An Artificial Neural Network Approach for Screening Test Escapes

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Outline

- Motivation
- Feature Generation
- Artificial Neural Networks
- Data Setup
- Experimental Results

Motivation

Test Escapes are chips that pass the entire test program but fail at system-level tests or in field

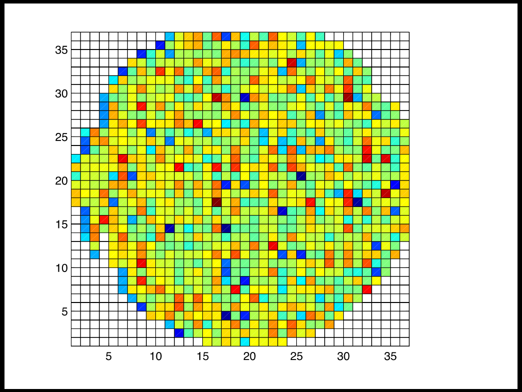
Machine Learning techniques have demonstrated promising results for predicting test escapes based on parametric production test data

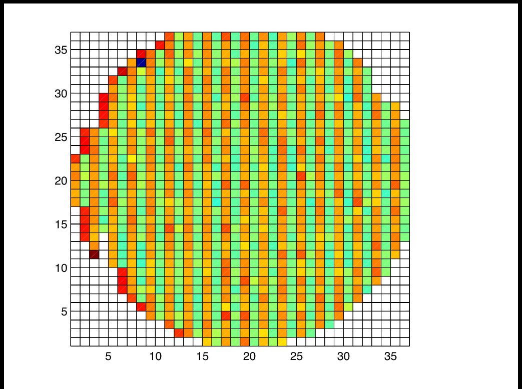
Artificial Neural Networks have great potential and achieved higher performance in complicated tasks such as object / speech recognition

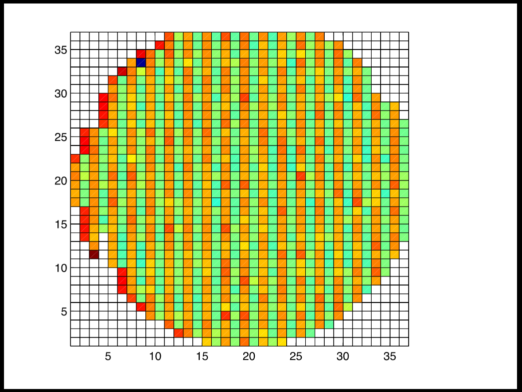
Features: Residual Vector

For a chip with N test measurements

$$\mathbf{r} = \mathbf{x}_m - \mathbf{x}_e$$







$\mathbf{x}_m$: N by 1 vector of measured values

$\mathbf{x}_e$: N by 1 vector of expected values

Selecting the Expected Values x_e

- **Mean of the wafer**
  - produces feature set F_M

- **Bilateral filtered spatial pattern of the wafer**
  - produces feature set F_B

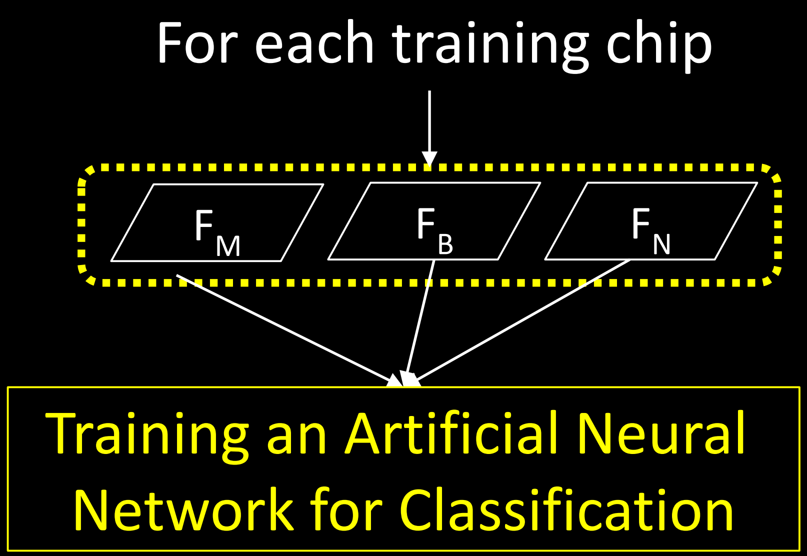
- **Median of the eight closest neighbors' values**
  - Produces feature set F_N

