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Improving SiP Quality and Reducing Their Cost with Machine Learning and Predictive Analytics
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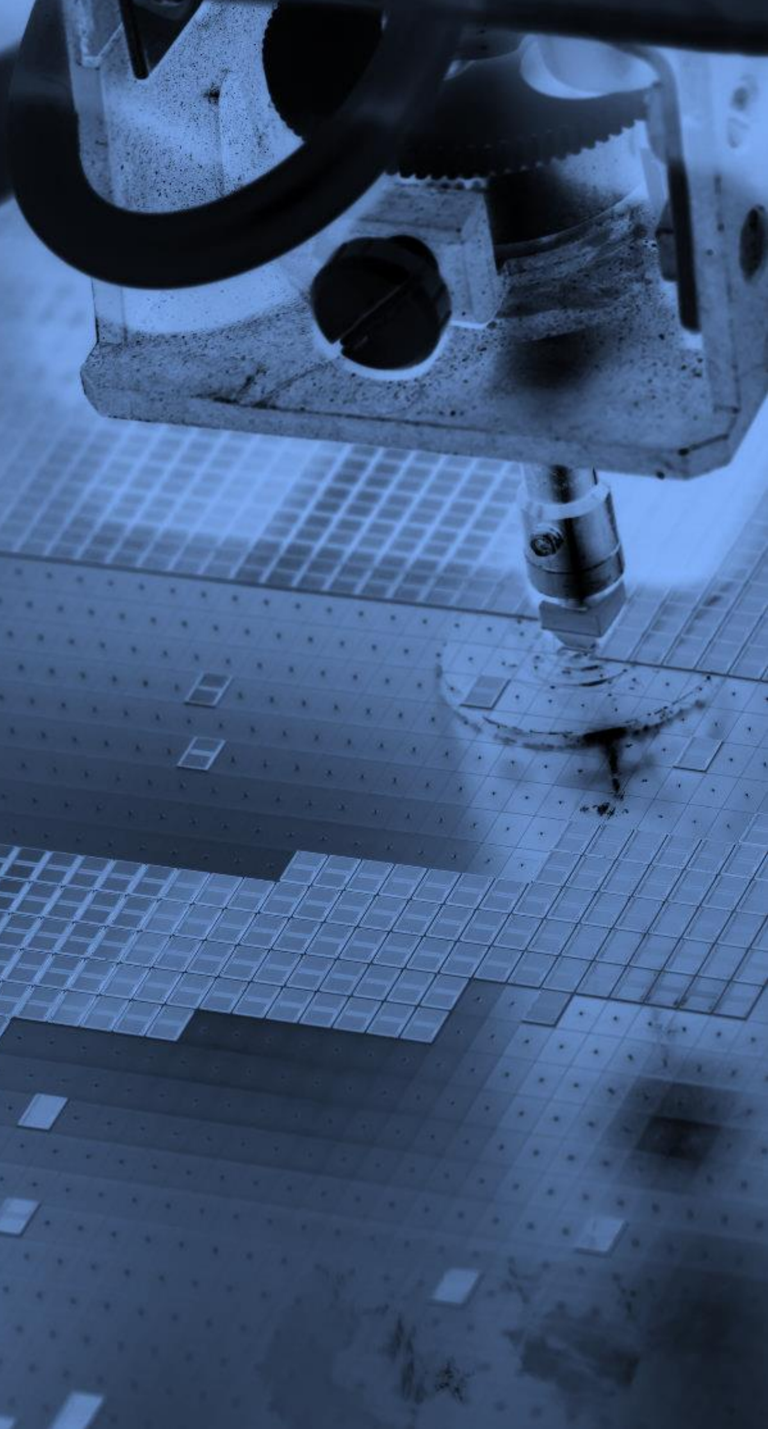
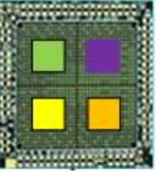


Value Proposition and Challenges for SiP "Chiplets"



- **Value Proposition**[1] :
  - Better yield due to small die size.
  - Optimize yield, performance, and overall cost by mixing chiplets from different technology nodes.
  - Shorter IC design cycle / less integration complexity by using pre-existing chiplets.
  - Lower manufacturing costs by purchasing known-good die (KGD).
  - Volume manufacturing cost advantage when the same chiplet(s) are used in many designs.
- **Challenges**[2] :
  - Chip compatibility and integration challenges due to interface standardization.
  - More complex data integration and storage.
  - Data standards.
  - Security (e.g. "man-in-the-middle" attacks, hardware Trojans).

References:
(1) "Moore and More", Paul McClellan, Semiconductor Engineering, May 2020
(2) "Chiplet Reliability Challenges Ahead", Ed Sperling, Semiconductor Engineering, Aug 2020

