TestDNA: Novel Wafer Defect Signature for Diagnosis and Yield Learning

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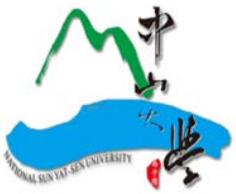
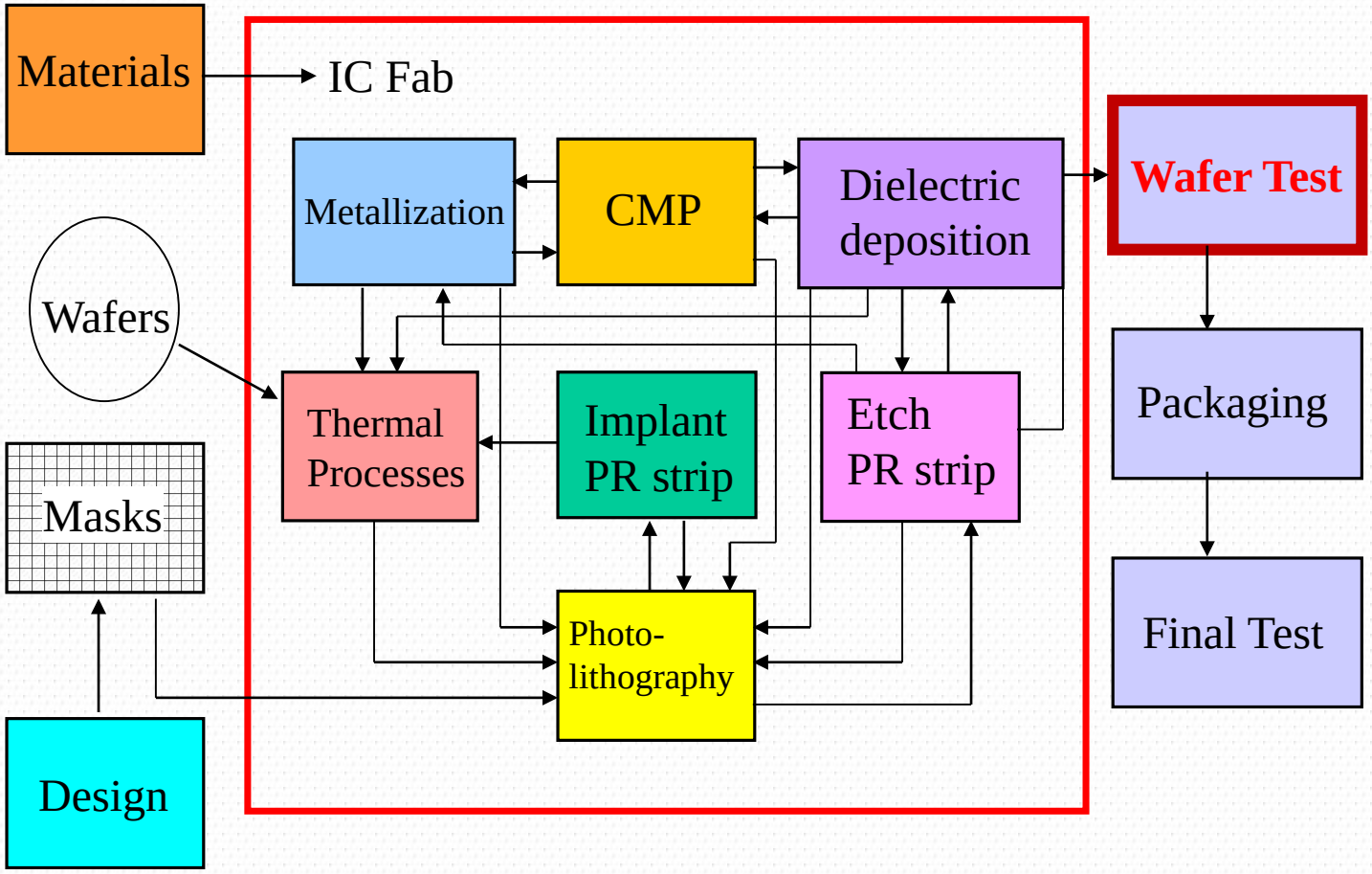