Each feature set is expressed as an N by 1 vector

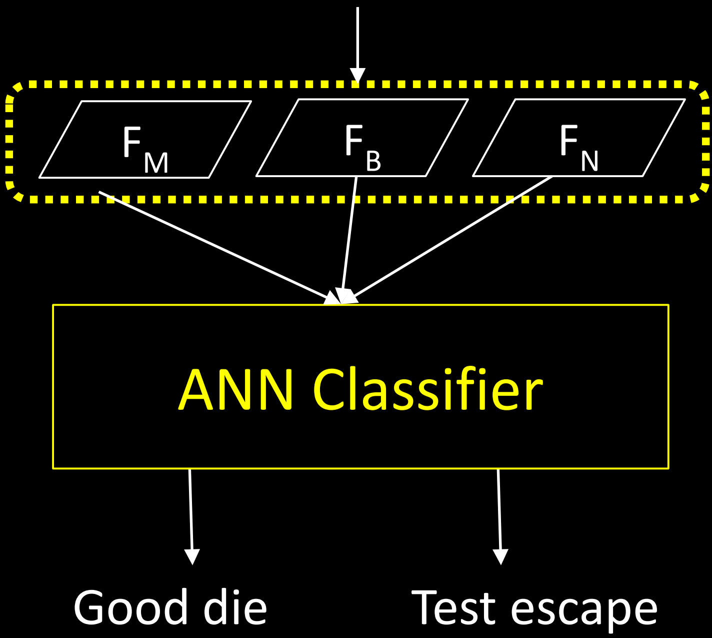
F. Lin, C-K. Hsu, K-T. Cheng, "Feature Engineering with Canonical Analysis for Effective Statistical Tests Screening Test Escapes", ITC, 2014

Use of ANN for Test Escape Screening

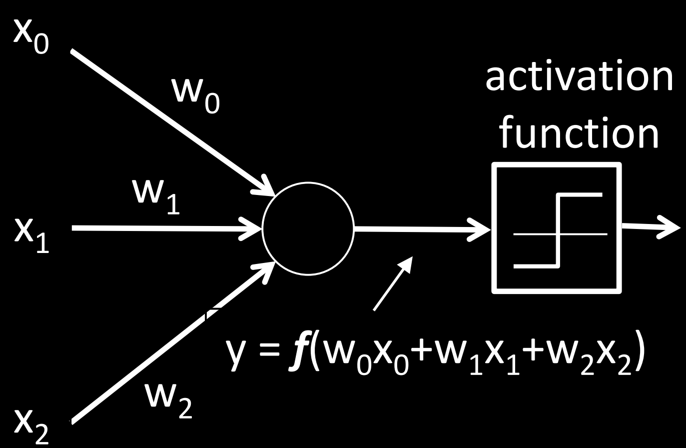
Training using a set of good chips:

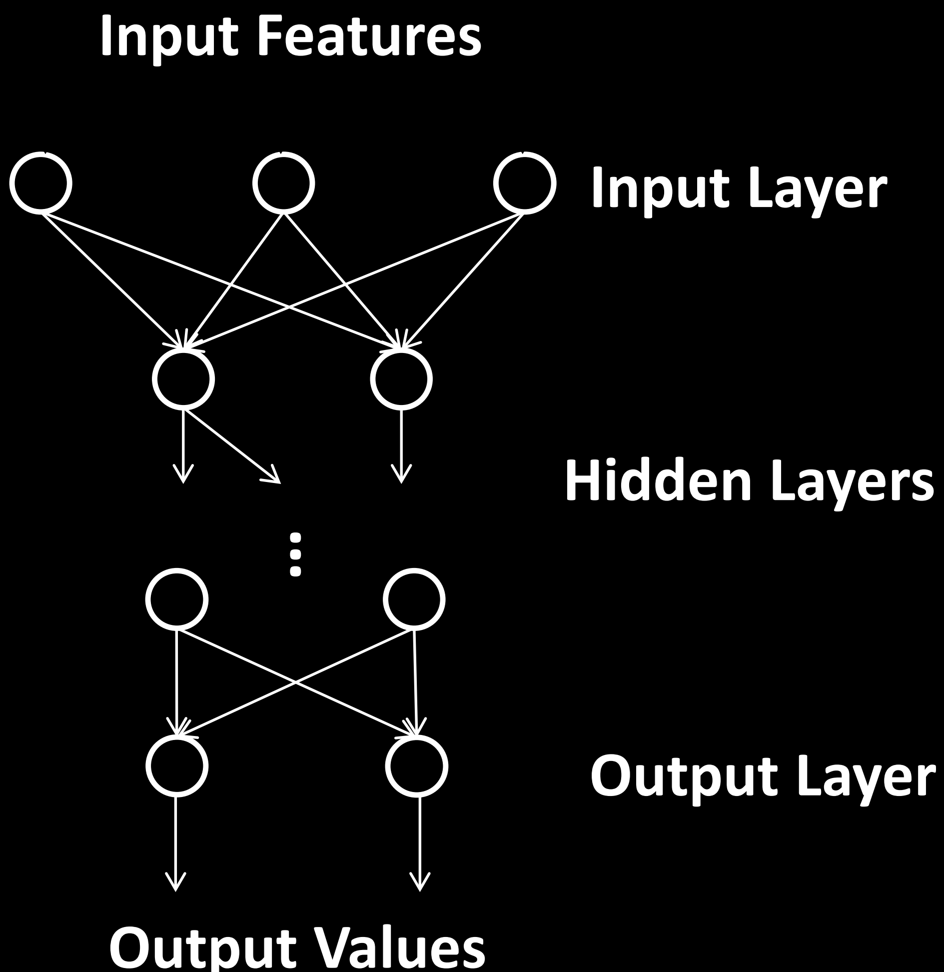


For each chip under screening:



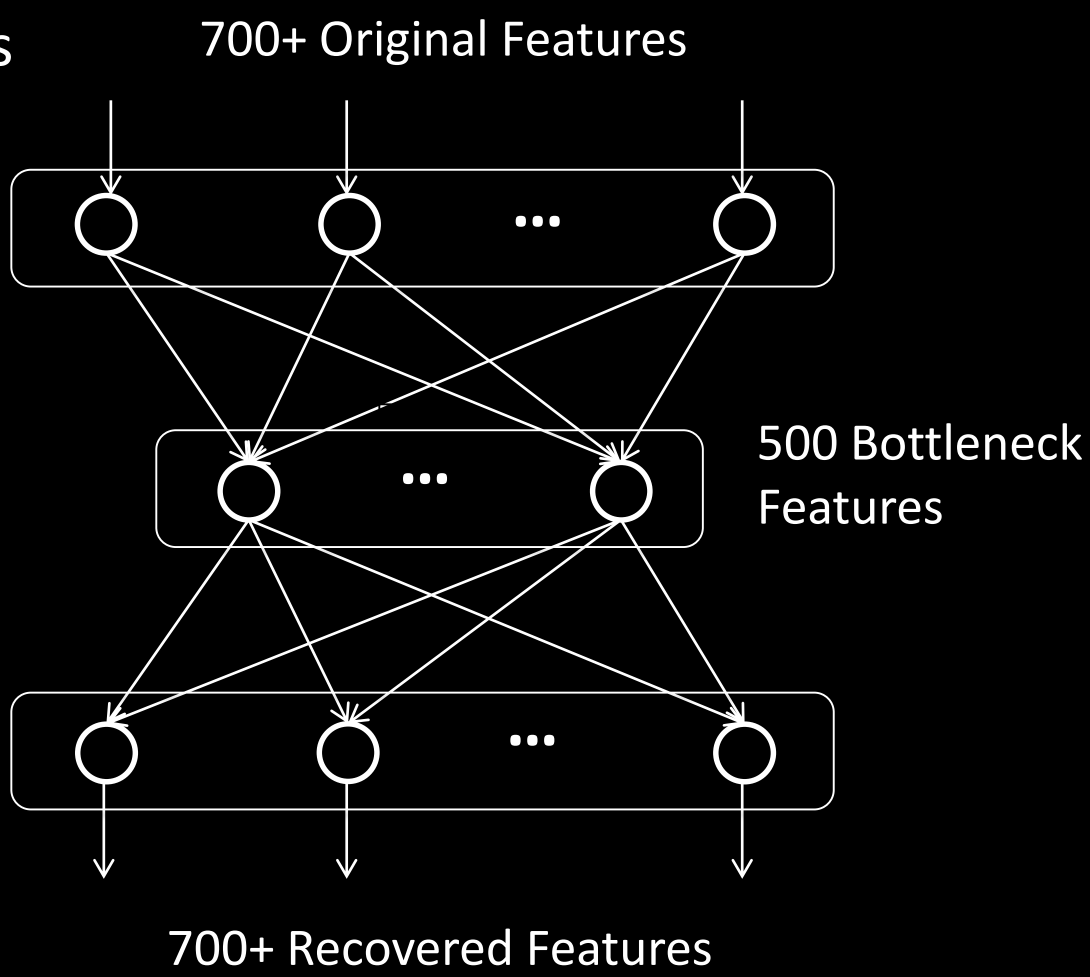
Artificial Neural Networks





The *Autoencoder* Model

- One to several hidden layers
  - The bottleneck layer(s)
  - 500, 250, 125,… neurons
- No activation functions
- Fully-connected layers
- Cost function
  - Euclidean Distance between original and recovered features