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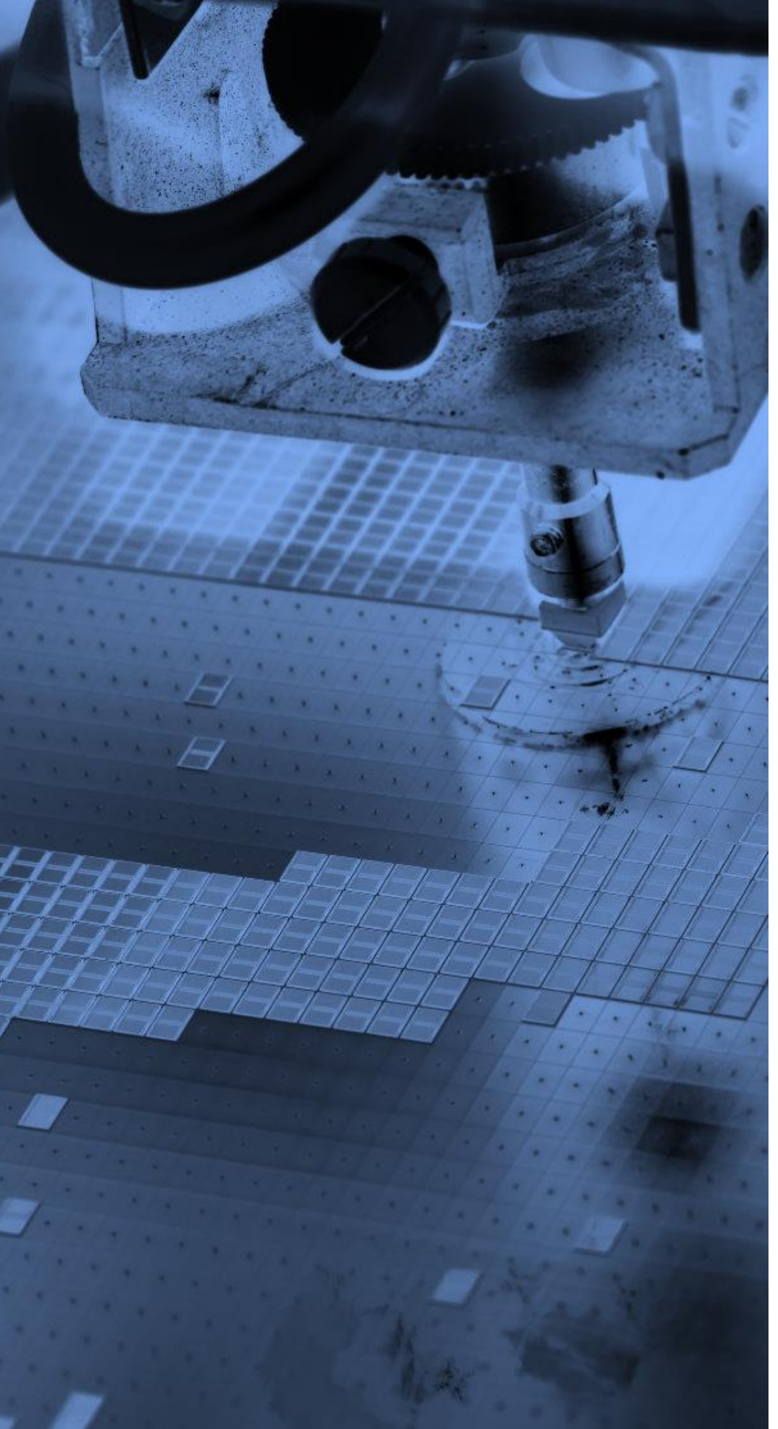

Meeting the Challenges of SiP Manufacturing

- *Conventional test techniques based on specification limits often fall short of guaranteeing acceptable quality levels, and statistical outlier mechanisms fail to perform well due to the large number of measured test parameters.*

➡ **ML can be leveraged to better predict SiP quality, as large quantities of parameters and their complex interactions are considered simultaneously.**

➡ **An advanced platform is needed that can integrate the complex SiP data flows end-to-end, and also meet the increased data storage needs.**

➡ ***Let's explore the application of modern machine learning techniques to predict devices at risk while concurrently expediting and/or reducing tests for die with little risk of defectivity.***

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Quantifying Predictive Power

- Look at the data relationships – is there predictive power in the data?
  - If the predictive power is low, then recommend tests that are more predictive (based on other experiences).
  - If the predictive power is sufficient, then we proceed with the relevant Solution.
  - Recommend if more data is needed, i.e. we determined the sample size is too low.

For example: Are there Final (Packaged die) Test or System-level Test failures that have no correlation to any upstream data? Those failures will never be captured – can additional test coverage address this?

- What are the value of individual tests run?
  - Identify tests that add no value, and remove them.
- If we need to propose tests, what are they? Which tests give the highest value? What data inputs help predict failures the best?
  - Create a master database of key indicators that predict failures at each phase.

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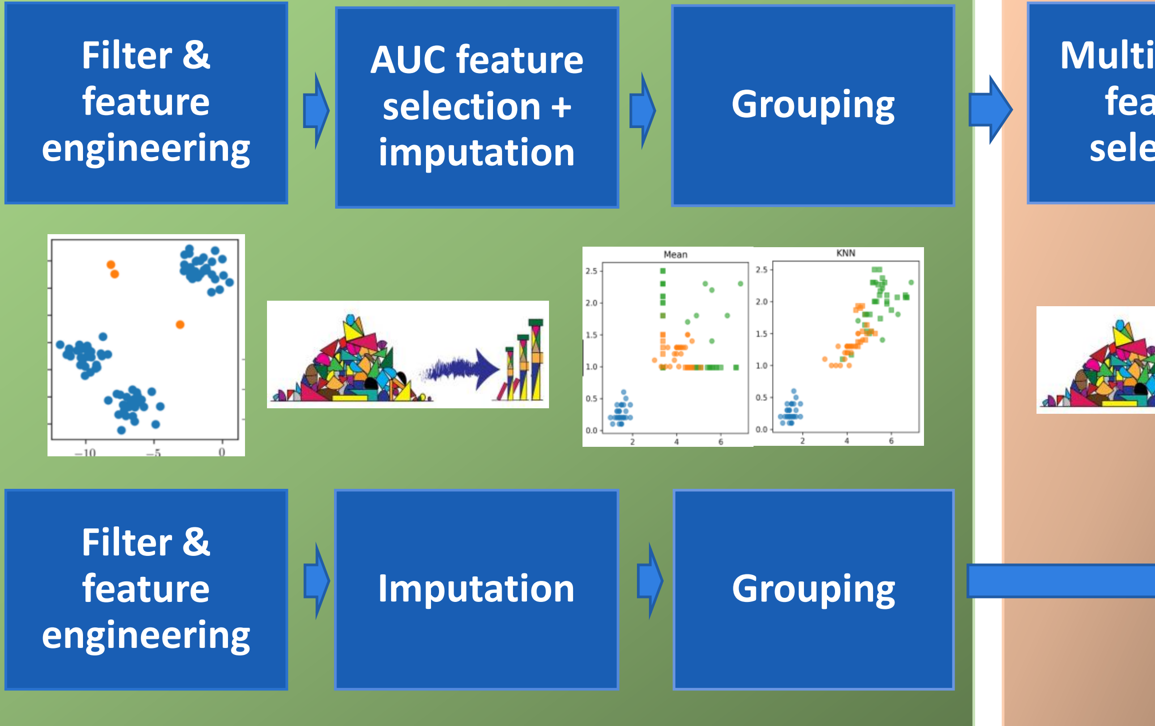
Model training and prediction pipeline example

