information that we couldn't find before, so we can do things more efficiently and effectively, and drive better results for our customers." –David Pardue, VP of Connected Vehicle and Uptime Services for Mack Trucks

"Our engineers can now see issues before they impact customer operations and change the truck's design, so we have the best product on the road." –Conal Deedy, Director of Connected Vehicle Services for Volvo Trucks North America

WARGAMING

Customer Success

https://www.sas.com/en_us/insights/articles/big-data/industrialized-modeling-helps-monetize-free-to-play-video-games.html?utm_source=TWITTER&utm_medium=social-sprinklr&utm_content=1036305675

WARGAMING

Customer Success

Every day, millions of people play World of Tanks to clash with other tanks in virtual battlefields.

Big Data = Wargaming scales its analytics to understand **terabytes** of daily customer data

Alex Ryabov – Head of Business Intelligence Data Services Wargaming.

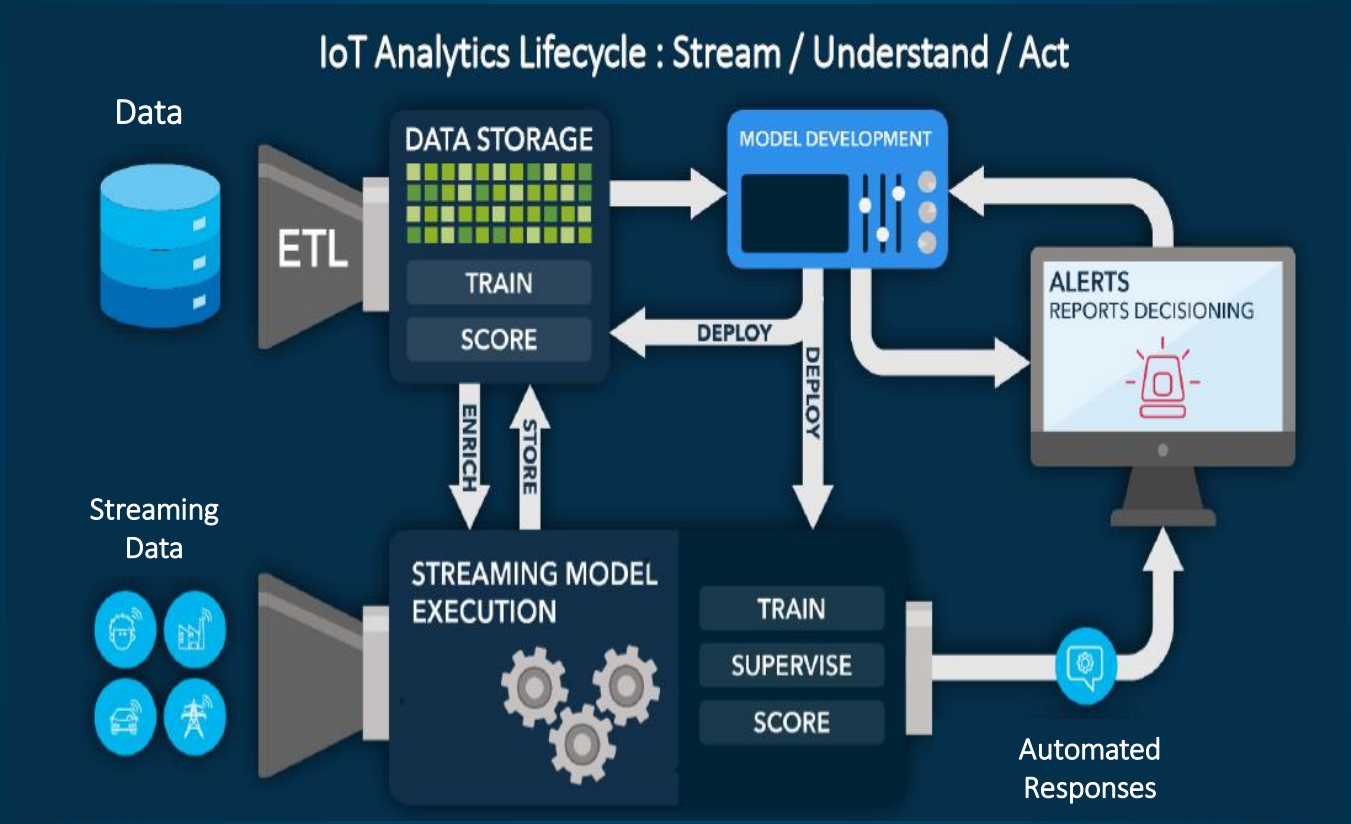
- "Once we understood the need for in-depth data analysis and data mining, we started doing some initial, advanced analytics modeling in R, Spark, Python and all the other open source solutions."
- "The biggest issue for us was scalability. Our data scientists come up with a model concept, do some data wrangling, some data extraction and then we need to automate the results. It was all manual. It was a lot of work for our developers."
- According to Ryabov, the first models his team created took three to six months to implement. "Once we realized that we're going to be running hundreds or even thousands of models for all of our games, all of our regions and in all of our time frames, we started looking for the solution that could make it scalable for us."
- "SAS Factory Miner and SAS Model Manager were perfect for our use cases," he says, "because we can take the same model and multiply it by time frames, regions and by different products. So a model is virtually the same, but we can put it into the production environment, where we run, maintain and promote it over and over in an industrial sort of way. In our research, SAS was the only viable option."