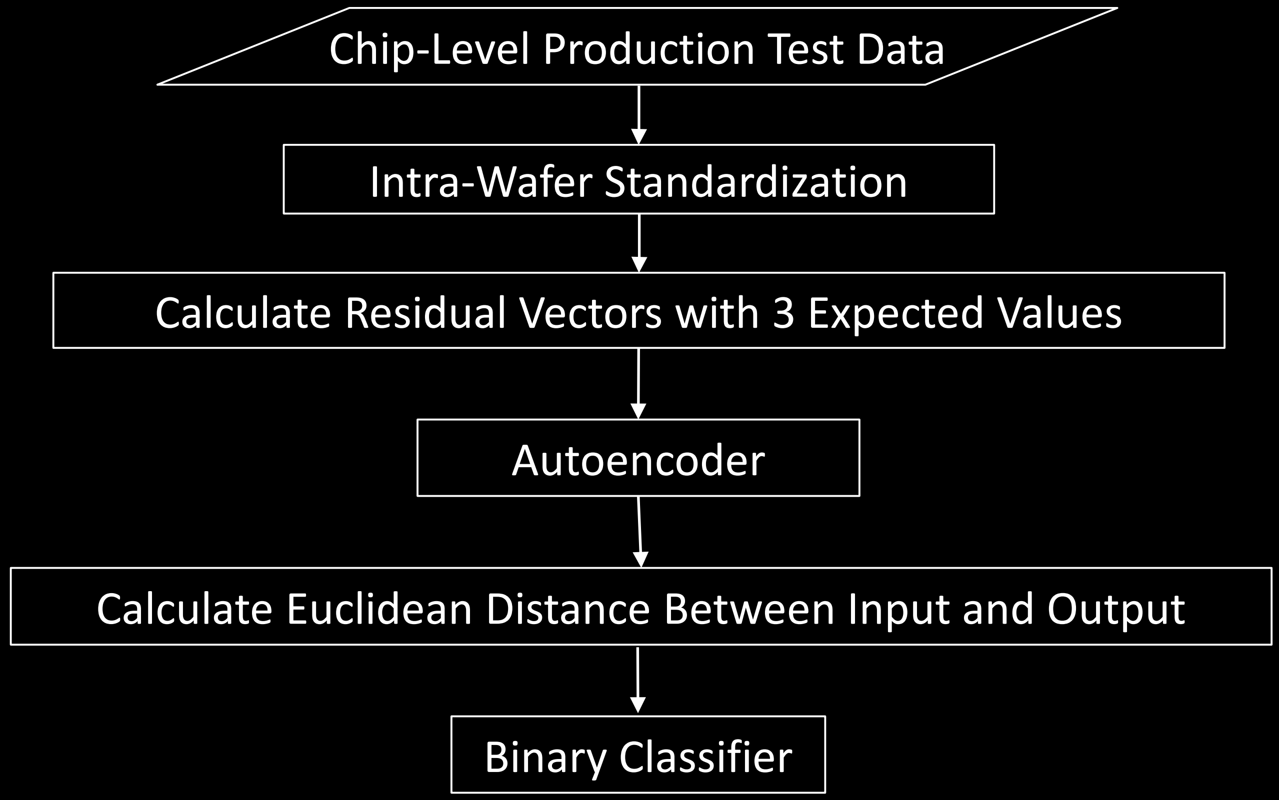


The *Autoencoder* Model

- Unsupervised training
  - Train with only good chips in the training set
  - Find a set of bottleneck features that best represent the dataset of good chips
- Testing
  - Apply the *autoencoder* to a query chip and calculate the Euclidean distance between the input and output layers
  - Classify a chip as anomaly if the value is greater than a threshold