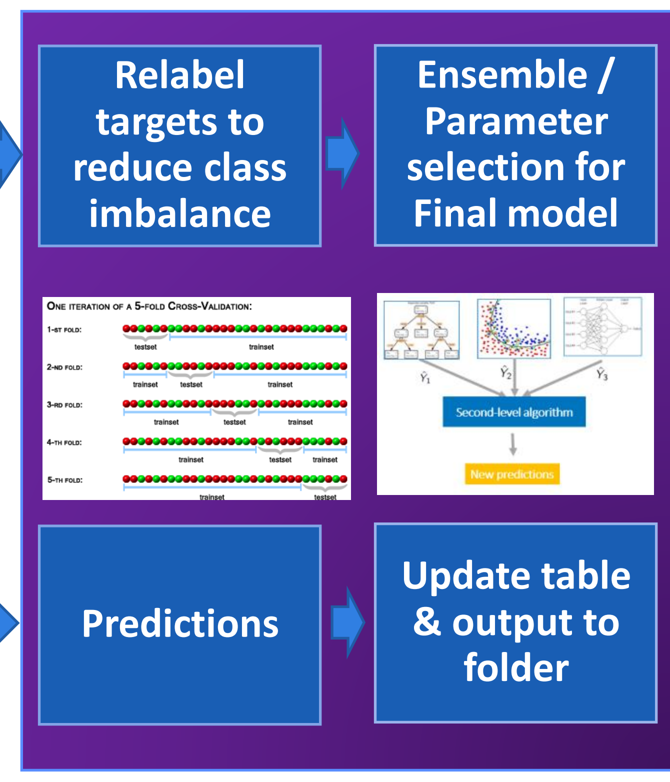
Data Preparation & Feature generation *Feature Selection* *Model Training / Execution*

Training

Prediction



Multivariate feature selection



- Handle incomplete data (retests etc)
- Clip extreme values & impute missing data
- Remove highly correlated features
- Adjust to shifting input data schema

- Tree-based classifiers
- Proximity based classifiers
- Linear classifiers

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Exensio® Manufacturing Analytics : Yield & Quality Examples

Product / Solution	Description	ROI
Smart Testing – Predict Final Test & Burn-in	AI Prediction of test requirements based on electrical wafer sort parametrics	Reduce test or burn-in requirements by > 30-60%
FPM – Fab & Final Test Predictive Modeling	Predict wafer and die level yield & parametric prior to sort & Final Test operations (or other responses).	Predict yield loss prior to BIN SORT. Reduce yield loss & excursions. Reduces Eng investigative resources.
ASD – Adaptive Signature Diagnostics (Smart Analysis)	Uses spatial signature analysis, ML, to classify SORT BIN failures and auto-diagnose likely root cause of yield loss	Identify sources of yield loss immediately after BIN SORT. 5x faster than conventional analytical techniques.
IMD – Intelligent Material Disposition (aka MRB)	Wafer level grading & disposition for MRB with near real time execution	Reduces engineering effort for lot disposition by >50%
ELF – Early Life Failure detection (die level MRB)	Comprehensive Die Quality Grading - Classify risk based on sort soft bin parametrics	Prevent quality and reliability escapes by detecting high risk die at Wafer Sort

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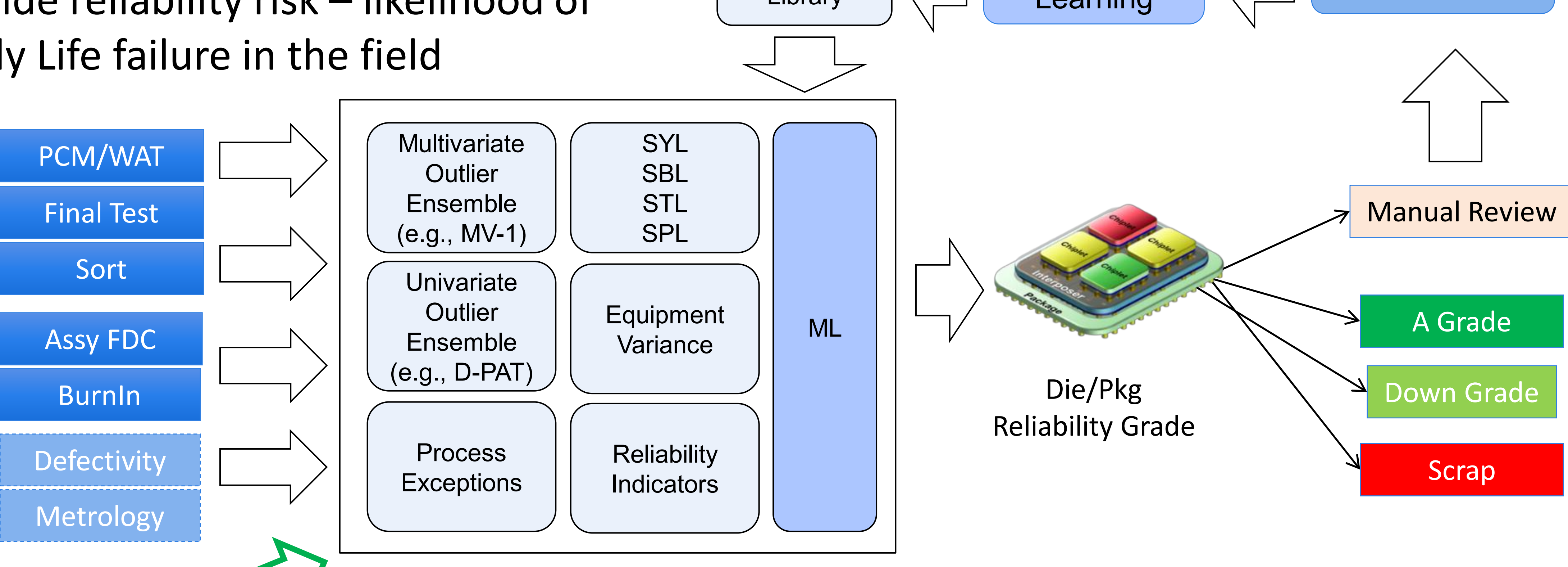
Example: Machine Learning for Early Life Failure Detection (ELF)

