An Artificial Intelligence Machine Learning (AI/ML) Approach with Cross-Technology Node Learning for Multi-Layer Process Defect Predictions

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Agenda

- Introduction
- Feature- vs. Pattern-based approaches
- Defect Prediction with ML Platform
- Key Factors in ML Model
- Single-layer/Multi-layer Defect Predictions
- Defect Prediction Flow
- Application Examples
- Cross Node/Cross Layer Defect Predictions
- Summary

Introduction

Defect Prediction

- Traditionally pattern matching is based on known defect patterns.
- The desired defect prediction in the industry has grown more than just pattern similarity matching.

Common Challenges

- Complex multi-layer interactions
- Understanding the root cause of the defects
- Cross-node/cross-layer defect predictions
- Incorporating previous learning data in defect predictions
- Utilizing variety of data inputs for model training/prediction beyond layouts

Challenges for Design Houses

- Limited known defects and FA data
- Lacking process knowledge and layout being the main input source
- Delays in foundry feedback

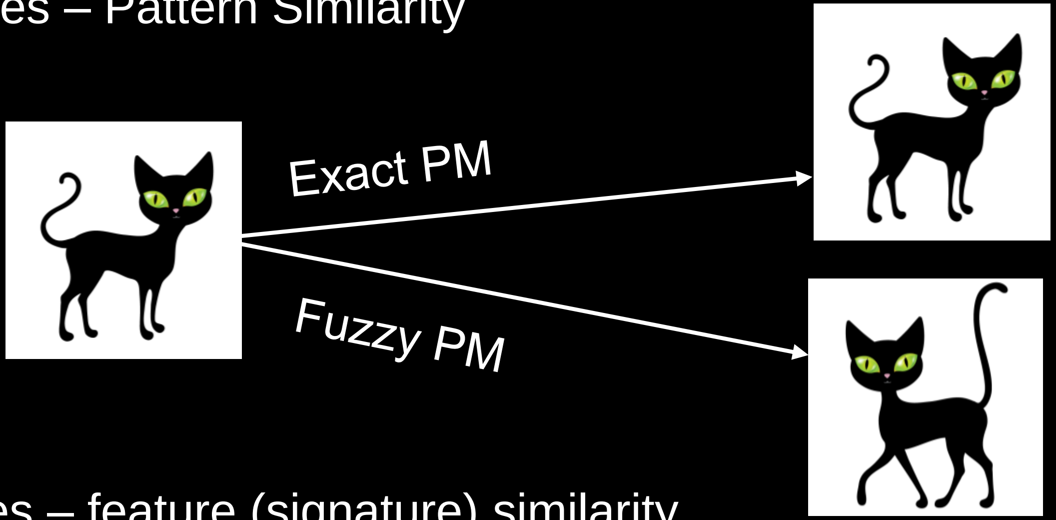
Solutions

- Use a feature-based AI/ML platform to overcome these challenges and reduce process improvement time:

  Unlimited multi-layer features, defect root cause analysis, cross-node/cross-layer predictions, reuse the past learnings, ML platform to accept different types of features.

Analogy: Difference between Feature and Pattern based Approaches

- Pattern Based Techniques – Pattern Similarity

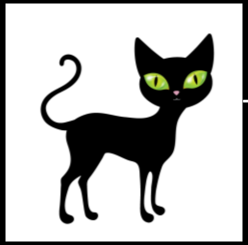


- *A larger number of patterns is required to learn the critical features in pattern-based approaches.*
- *The input patterns are limited for a design house.*
- *Some patterns could not be found in the predictions by pattern-based approaches.*

