HAUPTSEMINAR

Data Mining And Machine Learning Approaches For Semiconductor Test And Diagnosis

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Title: Dimensionality Reduction for Test Optimization

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OUTLINE

Introduction

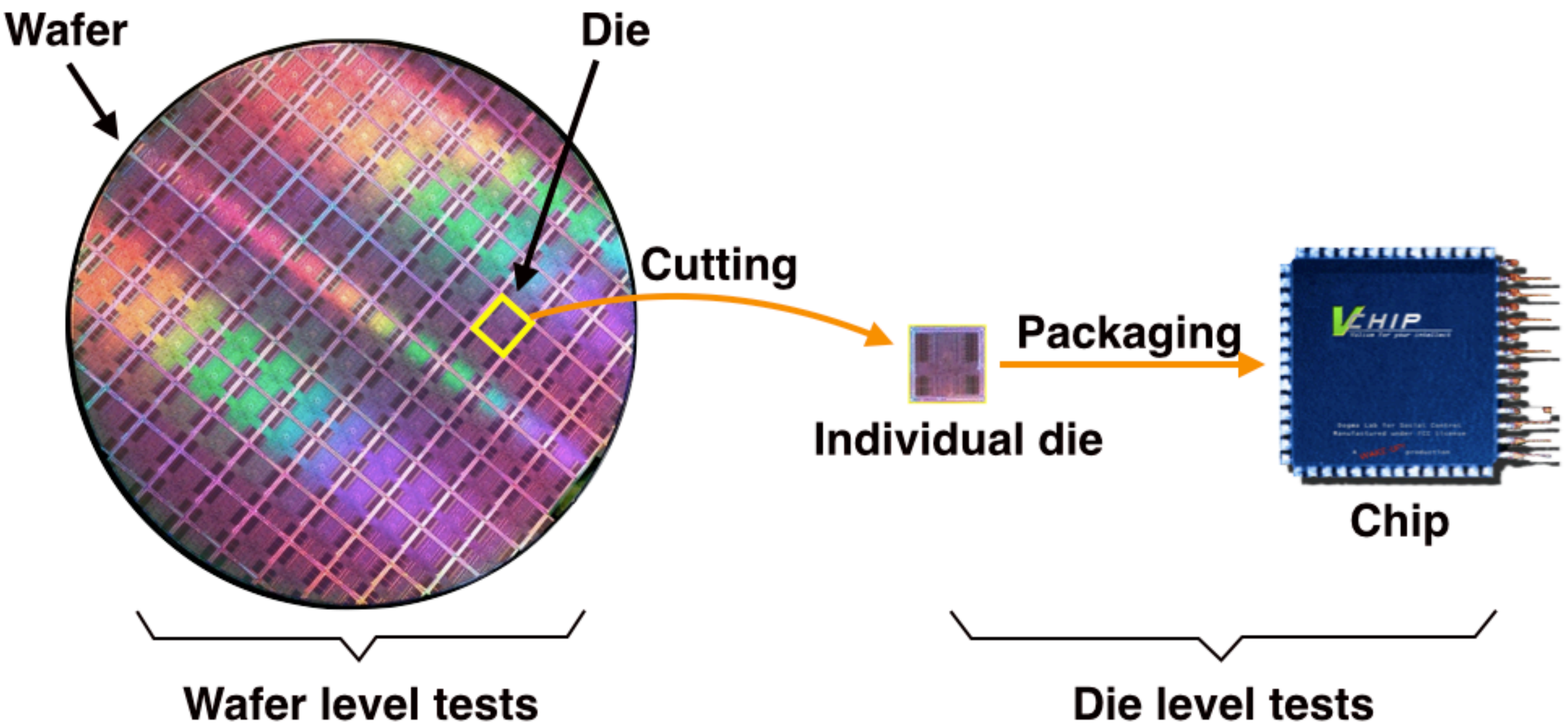
Methodology
- PCA
- Outlier Removing
- Variable Reduction
- Classification Criteria