Machine Learning based solution to decide reliability risk – likelihood of Early Life failure in the field



Multiple data types, Multiple algorithms, Machine Learning, Potentially large data sets, Collaborative Learning, ...

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Limitation of ML algorithms

- ***No Free Lunch Theorem*** (Wolpert 1996) shows that no single algorithm works for classification-related Machine Learning and Statistical Inference problems. This concept is applicable for Anomaly Detection as well.

- Given different datasets, the anomaly detection algorithm that works best will vary.
  – Different algorithm may provide additional insight into the dataset.

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Anomaly Detection vs Supervised Learning

Why Anomaly Detection?

- Anomaly Detection usually works well when there is pre-dominantly single "normal" class with possible multiple different disjoint "abnormal" classes.

- Anomaly Detection usually works better than Binary / Multiclass Classification when classes are skewed / imbalanced.

Type of Anomaly Detection:

- Clustering based Anomaly Detection
- Classification based Anomaly Detection
- Hybrid Anomaly Detection

	Category	Dataset	Class
Anomaly Detection	Supervised Semi-Supervised Unsupervised	Imbalanced	Binary
Classification	Supervised	Balanced	Binary Multi-class

Agrawal, Shikha, and Jitendra Agrawal. "Survey on anomaly detection using data mining techniques." Procedia Computer Science 60 (2015): 708-713.
https://talkai.blog/2019/04/01/classification-vs-anomaly-detection/

⇒ First identify the parameters that have predictive power, before applying multivariate anomaly detection.

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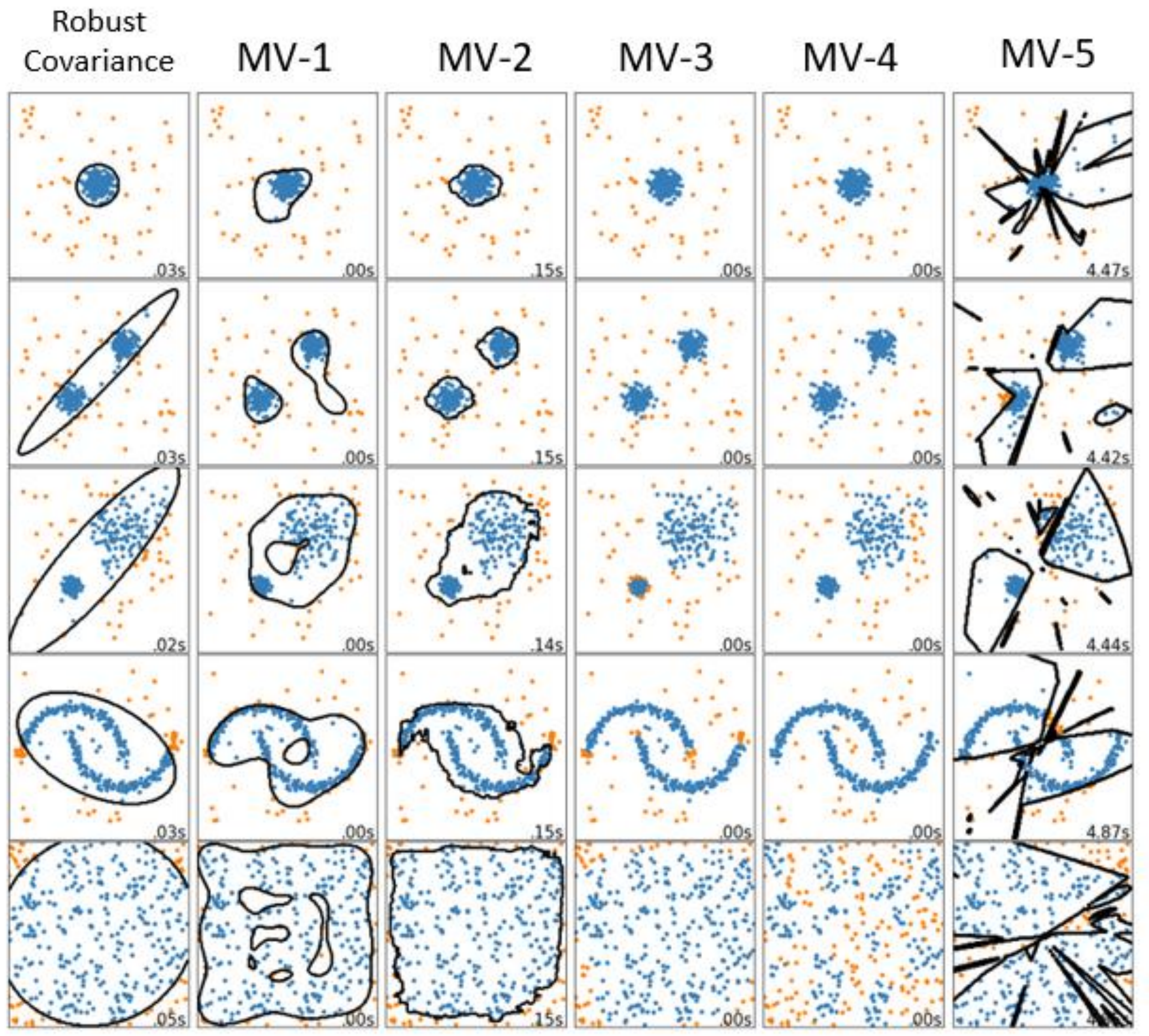
Illustrative example

- The best approach depends on the underlying data.
- Note: Each algorithm is designed to work well under particular underlying assumptions.