Outline

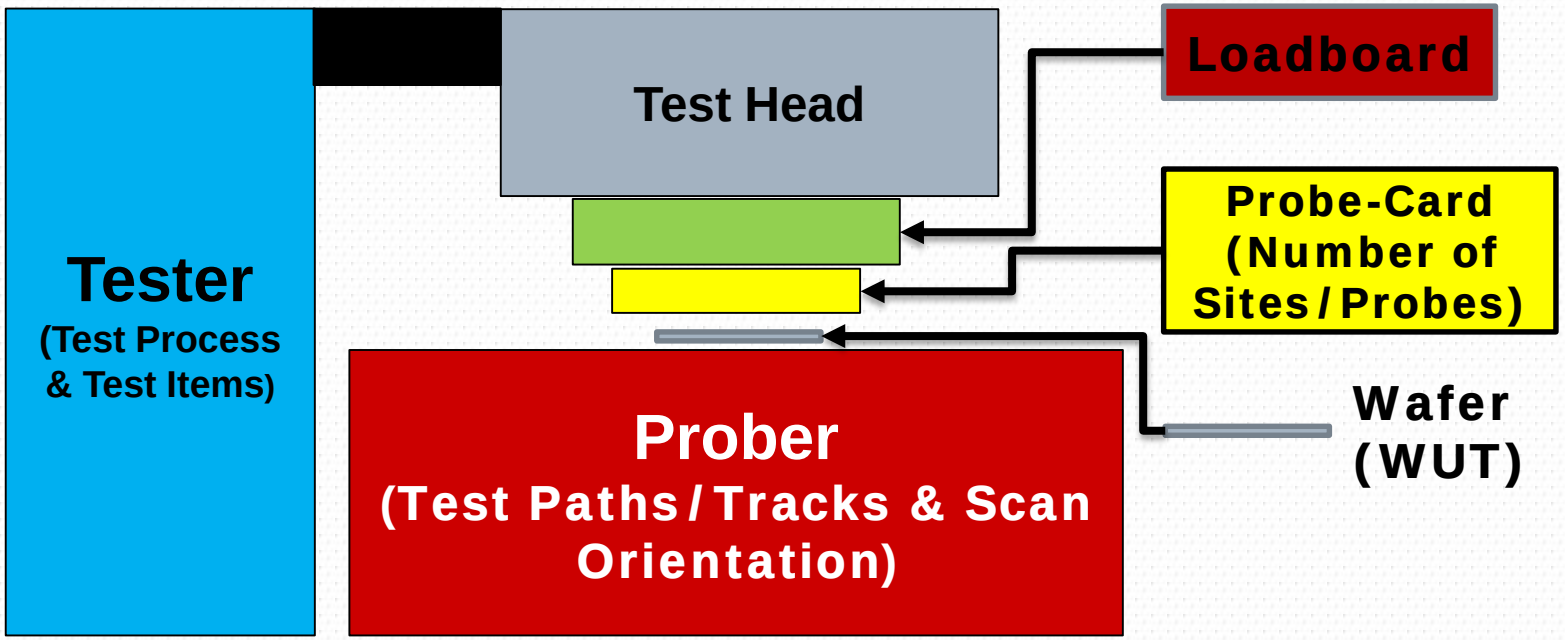
- Wafer Test and Diagnosis
- Proposed TestDNA Solution
- Experimental Results
- Conclusion

A Typical Wafer Process Flow



https://www.istgroup.com/tw/business_20180627/, Digitimes, July 13, 2018, https://www.istgroup.com/

Wafer Probe Interface and Test Configurations



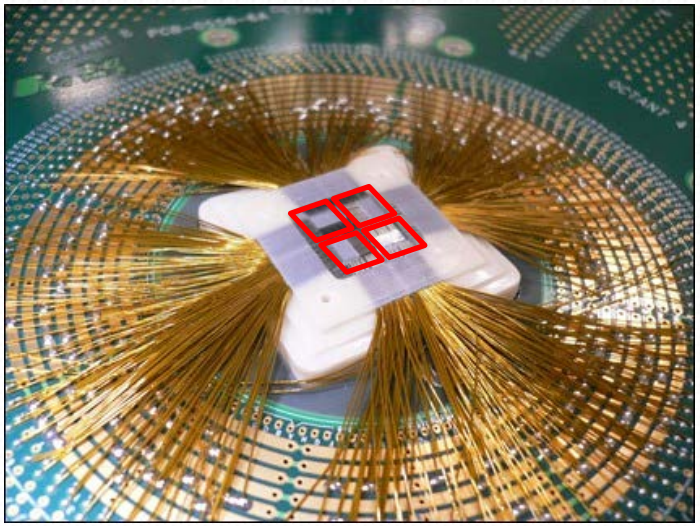
Test Configurations:

1. # Sites/# Probes
2. Test Paths/Tracks with Test Order
3. Scan Orientation

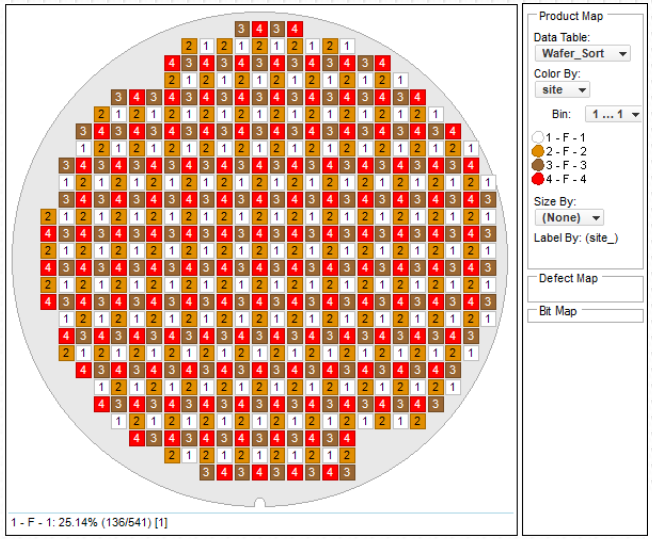
Site Probing

- **Multiple dies tested simultaneously in the same touchdown**
  - Reducing testing time
  - Increase output rate

A 4-site probecard

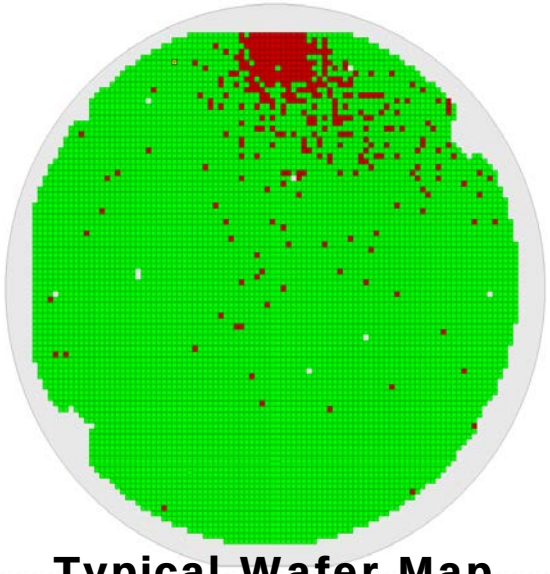


A wafer map colored and labeled by site

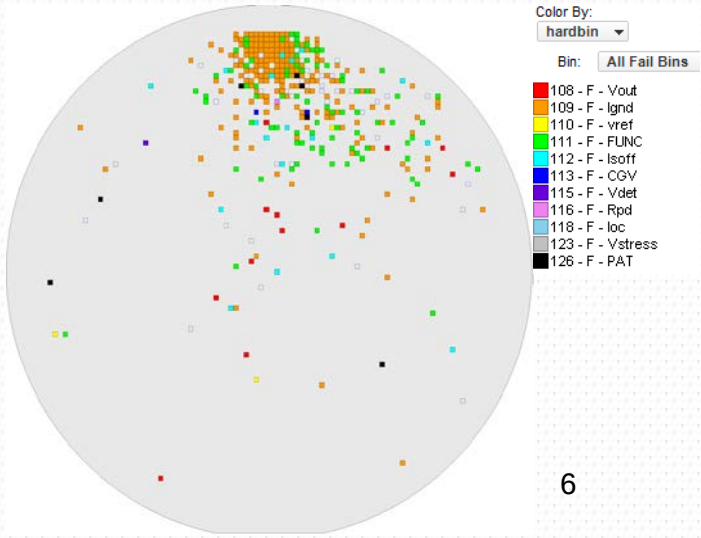


A Typical Wafer Map & Distribution of hardbins

- **Typical Wafer Map**
  - Red dots: Failed dies
    - The exact cause of failure is not shown in the wafer map
  - Green dots: Dies that pass all test items
- **Distribution of hardbins**
  - Each color represents a **test item**