- Feature based techniques – feature (signature) similarity

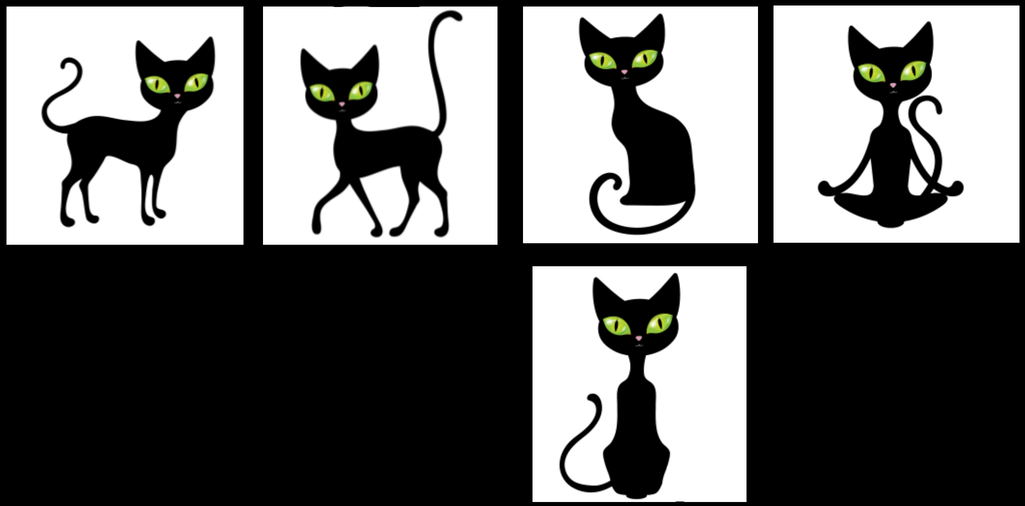
<u>Features used:</u>

- Eyes
- Nose
- Ears
- Face
- Tail



Finding the similarity in features by ML:

- Two diamond-shaped eyes
- A triangular shaped nose
- Two pointed ears
- Round face
- One tail



Similarity ranking

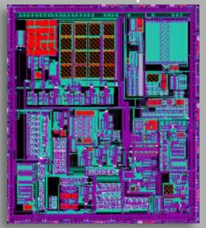
Feature-based Defect Prediction with ML Platform

- Feature-based ML platform:
  - Catching varieties of patterns with the same root cause
  - Root cause analysis

- *Features:*
  - *Geometric features*
  - *Process features*
- *ML: Learn the criticality of the features and connect the features to the defect root cause(s)*

Design

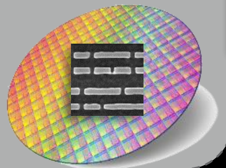
Test Chip



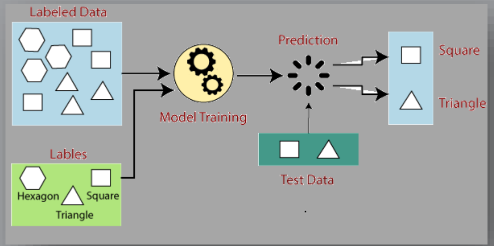
Products

Feature collection:
Features from layout based on the defect schemes

Historical Learning



ML model training



F1_train	HR_train	FA_train	F1_test	HR_test	FA_test
1.0	1.0	0.0	0.857143	0.750000	0.0

Training Set Confusion Matrix

		ACTUAL	
		HS	NHS
PREDICTED	HS	1000	0
	NHS	0	1000

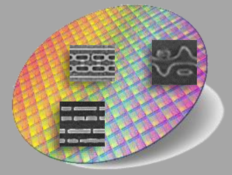
Test Set Confusion Matrix

		ACTUAL	
		HS	NHS
PREDICTED	HS	3	0
	NHS	1	103

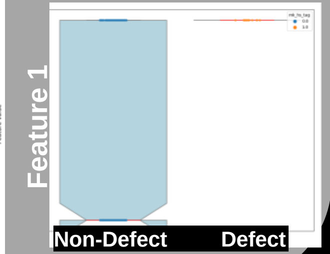
Prediction and feature analysis

Full Chip Analytics

Defect Prediction



Defect analysis



Key Factors in Machine Learning Model

- Point of Interests (POIs)
  - Locations where the defects could occur.
  - Depends on defect scheme (*e.g.,* vias as POI in vias open).