Business Results:

- Transitioned most coding to a point-and-click based workflow for model building efficiencies.
- Reduced the amount of time needed to develop and deploy models by 60 percent.
- Reduced the need for data warehouse administration in the deployment and automation of models by 80 percent.
- Most importantly, the players benefit too. "SAS helps increase overall satisfaction and make the player experience even better."
- Taken steps to realize an ROI of US $20 million to $30 million by identifying player microsegments and extending the next best offer to individual gamers.

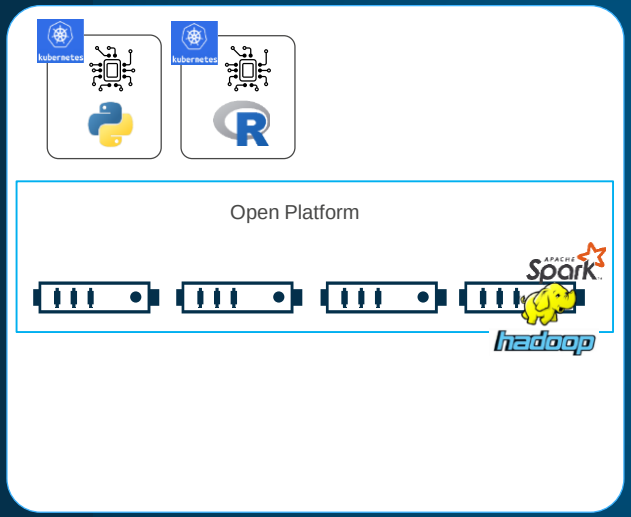
https://www.sas.com/en_us/insights/articles/big-data/industrialized-modeling-helps-monetize-free-to-play-video-games.html?utm_source=TWITTER&utm_medium=social-sprinklr&utm_content=1036305675