Typical Wafer Map

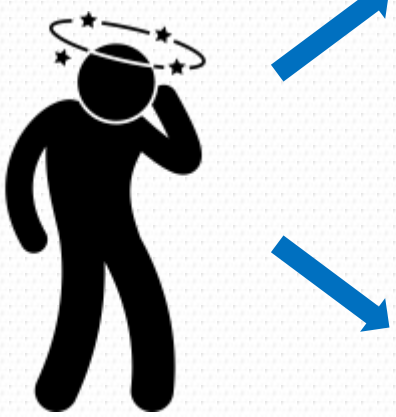


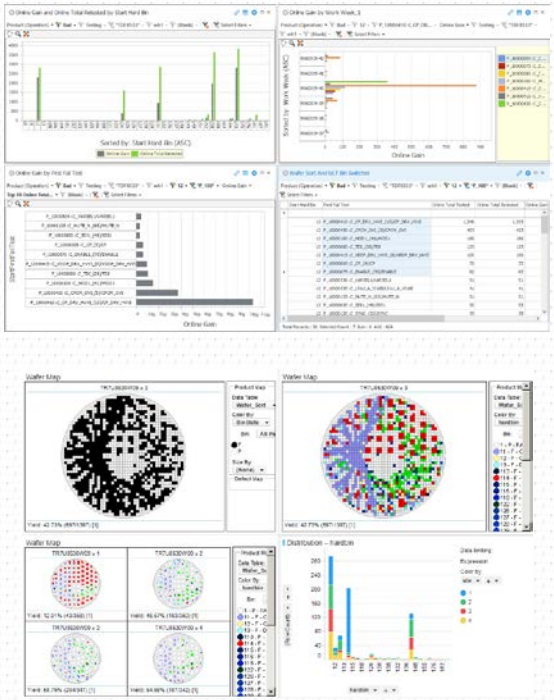
Distribution of hardbins

Benefits

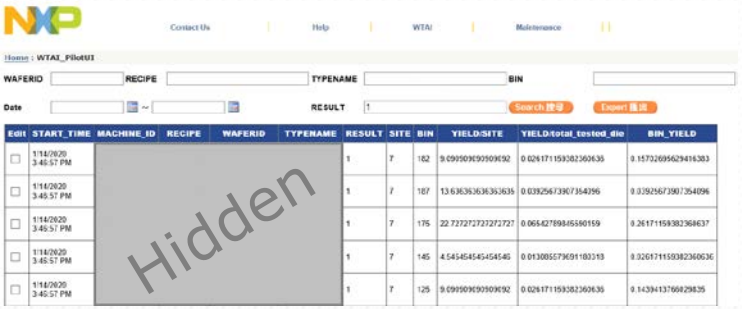
For engineer to analyze and improve

Digging out data
takes a lot of effort

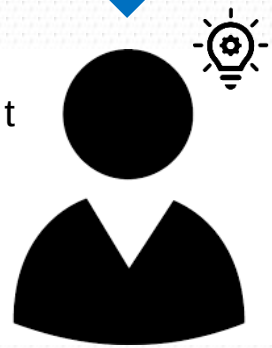




TestDNA



AI assists to dig data
and consolidate result



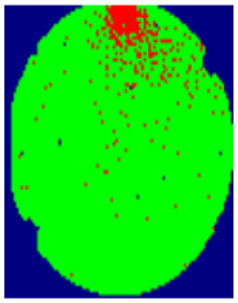
Contributions

- Related works: focus on identifying spatial defect patterns in wafer maps
  - Diagnosis resolution problem
  - Small percentage of proper classification

- **TestDNA**
  - **Visualization**
  - **Statistical model for root-cause analysis and yield learning**
  - **Strong correlation between TestDNA classification and wafer map defect patterns**