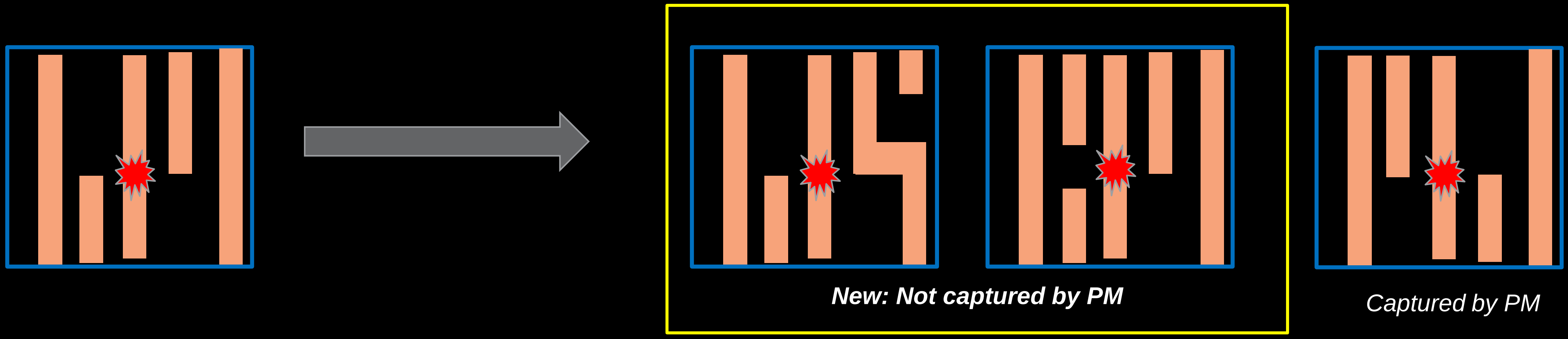
- Hotspots(HS)/Non-hotspots(NHS) inputs
  - HS: POIs containing defects
  - NHS: POIs within a certain range of HS of, say, 1um, excluding HS

- Features
  - Depending on defect schemes
  - A generic set of features/defect scheme: ML to learn the criticality

- ML Model Metric
  - F1 score to evaluate ML model and to feedback for feature engineering, HS/NHS labeling, etc.

Single-Layer Defect Predictions

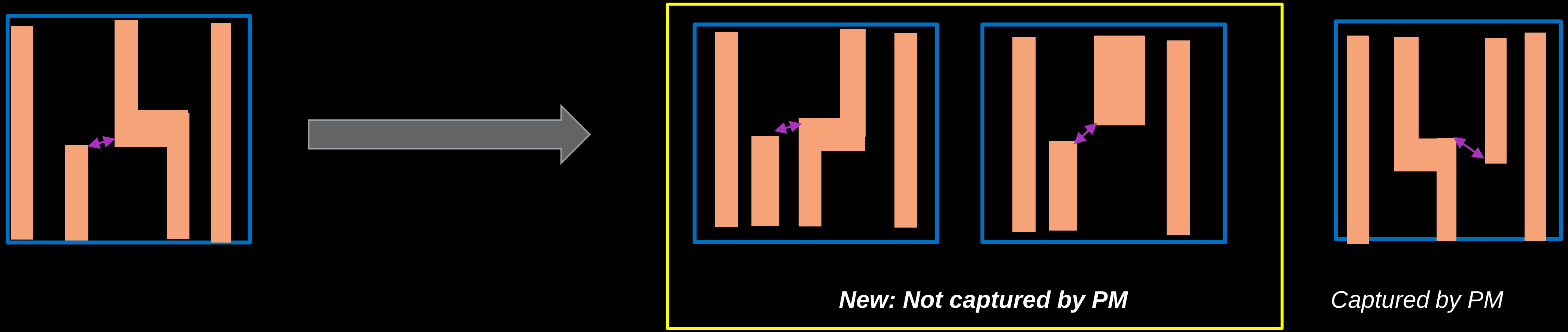
- Defect: Long metal with line ends on both sides in a dense line environment.
- HS predictions: new patterns involving jogs and multiple line end interactions



New: Not captured by PM

Captured by PM

- Defect: metal line corner to corner short.
- HS predictions: new patterns with different corner configurations