The Proposed Test Flow

- Standardize test data based on each wafer to remove wafer-to-wafer variations



Data Setup

Industrial Production Test Data

Training set: 200+ wafers

Validation set: 200+ wafers

Testing set: 200+ wafers

200+ parametric test items

1000+ chips per wafer

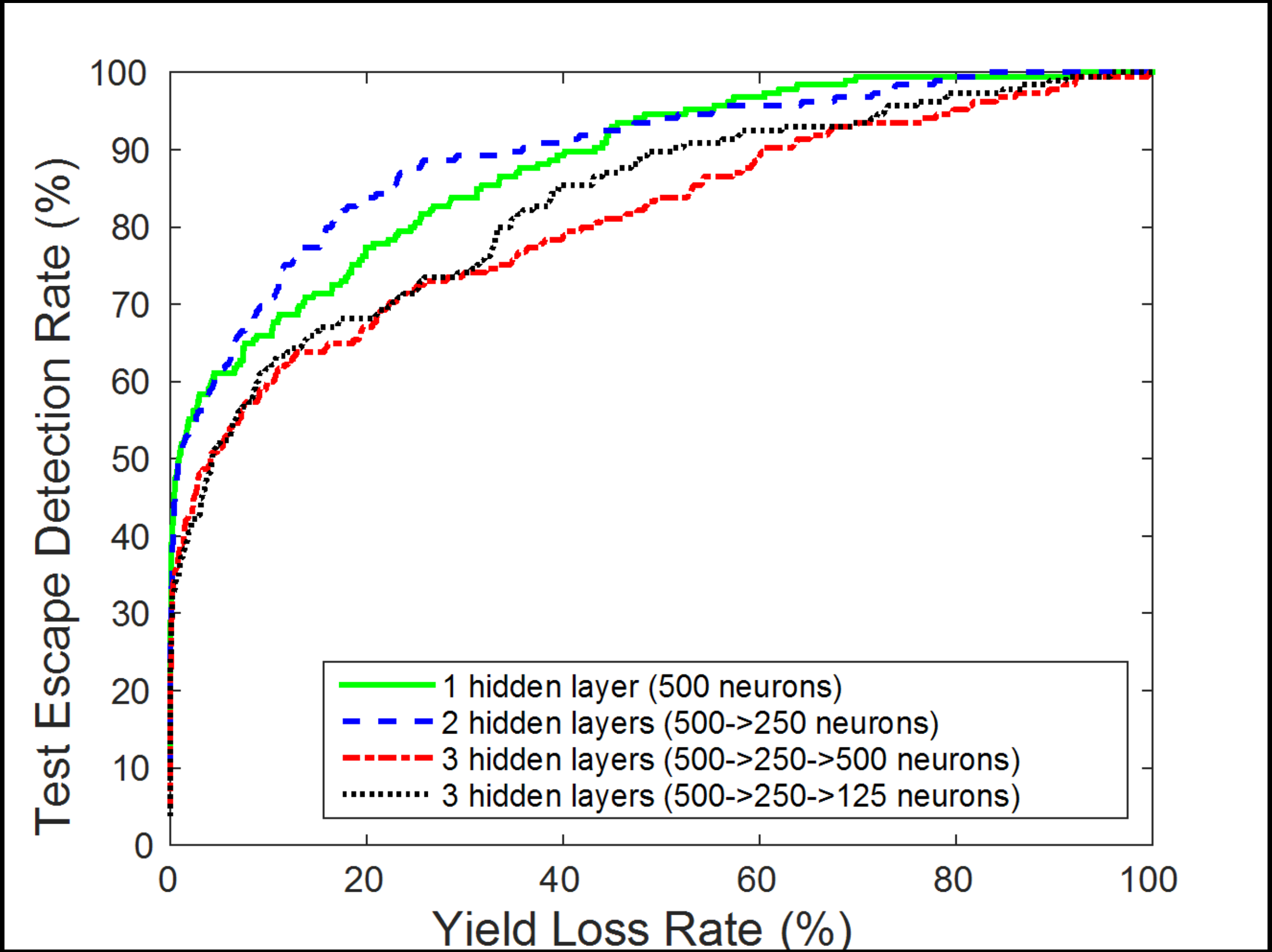
***Emulated Test Escapes**

560 PPM

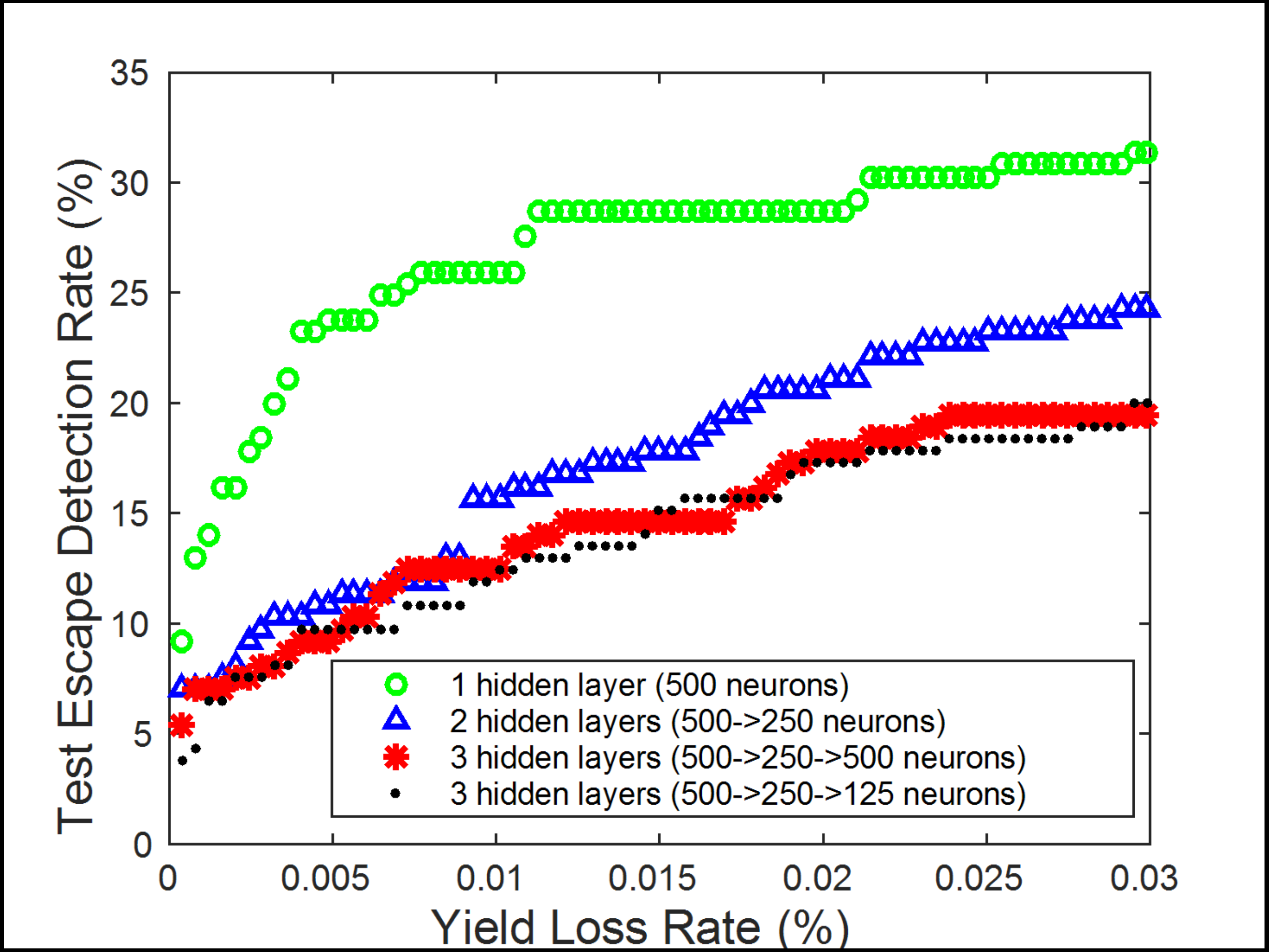
*F. Lin, C-K. Hsu, K-T. Cheng, “Feature Engineering with Canonical Analysis for Effective Statistical Tests Screening Test Escapes”, ITC 2014