Problem Definition

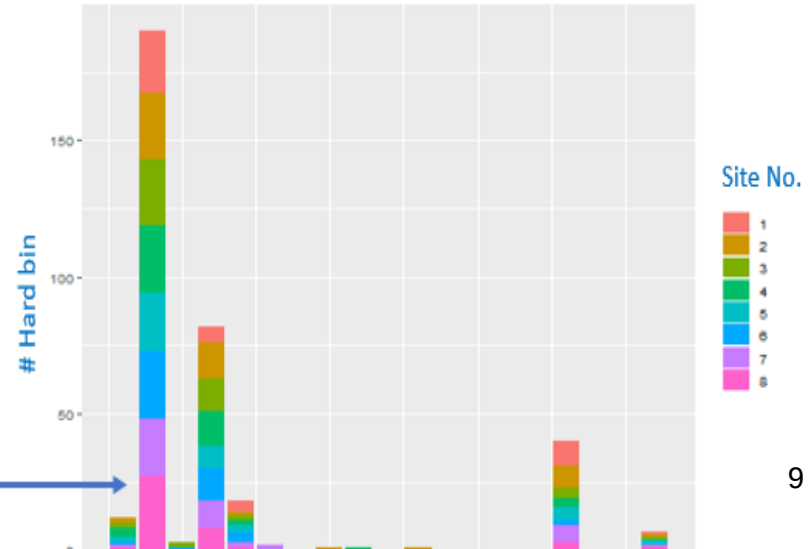
- Input: Wafer-under-Test (WUT) with product specifications and test specifications
- Output:
  - Database with **TestDNA Sequence**
  - **TestDNA matrix**
    - x-axis: Hardbin No.
    - y-axis: #defect dies with colored Sites/Probes
  - TestDNA Feature Space



TestDNA Matrix

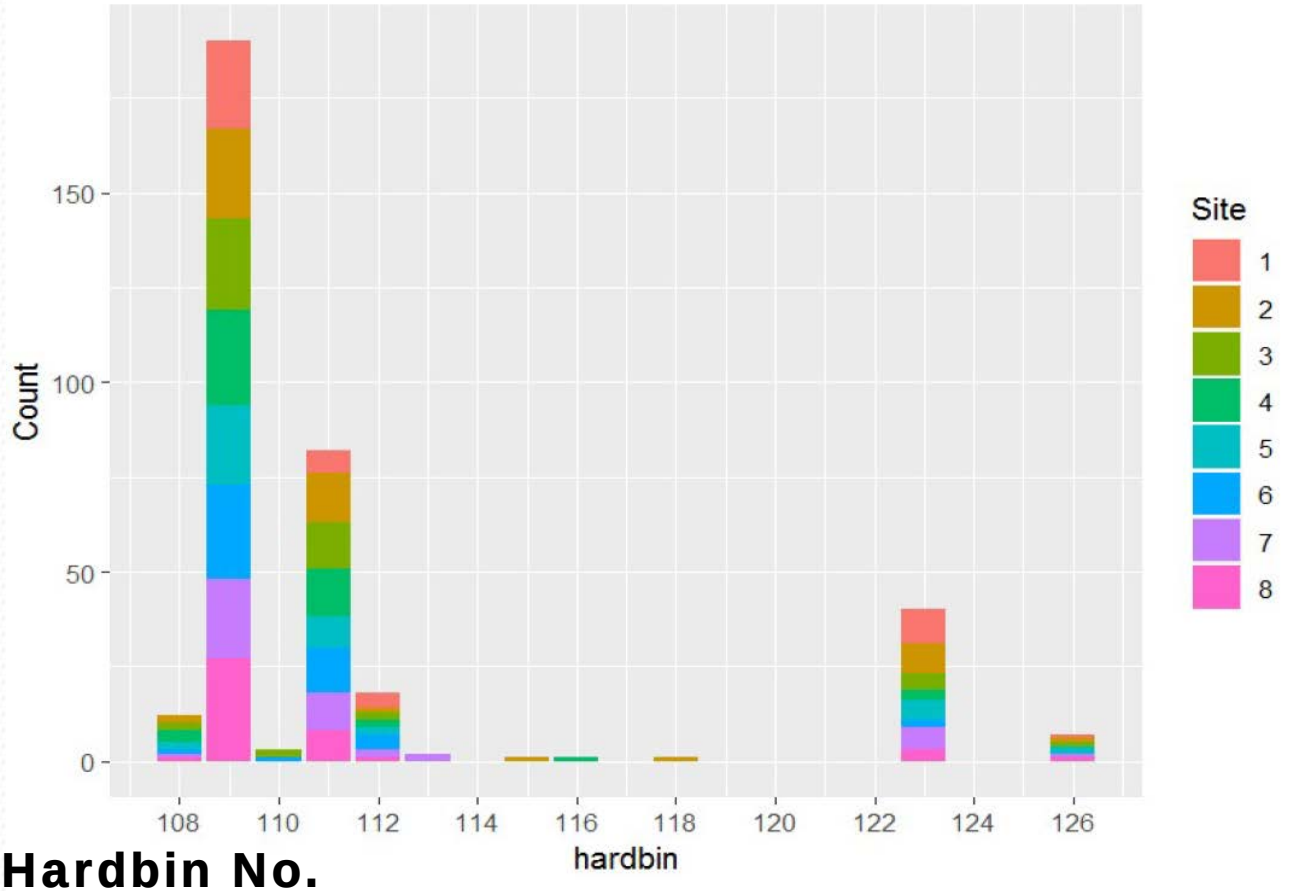
Site No.