A Special Case: Burn-in Reduction

Experiment Analysis

Conclusions

INTRODUCTION: Chip Test



INTRODUCTION: Challenges

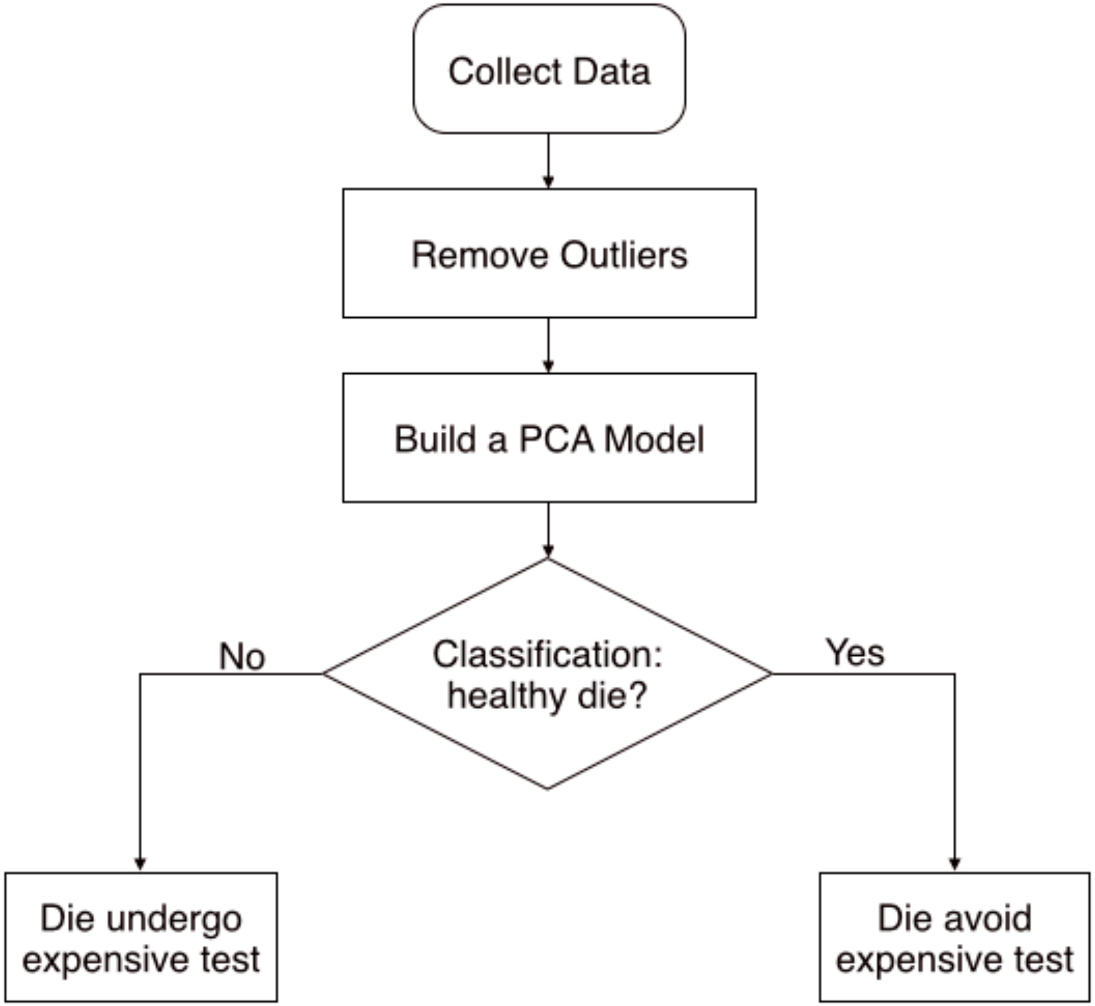
High Dimensionality
Costly & Time-Consuming Test