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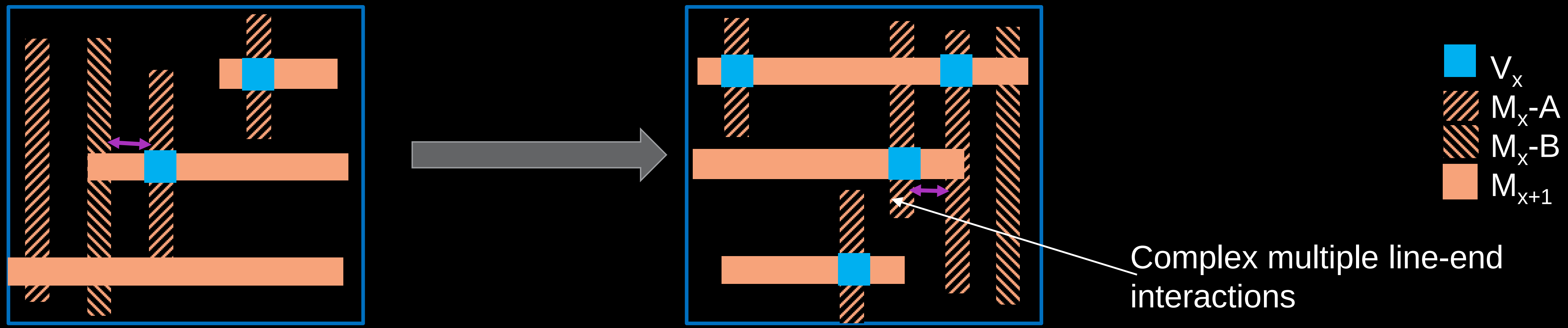
Multi-Layer Defect Predictions

- Defect: V_x-M_x Short (V_x Short to M_x in Non-SAV direction).
- Inter-layer features: via to metal enclosures, via-metal space, M_x/M_{x+1} combinations
- HS predictions: varieties of patterns with potential small process windows



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Feature Ranking for M_x-V_x Short

- Feature ranking is done by SHAP (SHapley Additive exPlanations).
- SHAP Inputs: Features for HS/NHS, ML model
- SHAP Outputs: Feature ranking by SHAP values