Hard bin	0	1	2	3	4	5	6	7
100	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0
102	0	0	0	0	0	0	0	0
103	0	0	0	1	0	0	0	0
104	0	0	0	0	0	0	0	0
105	0	0	0	0	0	0	0	0
106	1	0	0	1	0	0	0	0
107	0	0	0	0	0	0	0	0
108	0	2	4	5	0	2	1	4
109	9	8	8	5	3	8	5	9



TestDNA

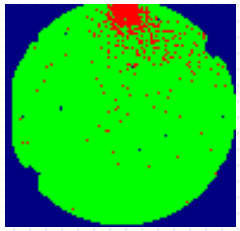
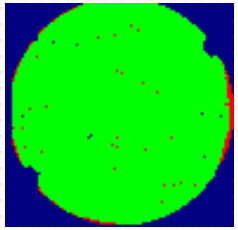
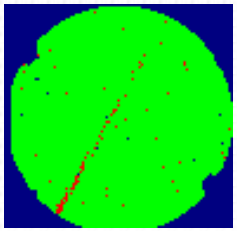
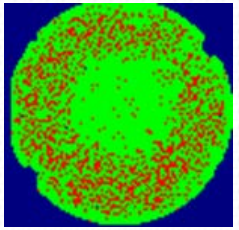
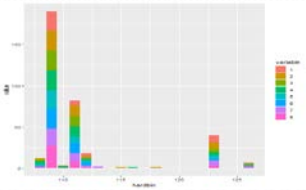
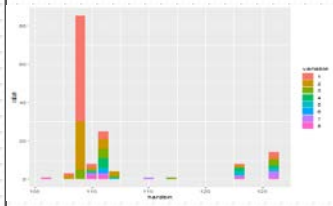
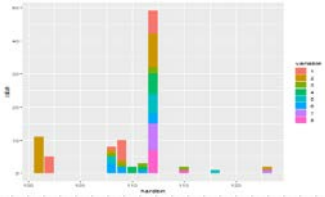
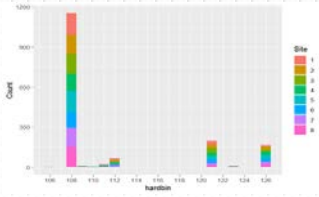
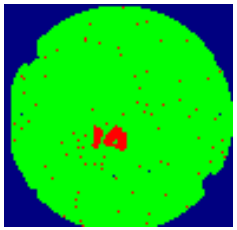
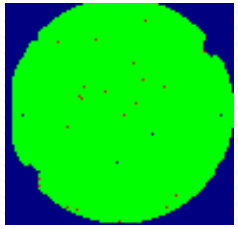
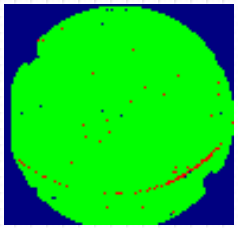
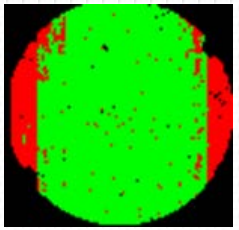
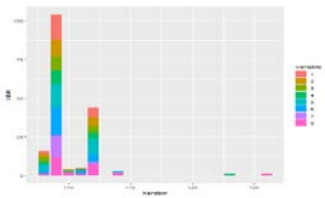
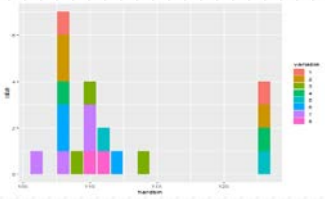
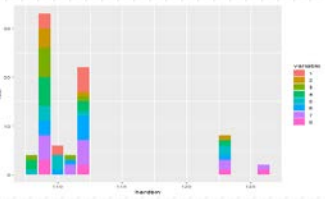
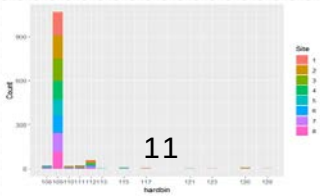
- Every manufactured wafer has a unique TestDNA
- Wafers suffering from the same fabrication problem tend to have similar TestDNA structure