Motivation

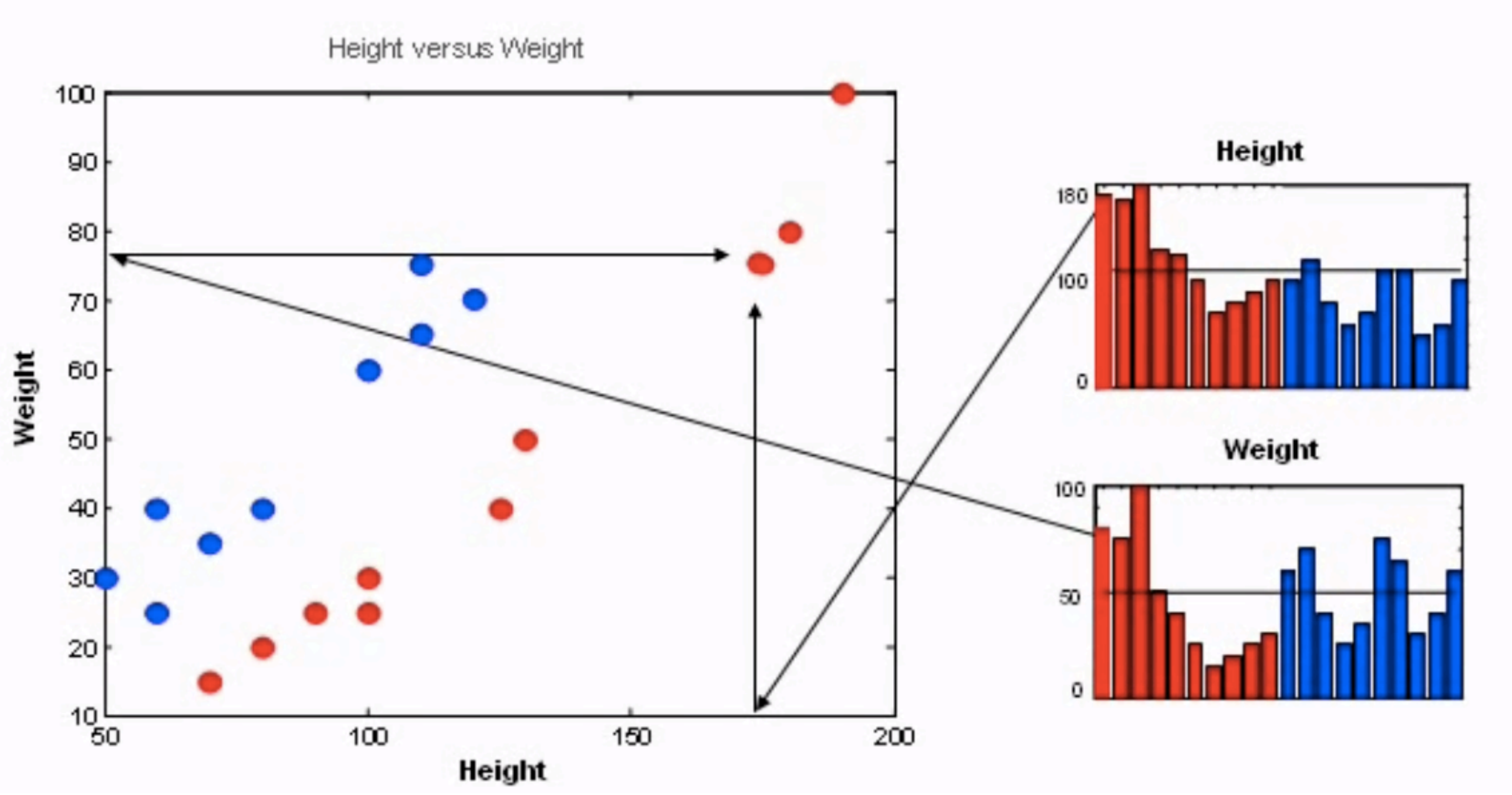
Test Optimization:
Dimensionality Reduction
Time & Cost Saving

Burn-in Test Machine

METHODOLOGY OVERVIEW