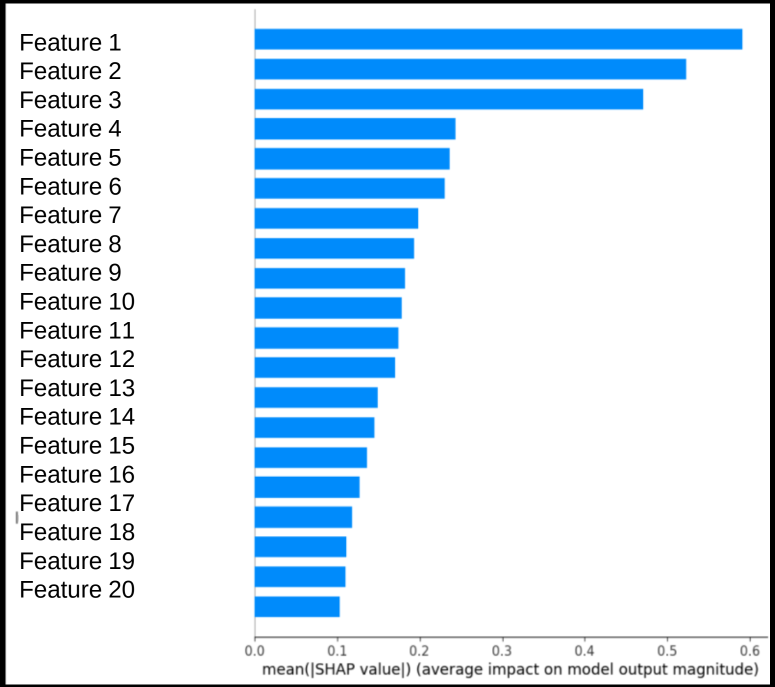
Inputs

MLDB
- Features
- Labels

ML model
Trained by user

SHAP tool

Output: feature ranking



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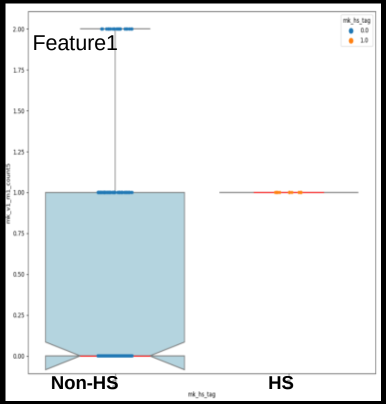
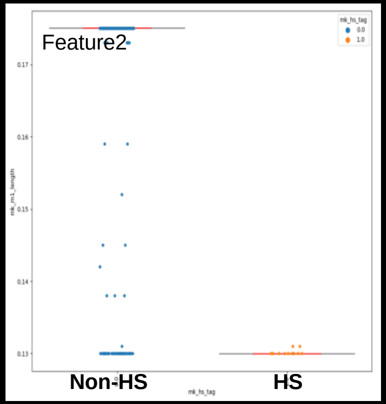
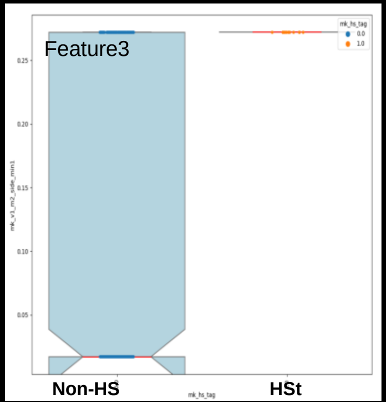
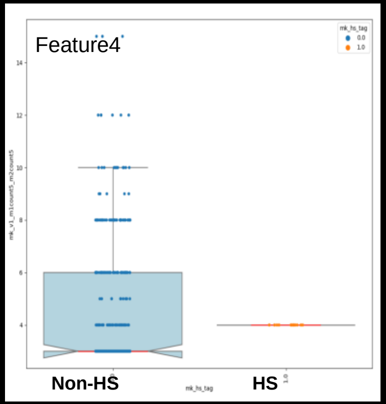
Root Cause Analysis

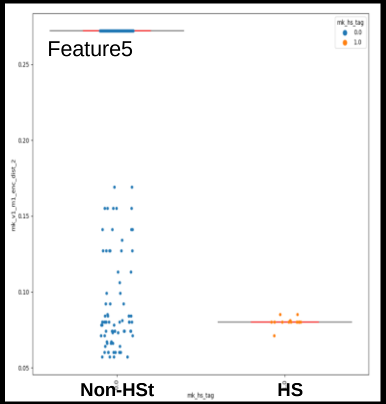
- Top features are selected from feature ranking.
- Compare feature distributions between Hotspots and non-Hotspots.
  - Physical root cause is a combination of the unique features in hotspots.











Physical root causes:

1) **Dense/semi-dense Mx**
2) **Short Mx**
3) **Iso Mx+1**
4) **min Vx enc by Mx**

Identified features/root causes, consistent with process understanding

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SONR Defect Prediction Workflow

Feature Vector (FV) Collections
- Features from the layout

HS/NHS Labels
- HS: Defect locations
- NHS: Non-defect locations

Supervised ML Model
- ML models such as Neural Network (NN) models or decision tree models
- Auto hyperparameter search.

Feature Rank and Root Cause Analysis
- Ranking critical features through SHAP Analysis
- Root cause analysis through feature analysis of the top-ranked features

User Inputs
For example: learnings from the previous technology

HS Prediction
- Predicted hot spots based on the AI/ML model and ranked by probability

Pattern Classification
- Combining the patterns with same process defect root cause into the same pattern category

Flow expectation:
- Analyze features and find out the process defect root causes from layout.
- Identify additional variants of process sensitive layouts.
- Classify the patterns for better downstream actions.
  - FA recommendations
  - HS replacements in design flow

Defect Prediction Applications for Design Houses

Collect more HS data

- Select new HS (not caught by PM) for FA (TEM/SEM) and gain process improvement experience.
  - 20-30% of the newly identified HS show similar process sensitivity to the original HS

Understand the process defect root causes

- Leveraging the HS data and working with foundries to fix process issues quickly

Early Defect Fix in the Design Flow

- Replacing the HS by known good pattern configuration in the design flow*

- **Cain, J. Fakhry M., Pathak P., Sweis J., Gennari F., Lai Y.-C., "Applying machine learning to pattern analysis for automated in-design layout optimization", Proc. SPIE 10588, Design-Process-Technology Co-optimization for Manufacturability XII, 1058805 (2018).*