x-axis: Hardbin No.

y-axis: #defect dies with colored Sites/Probes

Defect Types & TestDNA Sequence

Defect Types	edge_local	edge_ring	line	dount
Wafers				
TestDNA Sequence				
Defect Types	**local**	**non-patterns**	**scratch**	**tennis**
Wafers				
TestDNA Sequence				

Classifying TestDNA

- Every tested wafer has a unique TestDNA
  - Strongly correlated to the major defect types
  - Clues to trace the root causes of defects

- Classifying Algorithm
  1. Generate TestDNA database for wafers from the same products
  2. For every TestDNA, sort all hardbins according to their respective defect counts in a descending order
  3. Normalize defect counts of all hardbins, with the largest hardbin set to 1 (i.e., 100%).
  4. Classify all TestDNAs according to the normalized hardbins distribution

Prediction

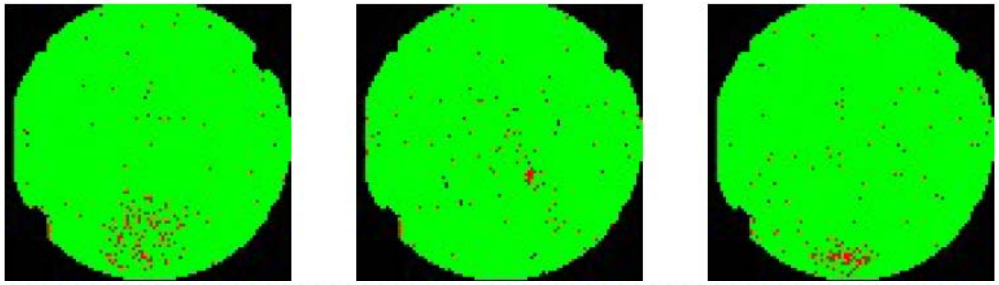
- Can we predict the type of a new TestDNA?

- In this work, we apply multinomial logistic regression to carry out the prediction
  - Site distribution in TestDNA
  - Hardbin distribution in TestDNA
  - Mean, maximum, and standard deviations of TestDNA

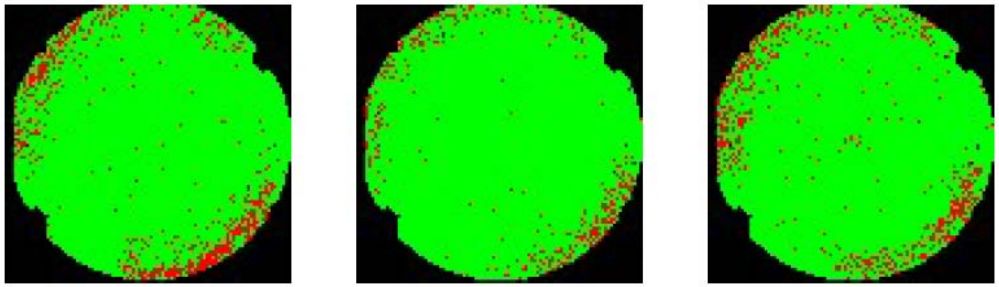
Advanced Defect Pattern Recognization

- Each TestDNA type may consist of multiple traditional spatial patterns
  - Type B TestDNA: tennis and local
    - Easily separate these two patterns by applying the mean of TestDNA values