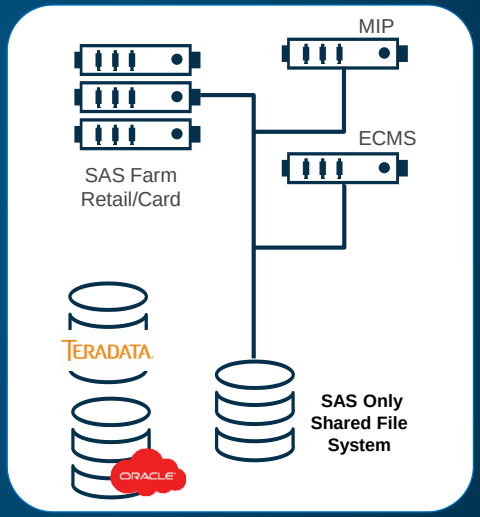
ENTERPRISE ANALYTICS PLATFORM: HIGH LEVEL



EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: CURRENT STATE

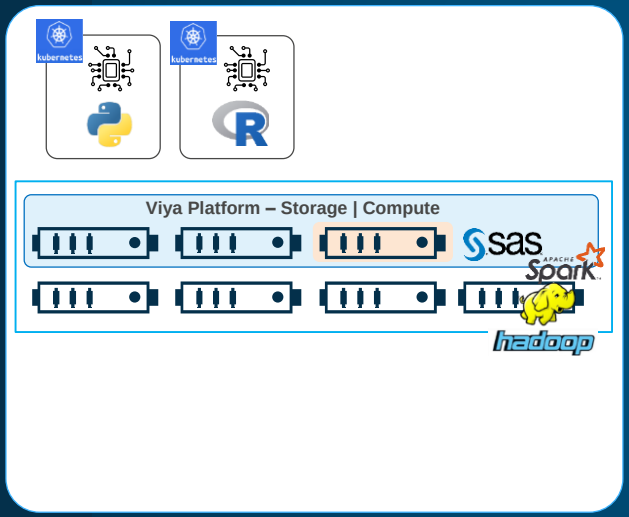
USER EXPERIENCES

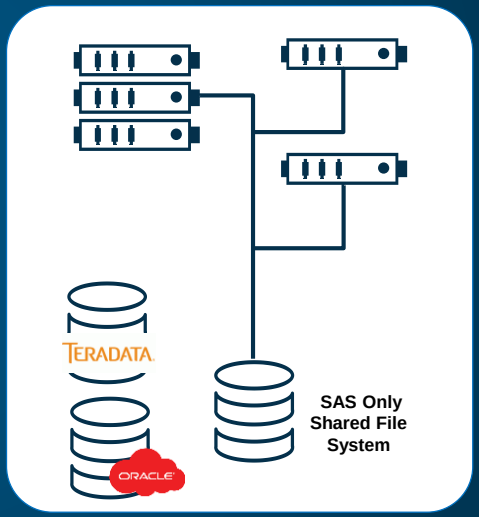




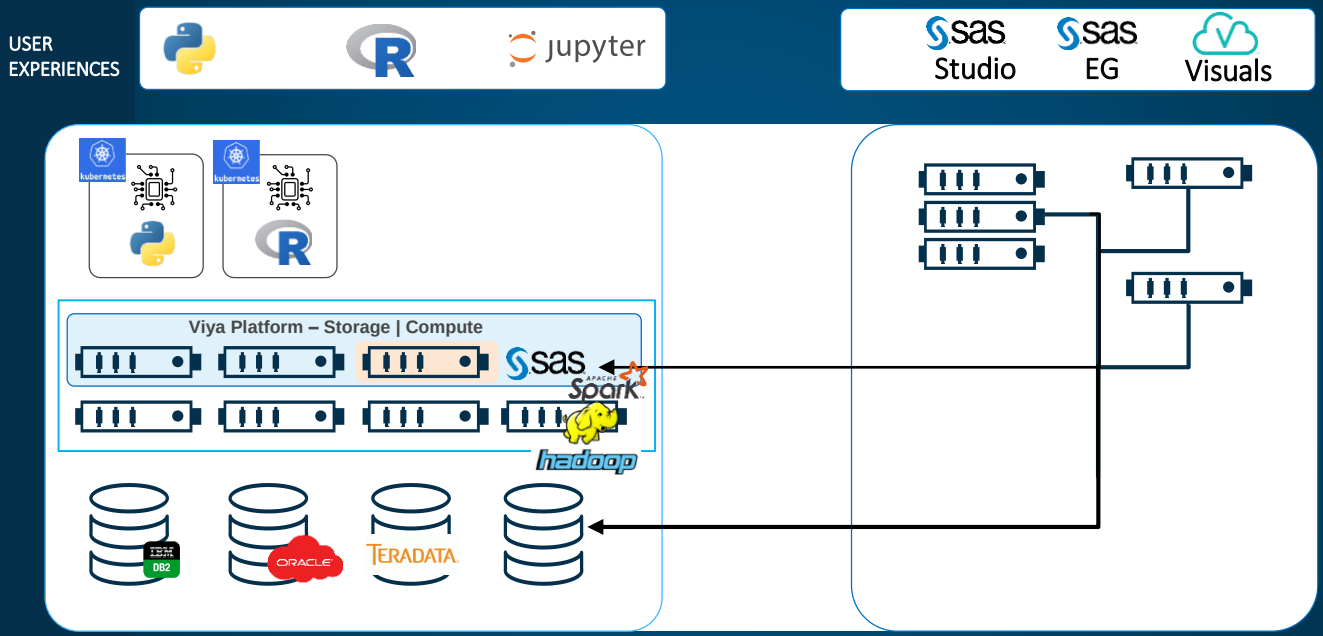
EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: ADD SAS VIYA