A USEFUL TOOL: PCA



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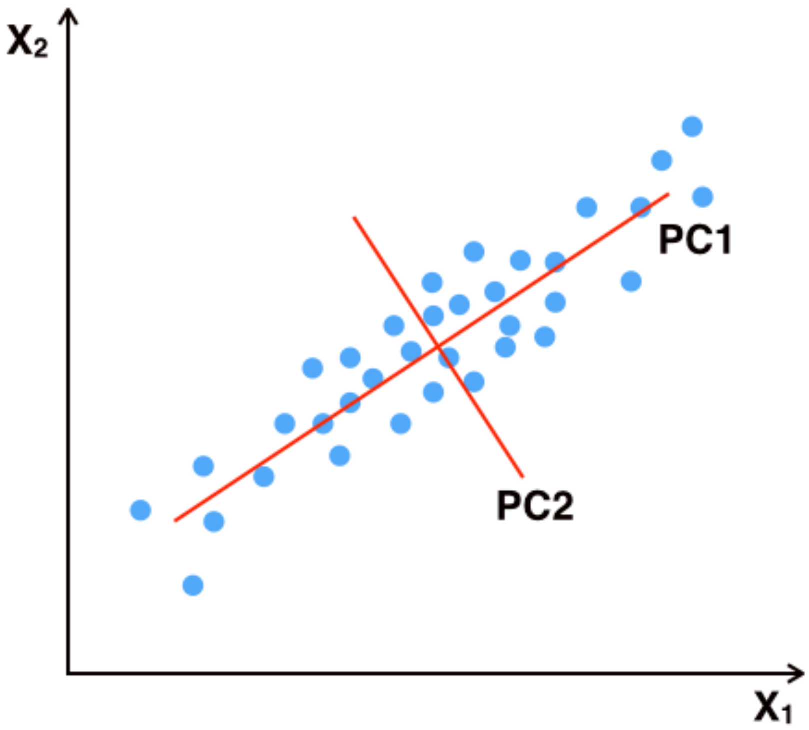
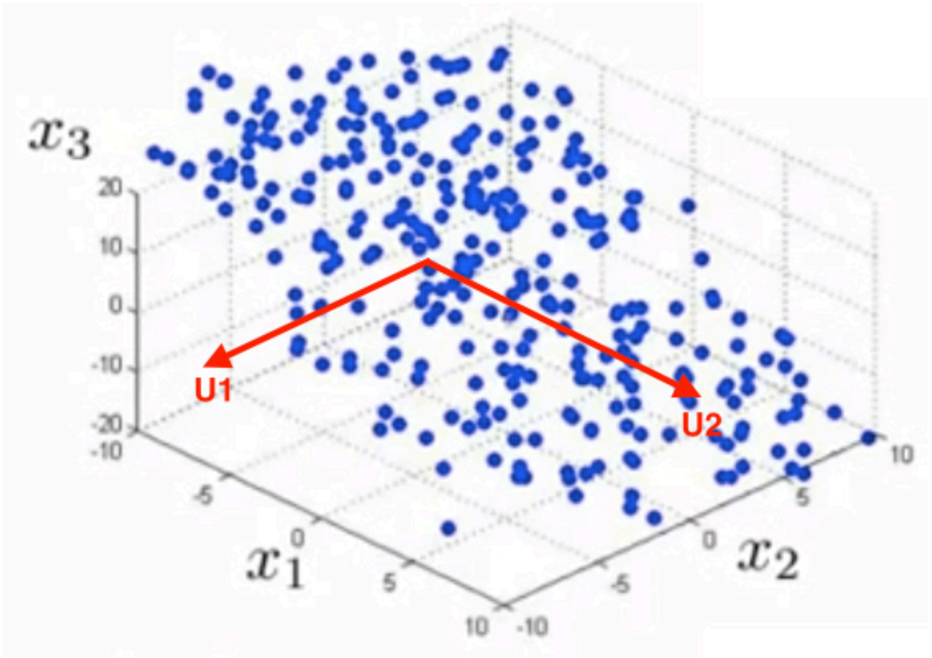