Cross Node and Cross Layer Prediction

- Why Cross-node Defect Prediction
  - Speed up defect learning before hotspot data available in early technology development stage.
  - Utilize the past learnings more effectively and take proactive actions to avoid similar defects.
  - Save costs and time: directly use the existing data for prediction. No need to collect FA on similar defects.
- The Approach for the Cross-node/layer Prediction
  - Use features which are independent of technology, (*e.g.,* number of metal lines in the nearest 2 pitches).
  - Scale and normalize features properly: the same features fall into the same feature space across technologies, *e.g.* min via enclosure. Most of failures happen at max/min feature values, e.g. min enclosure.
  - Cross layers: rotation in feature space if necessary

Old Node

FV Collections
- Features from the layout

HS/NHS Labels
- HS: Defect locations
- NHS: non-Defect locations

Supervised ML Model
- ML models such as Neural Network (NN) models or decision tree models
- Auto hyperparameter search.

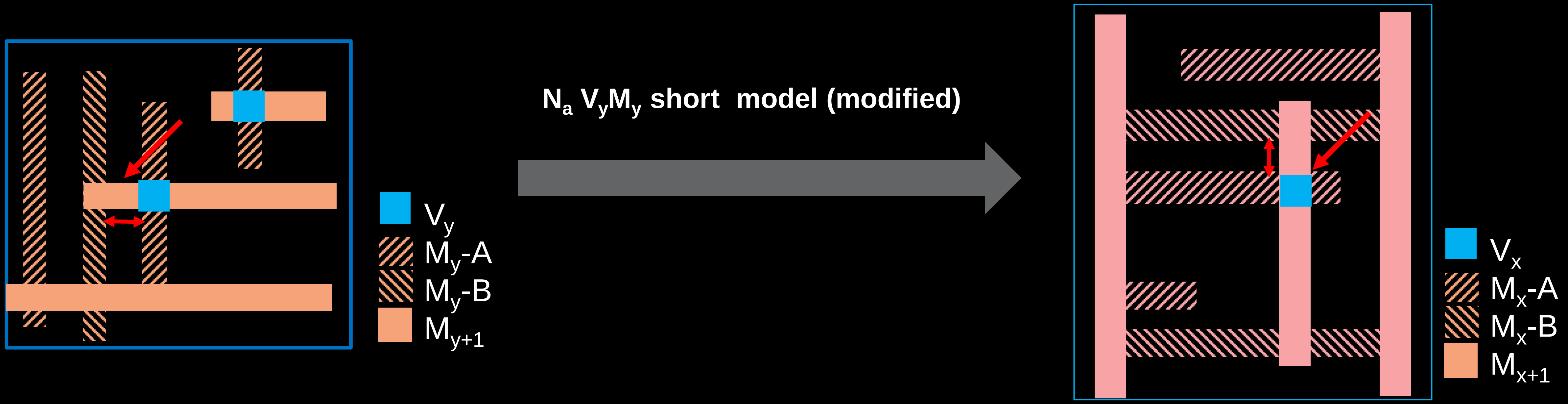
New Node

HS Prediction
- Predicted hot spots ranked by probability

Minor modification on ML based on the design rule change

N_{a+1} M_x/V_x Prediction with a N_a M_y/V_y ML Model

- A new node N_{a+1} and no FA available: the process of M_x/V_x is similar to that of M_y/V_y in the previous node N_a.
- Identify potential systematic V_x-M_x short patterns on N_{a+1} based on known V_y-M_y shorts in N_a.
- Run the Defect prediction flow on N_{a+1} with N_a M_x/V_x model.