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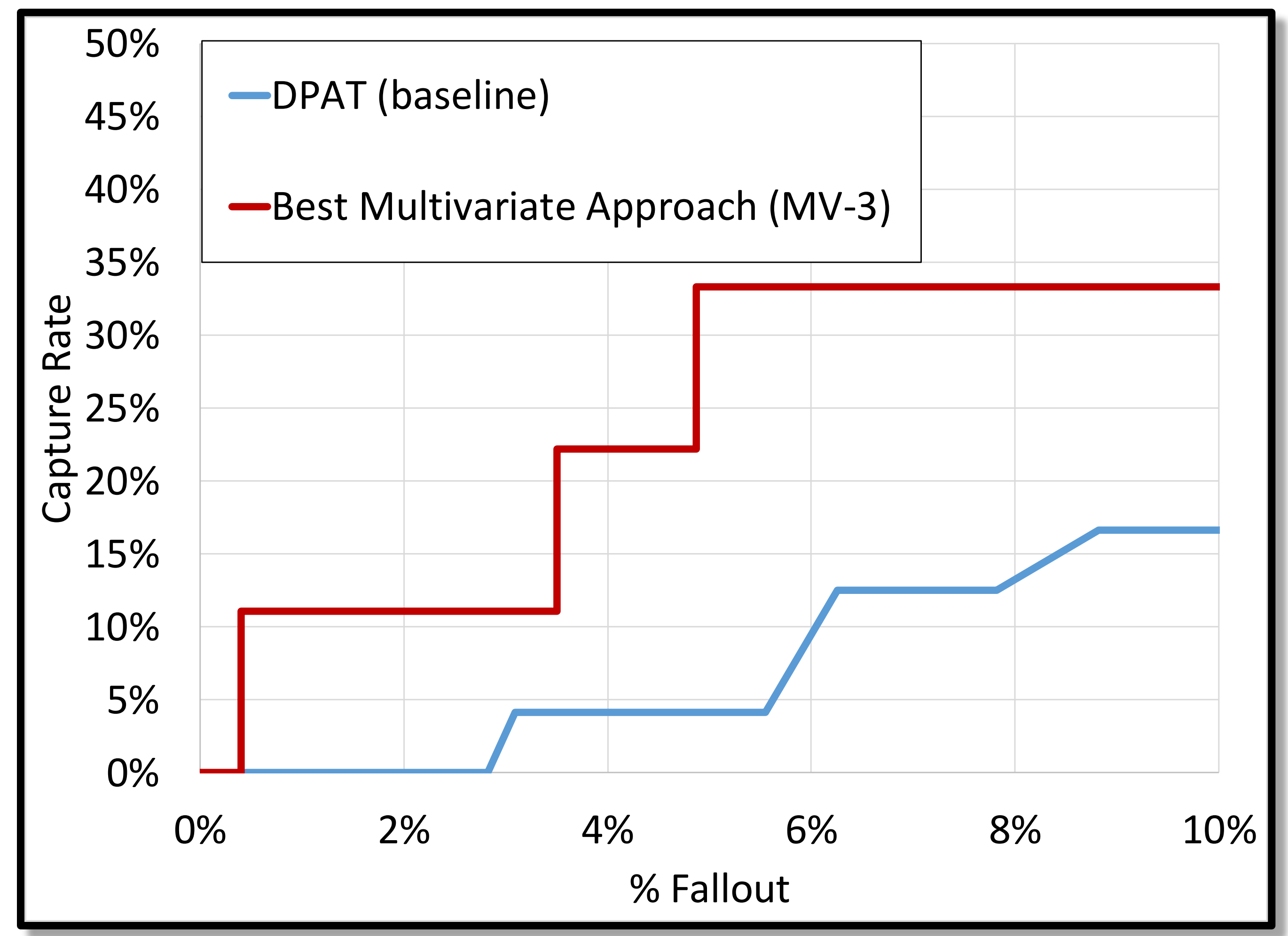
Results – Actual Production Dataset



VALUE:

- **Significantly more failures captured than DPAT with similar fallout**
- **Quickly identify parametrics significant to field returns**

DPAT -> Dynamic Part Average Testing
(Automotive Engineering Council AEC-Q001)

$$\textbf{Capture Rate} = \frac{\text{Correctly Predicted Failures}}{\text{All Actual Failures}}$$

$$\textbf{Fallout} = \frac{\text{Incorrectly Predicted Failures}}{\text{All Good Die}}$$

Advanced ML anomaly detection techniques used to screen out bad die with less fallout

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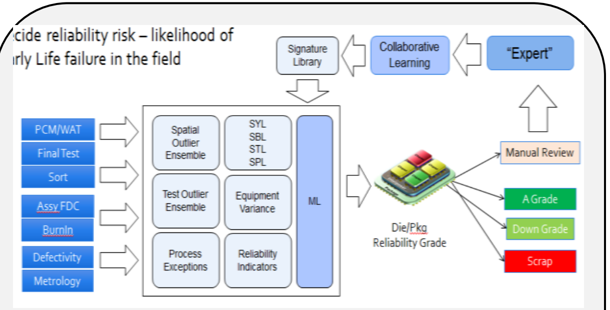
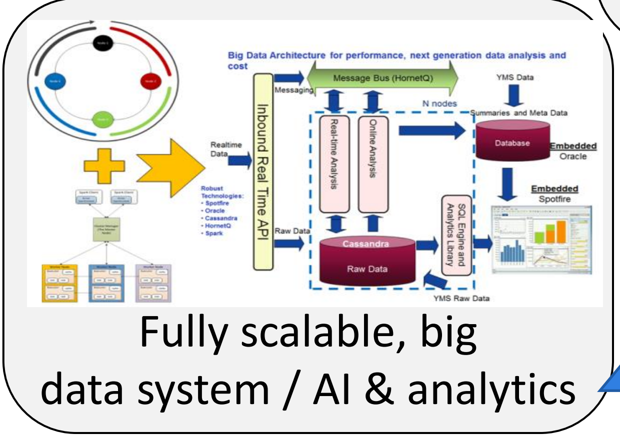
Analytics Platform – The Organizing Principles