USER EXPERIENCES

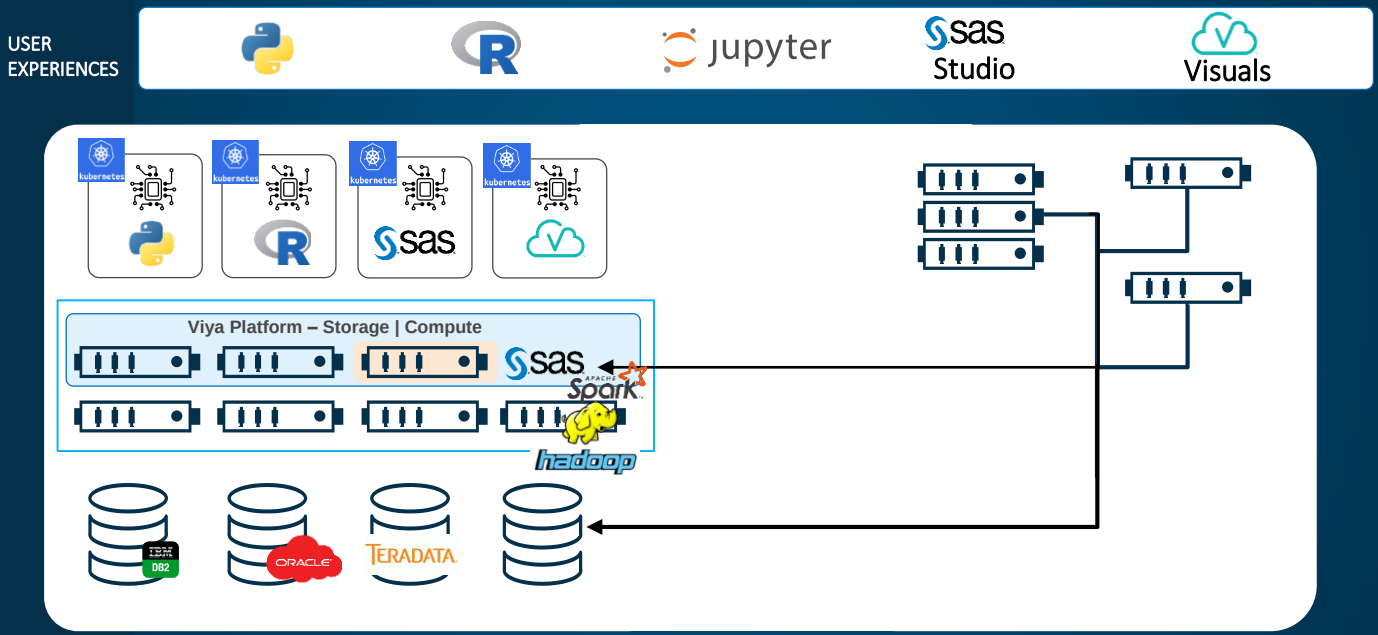




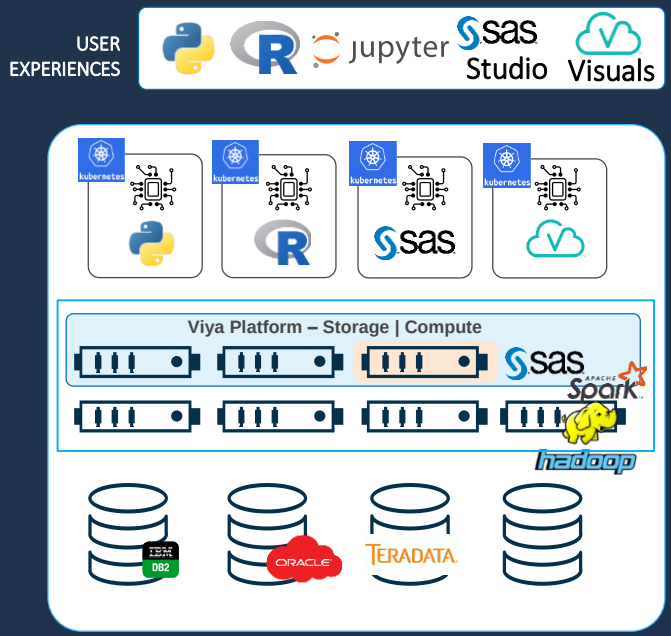
EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: REFACTOR



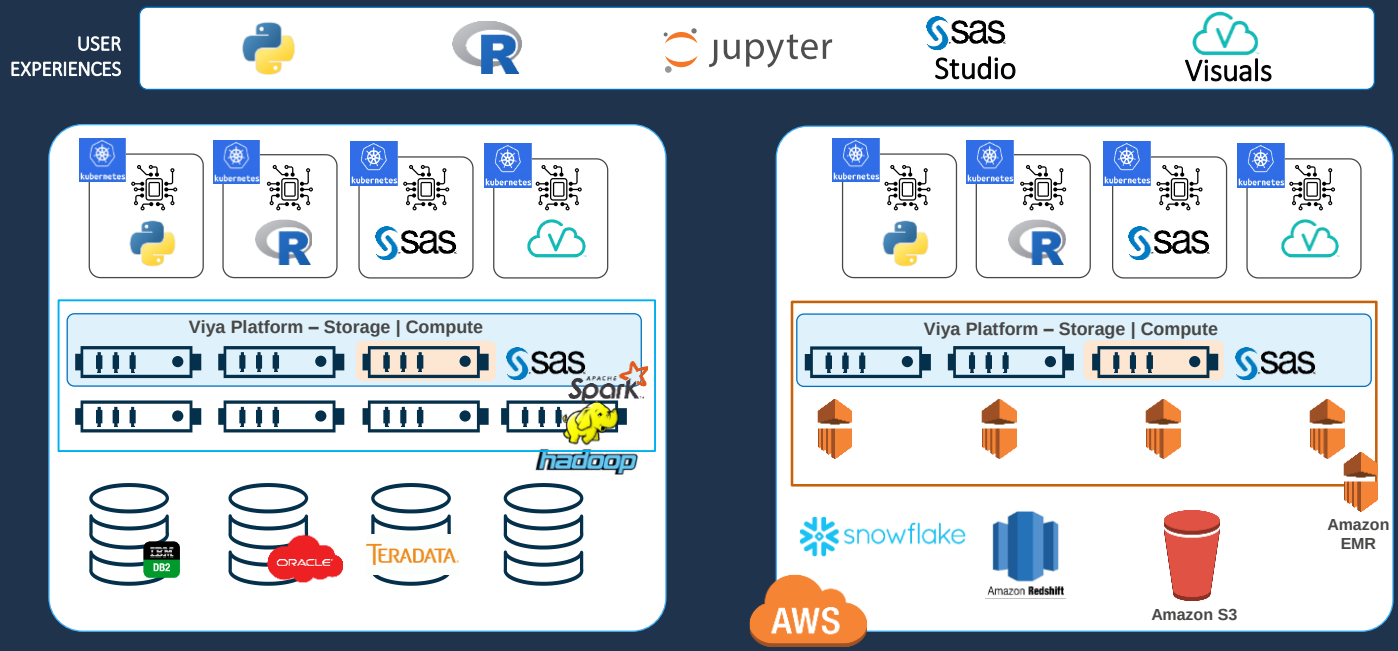
EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: REFACTOR



EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: END STATE 1 ON-PREMISE



EVOLVING YOUR ENTERPRISE ANALYTICS PLATFORM: END STATE 2
HYBRID ON-PREMISE WITH AWS



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