2 D to 2 D



3 D to 2 D

How PCA Works: Finding PCs

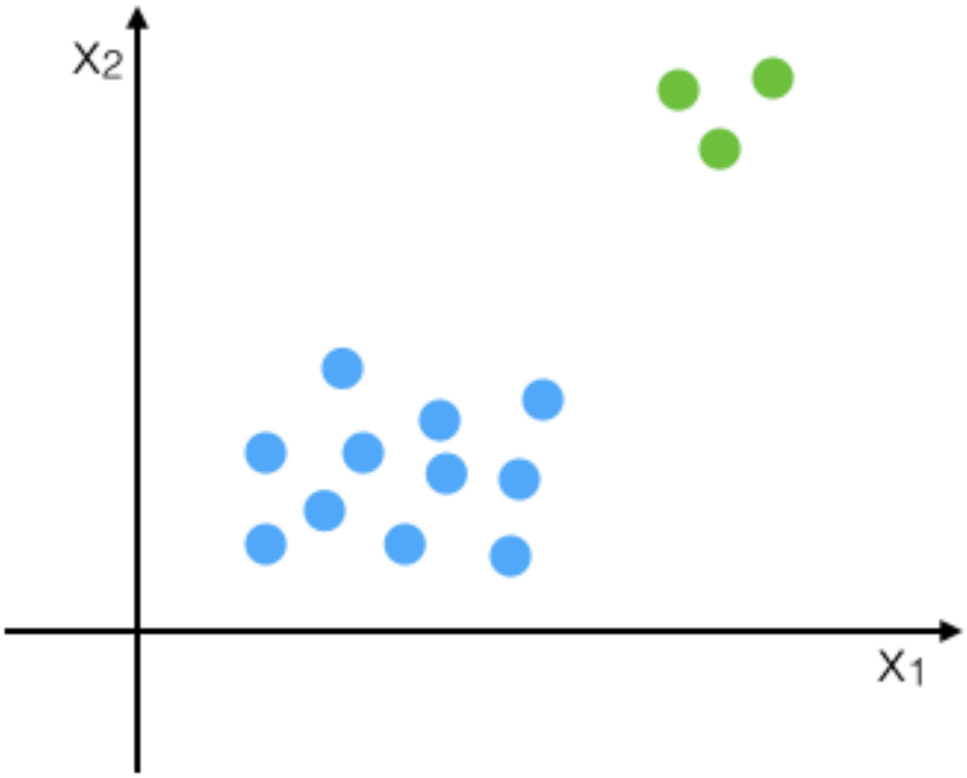
$$\begin{aligned} z_1 &= a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \\ z_2 &= a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \\ &\vdots \\ z_n &= a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n \end{aligned}$$

$$\begin{pmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_K \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \bullet \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