Automated Machine Learning Solutions

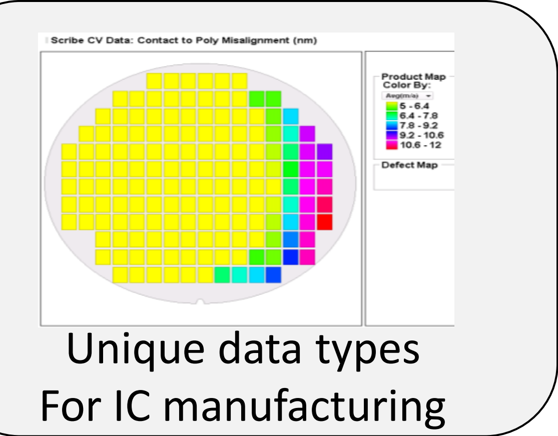
End-to-End Data



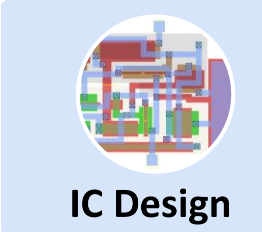
Fully scalable, big data system / AI & analytics

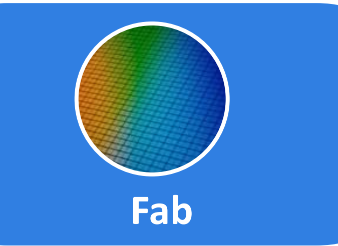
Domain Knowledge

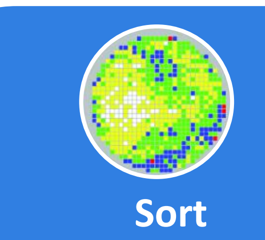
End-to-End Analytics & Control



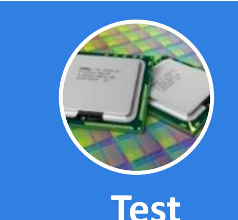
Unique data types For IC manufacturing

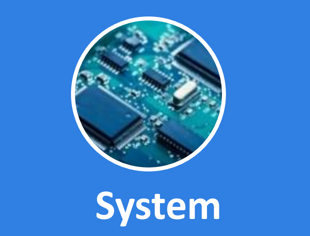

IC Design


Fab


Sort

Assembly


Test


System

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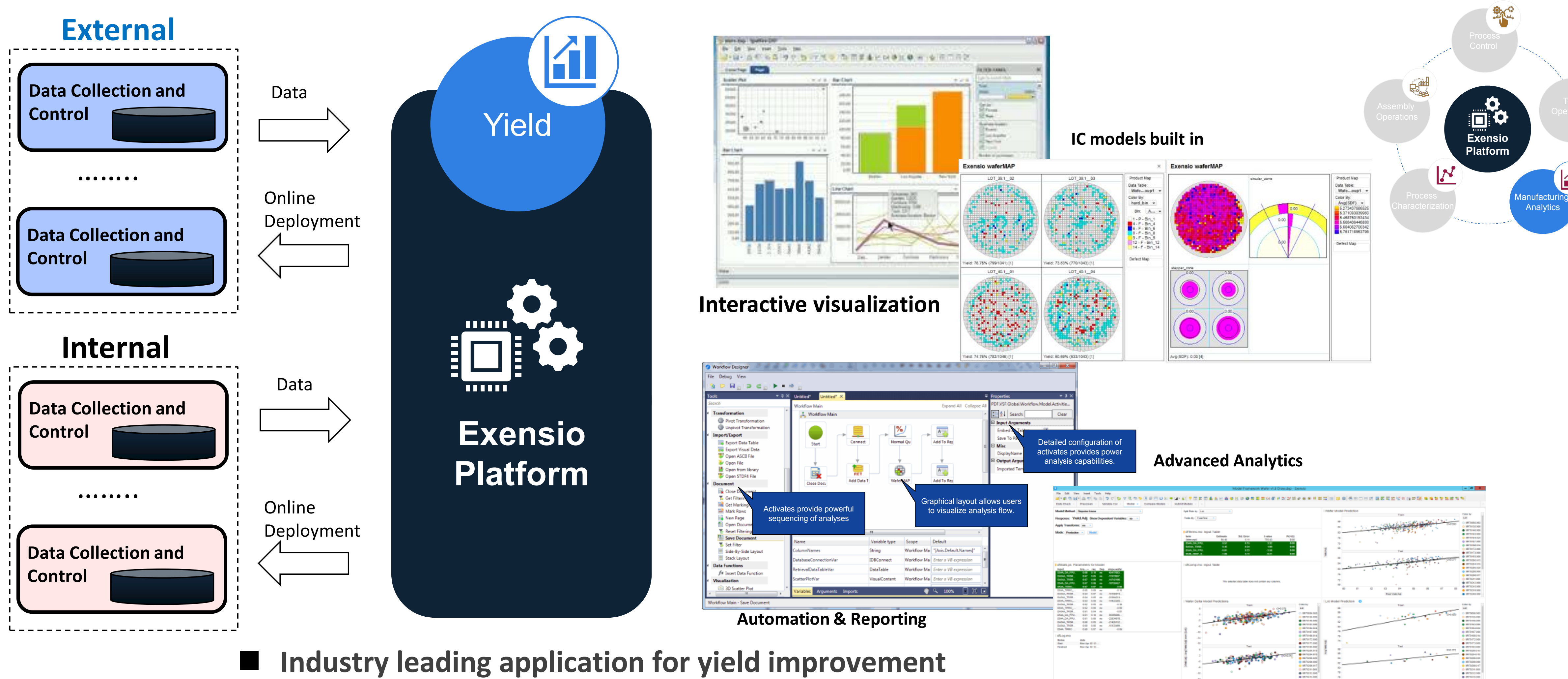
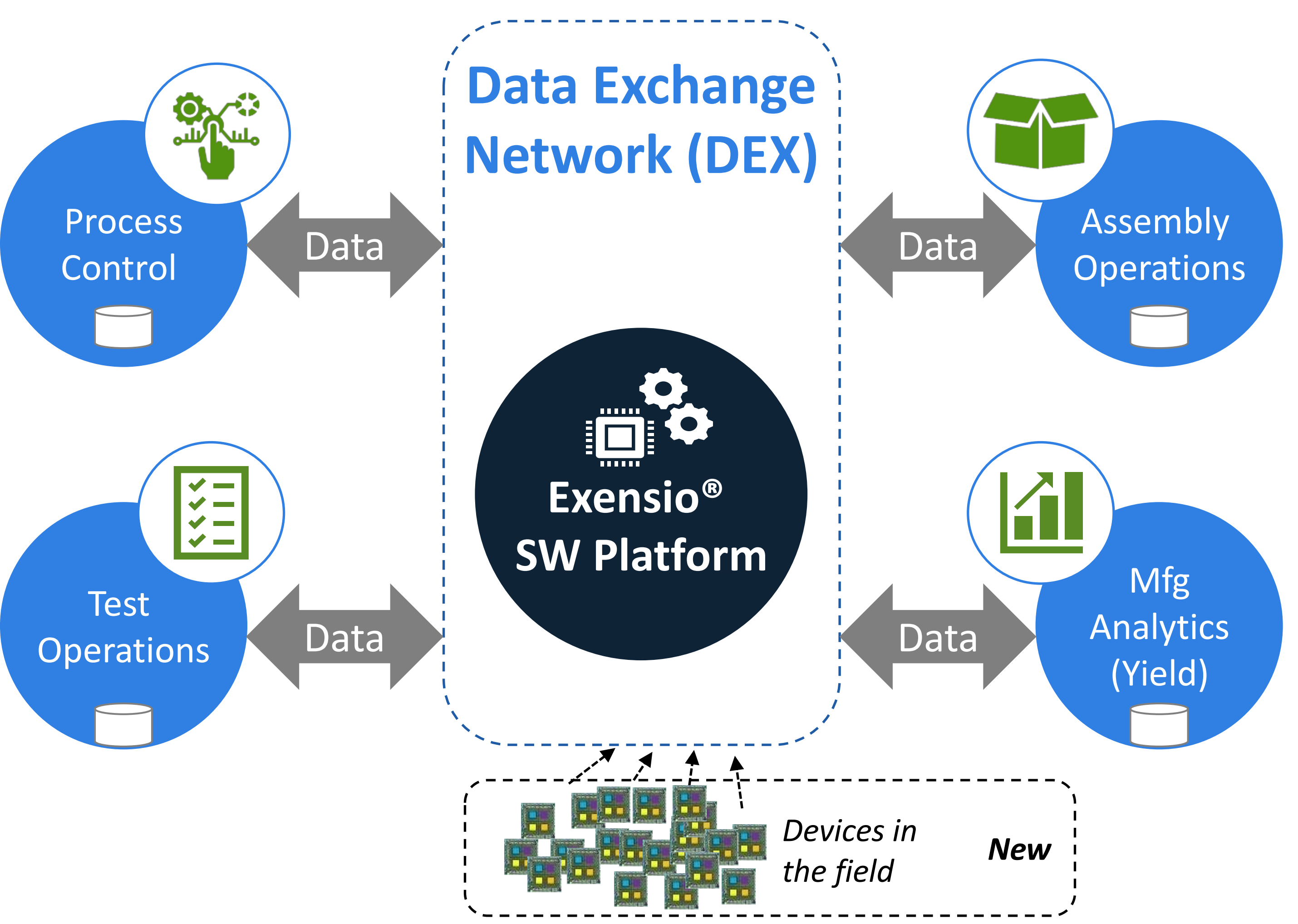
Manufacturing Analytics: Integrating all Fab & Backend Semi Data



- **Industry leading application for yield improvement**
  - High volume product analysis and NPI
  - Leverages both frontend and backend data (all raw data integrated together)
  - Powerful signature analysis and diagnostics

Complete Harmonized Data Collection and Analytics



Two-way, real time data exchange

- Stream data between fab, fabless, IDM and system partners
- Publish rules to OSAT & IDM test
- Real time rule events for immediacy

Controlled data exchange between partners

- Secure, sandboxed data access & transfer between partners
  - Fab to fabless, WIP, KGD data
  - IDM/fabless to system: quality, reliability, die provenance data
- Anonymized and sanitized data supplier and customer access
  - Fab to fabless: fab equip & operation data
  - IDM/fabless to IP providers: SerDes, memory, core data