N_a V_y-M_y Short

N_{a+1} V_x-M_x Short

Note x ≠ y

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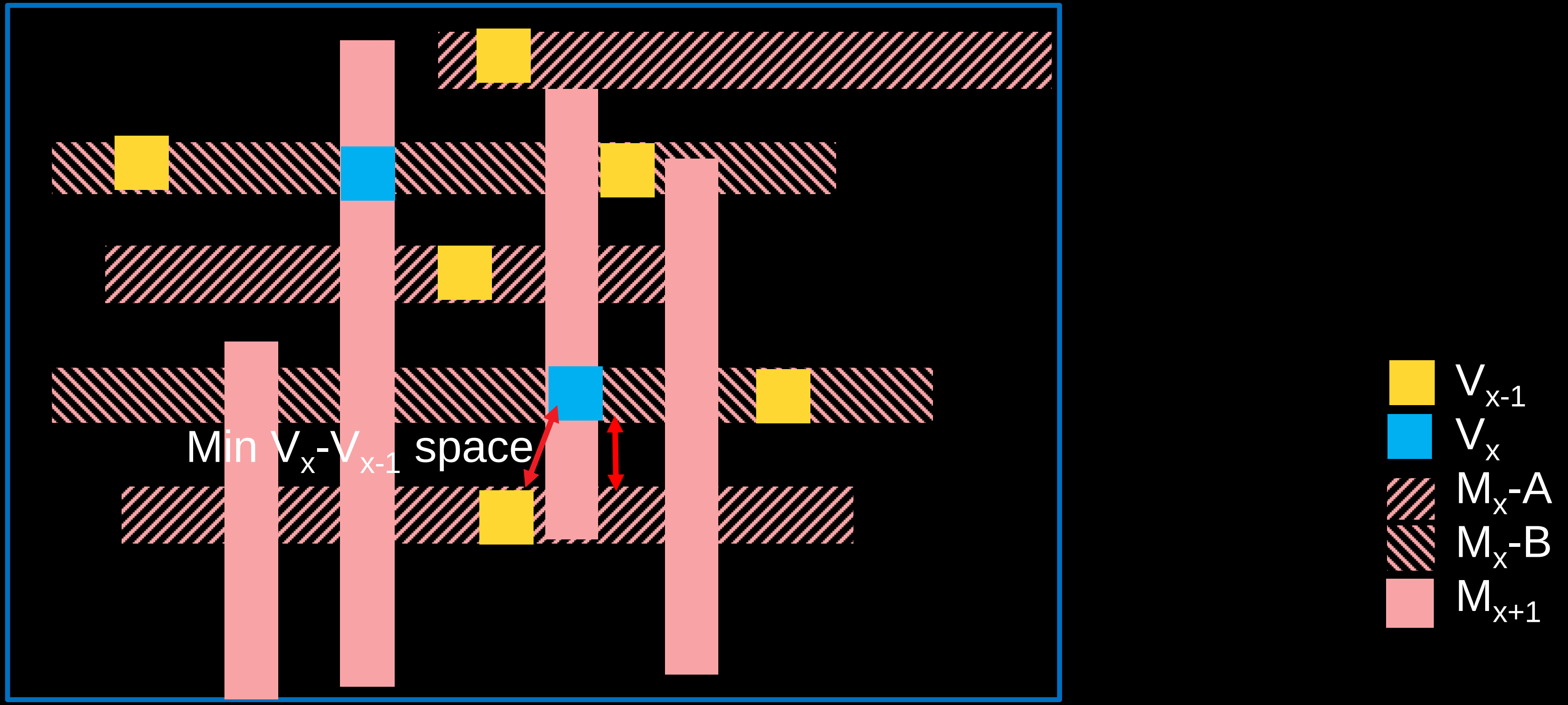
Applying Previous Learning to Identify the Potential Weak Process Corner

- Previous process learning: via tends to bulge, which reduces the short margin.
- Applying previous process learning in V_x-M_x short :
  - → Potential weak process corner : V_{x-1} - V_x at minimum space in the potential V_x/M_x short environment



N_{a+1} V_x-M_x short with V_{x-1}-V_x @ min space

Summary

Feature-based ML Defect Predictions to Accelerate the Process Improvement Learning

- Single/multi-layer predictions demonstrated
- More variants of potential defective patterns identified
- Process defect root cause analysis provided
- Cross-node/layer defect predictions
- Applying previous process improvement learnings experience to identify the potential weak process corners

Workflow Developed to Meet Design Houses' Needs

- Layouts and reduced # of HS as Inputs
- Understanding process issues with defect root cause analysis
- Providing HS varieties for FA recommendations
- HS patterns to feed in the design flow for design quality improvements

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