Covariance Matrix

$$\begin{pmatrix} Var(x_1,x_1) & Cov(x_1,x_2) & \cdots & Cov(x_1,x_n) \\ Cov(x_2,x_1) & Var(x_2,x_2) & \cdots & Cov(x_2,x_n) \\ \vdots & & & \\ Cov(x_n,x_1) & Cov(x_{n1},x_2) & \cdots & Var(x_{n1},x_n) \end{pmatrix}$$

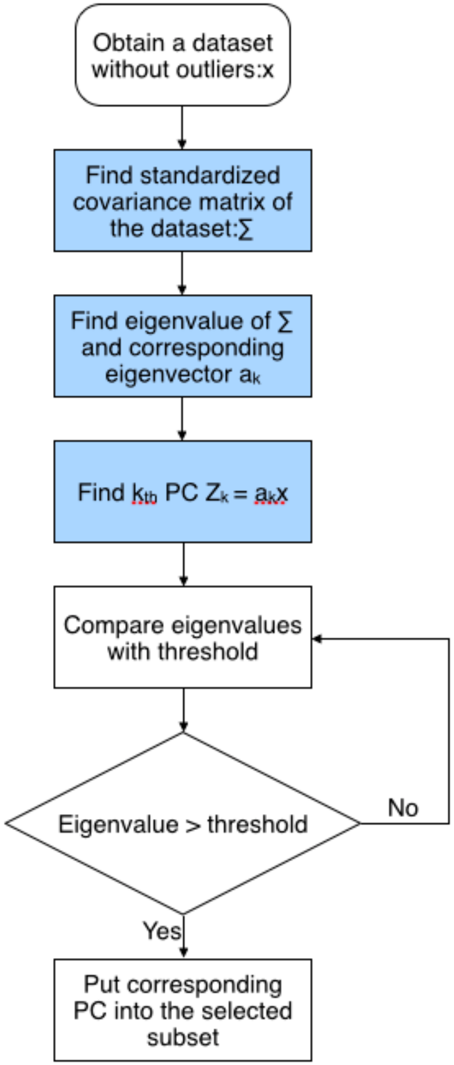
Outlier Removing



Outlier Removing Criteria

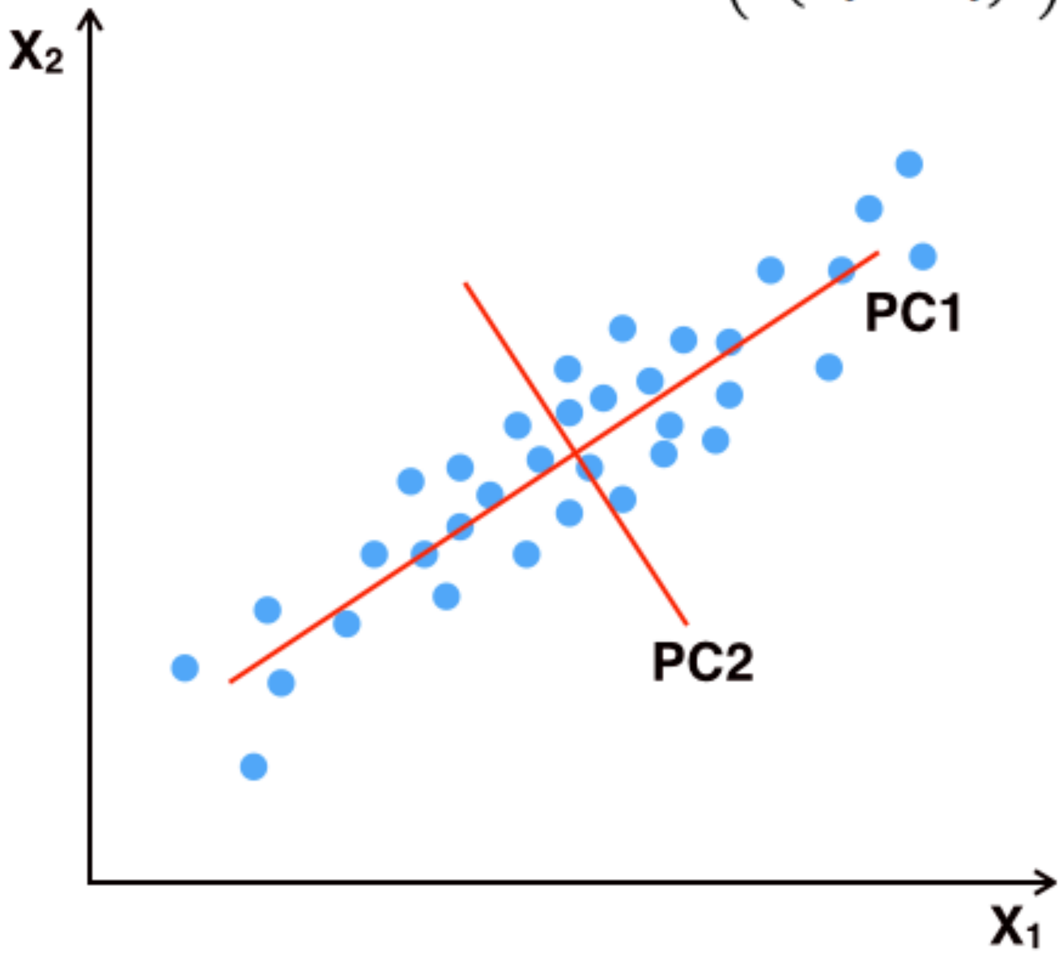
Criterion	Equation	Application Situation
1st	$d_{1i}^2 = \sum_{k=p-q+1}^{p} z_{ik}^2$	Data whose insignificant PCs have a narrow range of variances.
2nd	$d_{2i}^2 = \sum_{k=p-q+1}^{p} \frac{z_{ik}^2}{l_k}$	Data whose insignificant PCs have variances that are appreciable compared to the excursions caused by defects, and cover a wide range.
3rd	$d_{3i}^2 = \sum_{k=1}^{p} l_k z_{ik}^2$	The significant PCs are already strongly reflected in the original variables themselves.
4th	$d_{4i} = \underset{p-q+1 \le k \le p}{Max} \left(\left\| \frac{z_{ik}}{\sqrt{l_k}} \right\| \right)$	Sharp and unexpected excursion of PC is caused by adding it to all the other insignificant PCs.