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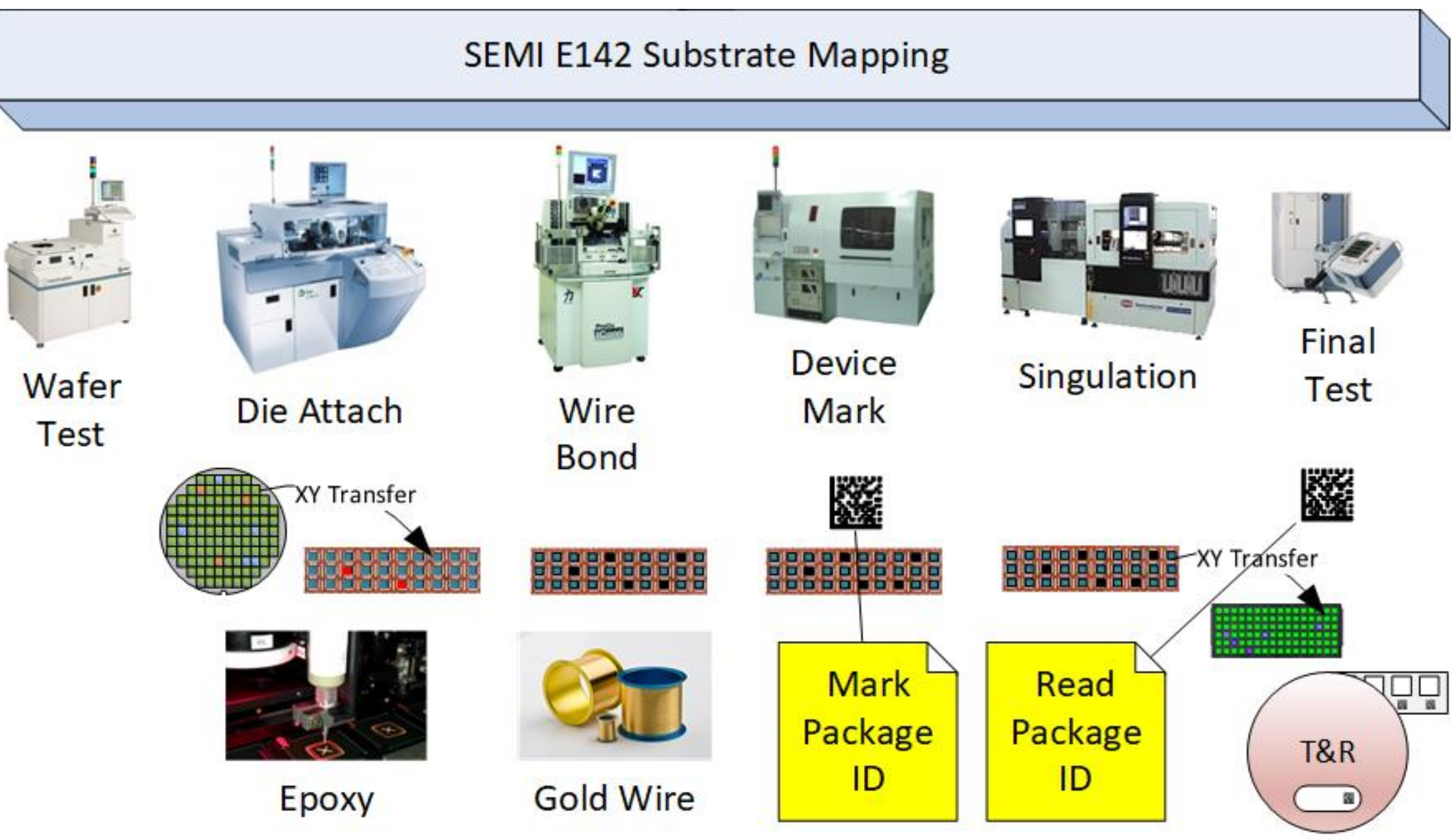
SEMI E142: Traceability Through the Assembly Process



Traceability standards support the semantics necessary for SiP Diagnostics (RMA) and Quality Assurance

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In Summation..

- SiP raises the stakes for KGD quality, final test yield, assembly traceability, and diagnostics.

- Machine learning can untangle the complex relationships in SiP data and enable AI for yield and quality improvement at reasonable cost.

- The right machine learning algorithm and approach needs to be chosen, as no single algorithm works for all use cases and problems.

- End-to-end analytics systems, with test data assessment and optimization capabilities, are an essential element for success.

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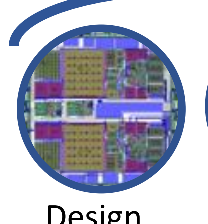
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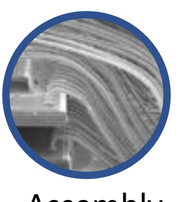
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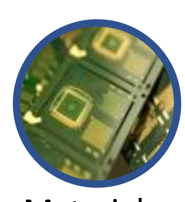
Test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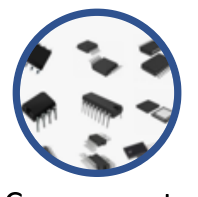
Components

Logistics

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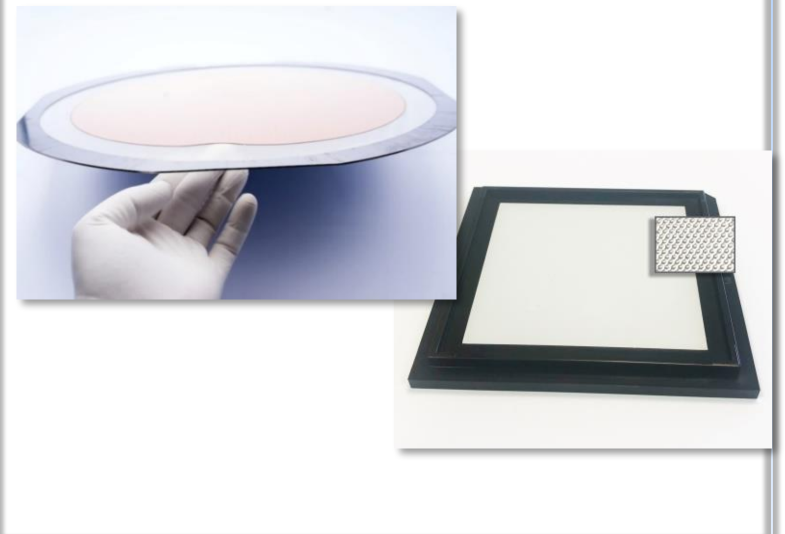

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