Local



Tennis



Experimental Setup

- We have applied the proposed TestDNA method to analyze 314 wafers from a product
- Training:188 (60%) TestDNA
- Test: 126 (40%) TestDNA

TestDNA Type	# Wafers	Wafer Map Defect Patterns
A	25	Tennis, Edge-Local, Scratch
B	28	Tennis, Local
C	17	Edge-Local, Tennis, Local, Scratch
None	102	None

- There is no obvious TestDNA distribution
- Defects in such wafers are largely caused by random errors
- TestDNAs usually consists of multiple bars with roughly the same heights

Experimental Results

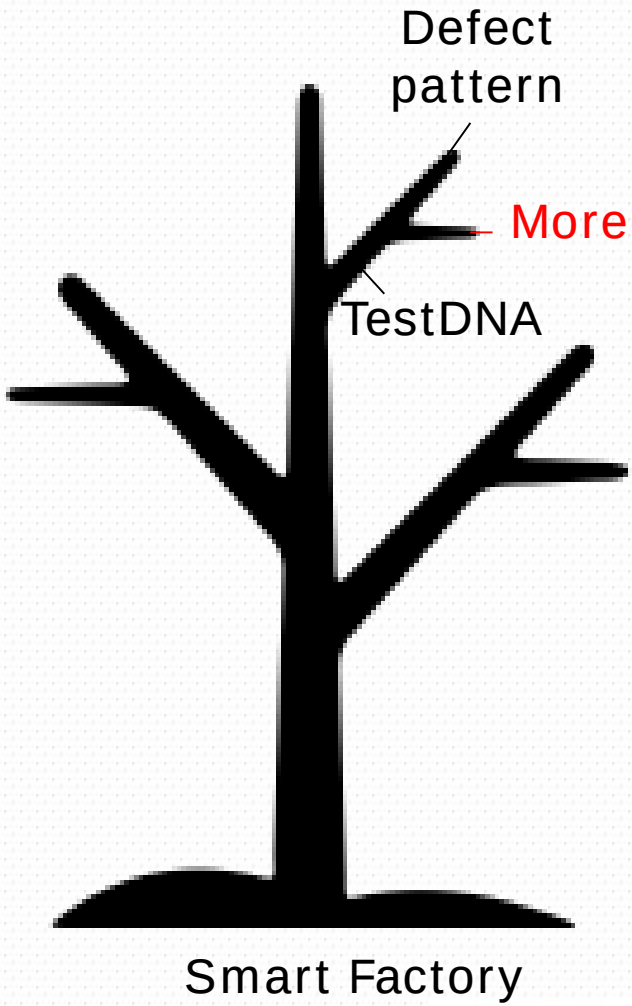
- The prediction accuracy is 92.0634%

		Annotation									
		A	B	C	D	E	F	G	H	I	None
Prediction	A	8 (88.9%)	0	0	0	0	0	0	0	0	1 (11.1%)
	B	0	6 (100%)	0	0	0	0	0	0	0	0
	C	0	0	7 (87.5%)	0	0	0	0	1 12.5%	0	0
	D	0	0	1 (2.8%)	34 (94.4%)	0	0	0	0	0	1 (2.8%)
	E	0	0	0	0	7 (100%)	0	0	0	0	0
	F	0	0	0	0	0	1 (100%)	0	0	0	0
	G	0	1 (6.25%)	0	0	0	0	14 (87.5%)	0	0	1 (6.25%)
	H	0	0	1 (16.7%)	1 (16.7%)	0	0	0	4 (66.6%)	0	0
	I	0	0	0	0	0	0	0	0	2 (100%)	0
	None	0	0	0	0	0	1 (2.9%)	0	1 (2.9%)	0	33 (94.2%)

Conclusion

- TestDNA
  - Visualization
  - Statistical model for root-cause analysis and yield learning
  - Strong correlation between TestDNA classification and wafer map defect patterns

- Prediction accuracy of TestDNA is around averagely 92%
  - 30%, which accuracy approaches 100%
  - 20% with accuracy in 90%-100%
  - 30% with accuracy in 80%-90%
  - only 3% with 66.6%



Thank you very much !