Variable Reduction Using PCA

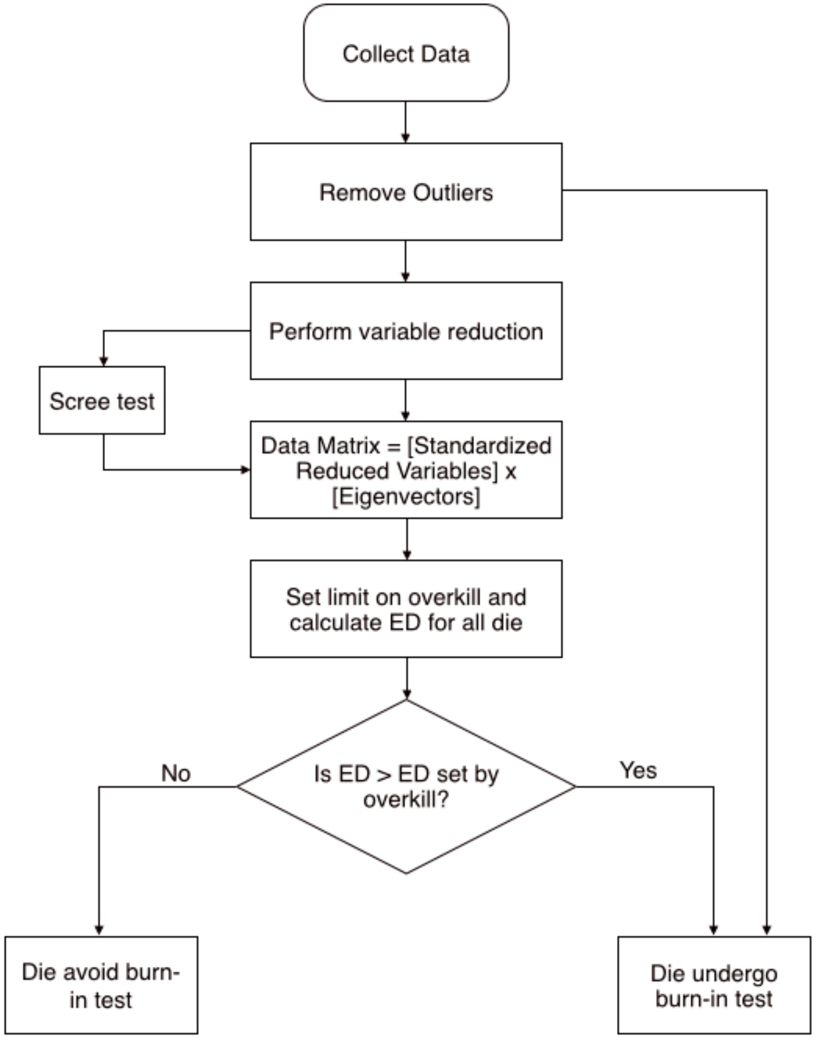


Classification

$$ED = \left(\Sigma\left(X_i - \overline{X}_i\right)^2\right)^{1/2}$$



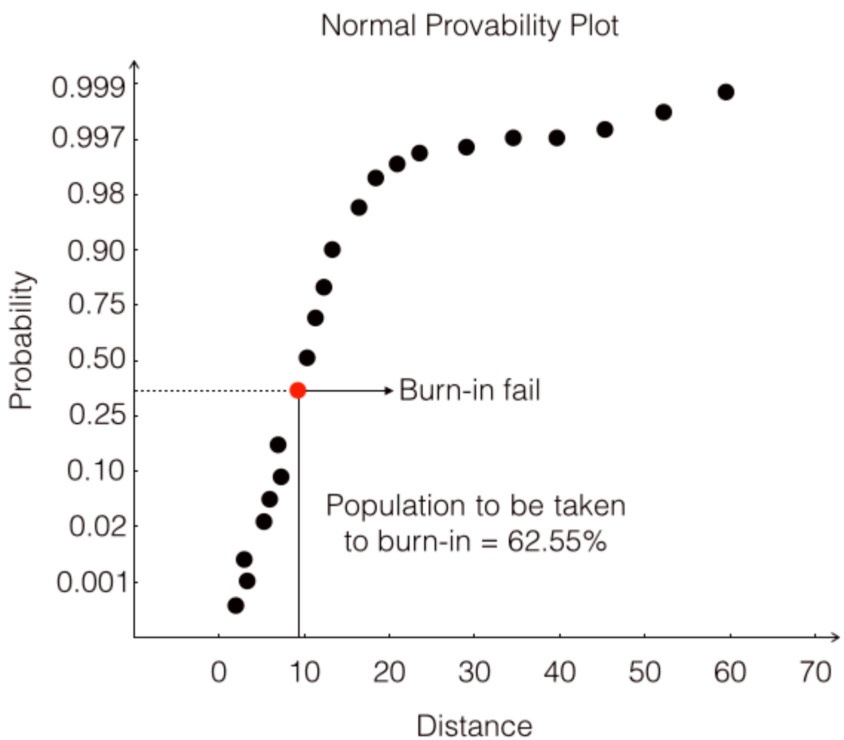
An Application Case: Burn-in Reduction



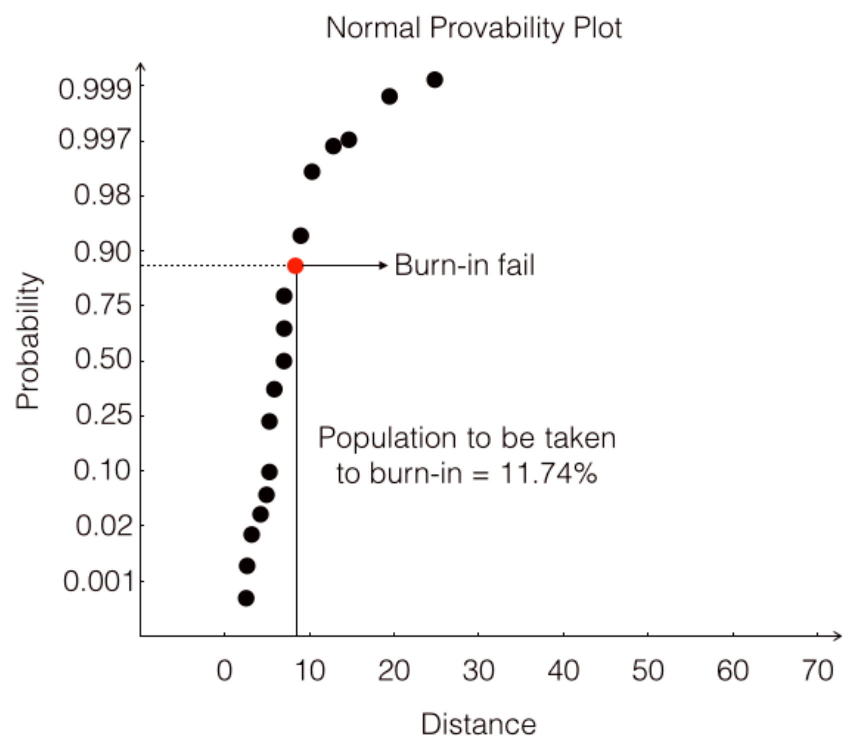
Experimental Analysis Basing on Burn-in Test Contribution 1: Dimensionality Reduction

	No. of variables retained				Variance retained (%)			
Wafer no. / Iteration no.	1	2	3	4	1	2	3	4
1	60	62	61	64	96	95	95	95
...	...	...	...	...	...	...	...	...
6	27	25	24	23	81	79	79	78

Experimental Analysis Basing on Burn-in Test Contribution 2: Cost & Time Saving for Test

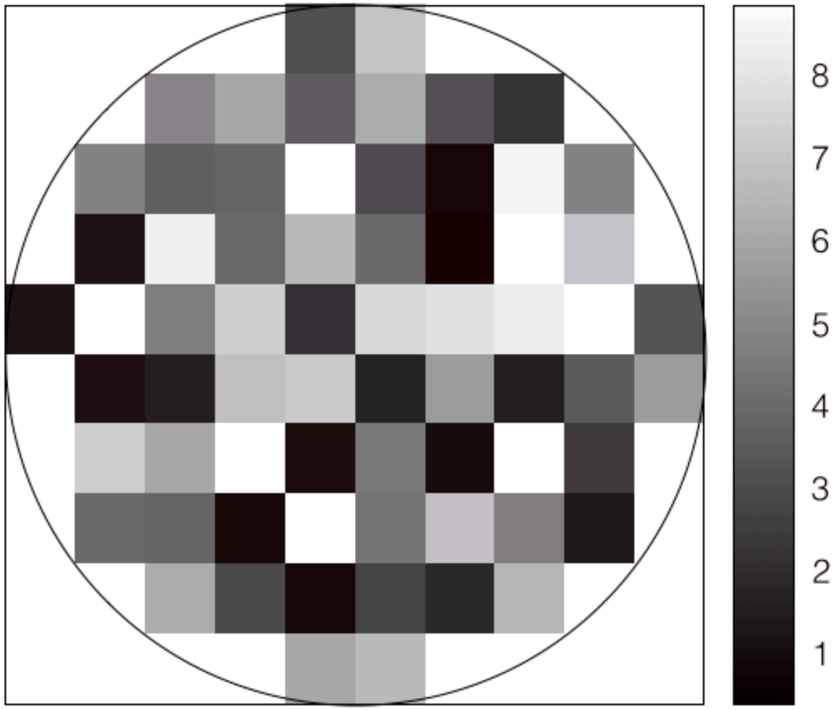


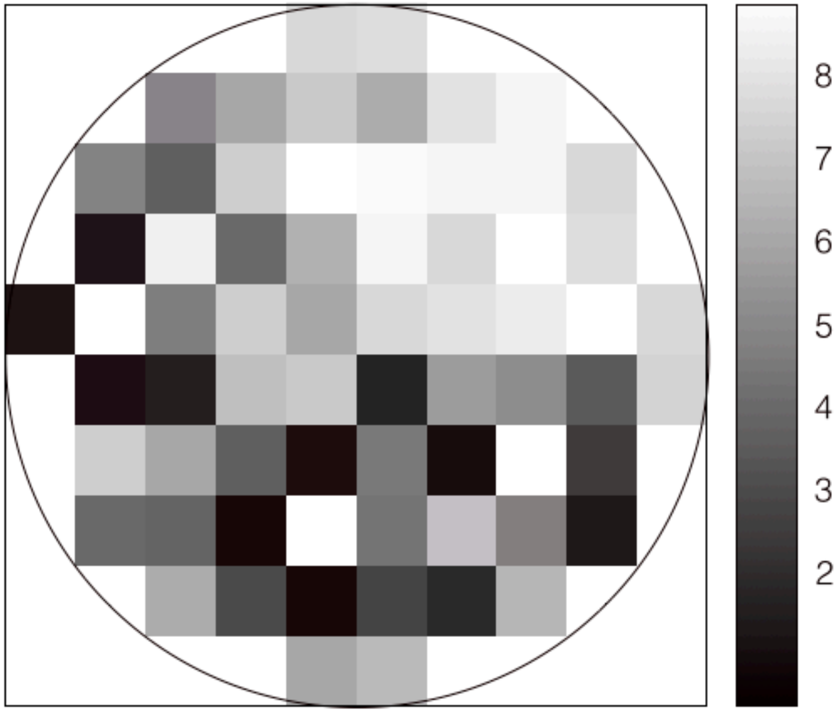
CDF of ED for single wafer before VR



CDF of ED for single wafer after VR

Experimental Analysis Basing on Burn-in Test Contribution 3: Identifying Process Problems





CONCLUSIONS

Contributions:

- **Reduce the dimensionality of the test dataset**
- **Reduce the number of dies undergoing costly and time-consuming test, thereby saving test expense**

Further Improvement:

- **Better methods for outlier removing**
- **Better threshold setting method for variable reduction**
- **Better classification approaches**