Comparison of Autoencoder Structures

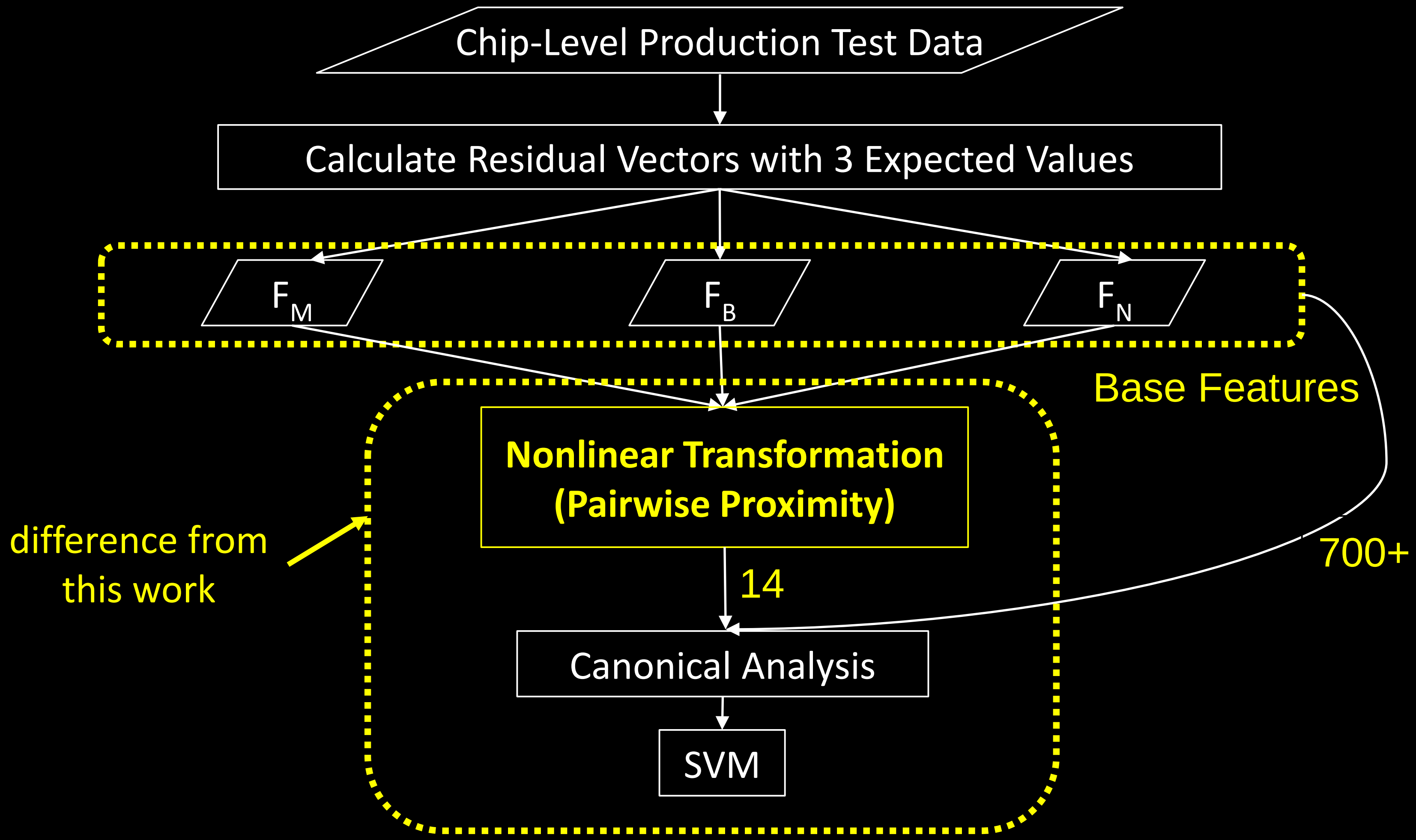
More hidden layers may better capture the characteristics of the training set, but the captured characteristics does not necessarily expose test escapes as anomalies.



Autoencoder with 1 Hidden Layer Performs Best at Target Region



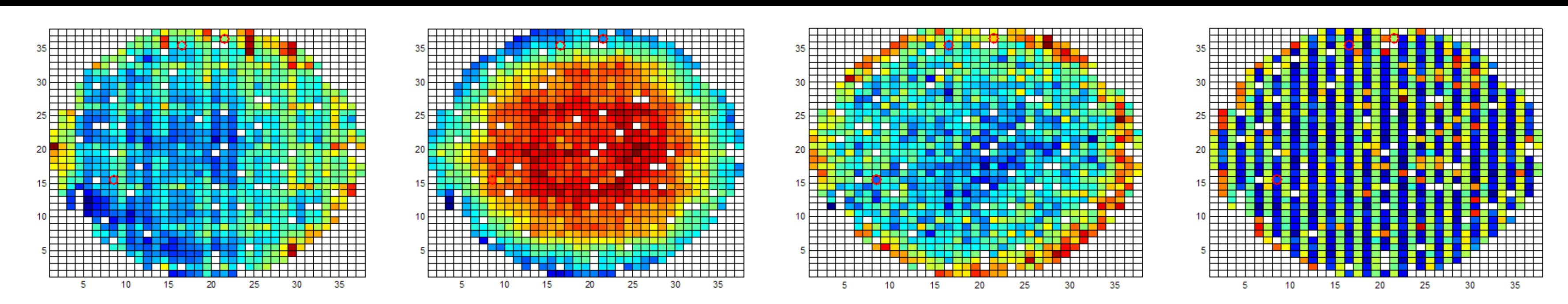
Comparison with Other Frameworks



F. Lin, C-K. Hsu, A. G. Busetto, and K-T. Cheng, “Pairwise proximity-based features for test escape screening”, ICCAD 2015

Pairwise Proximity

Test Item 1 Test Item 2 Test Item 3 Test Item 4



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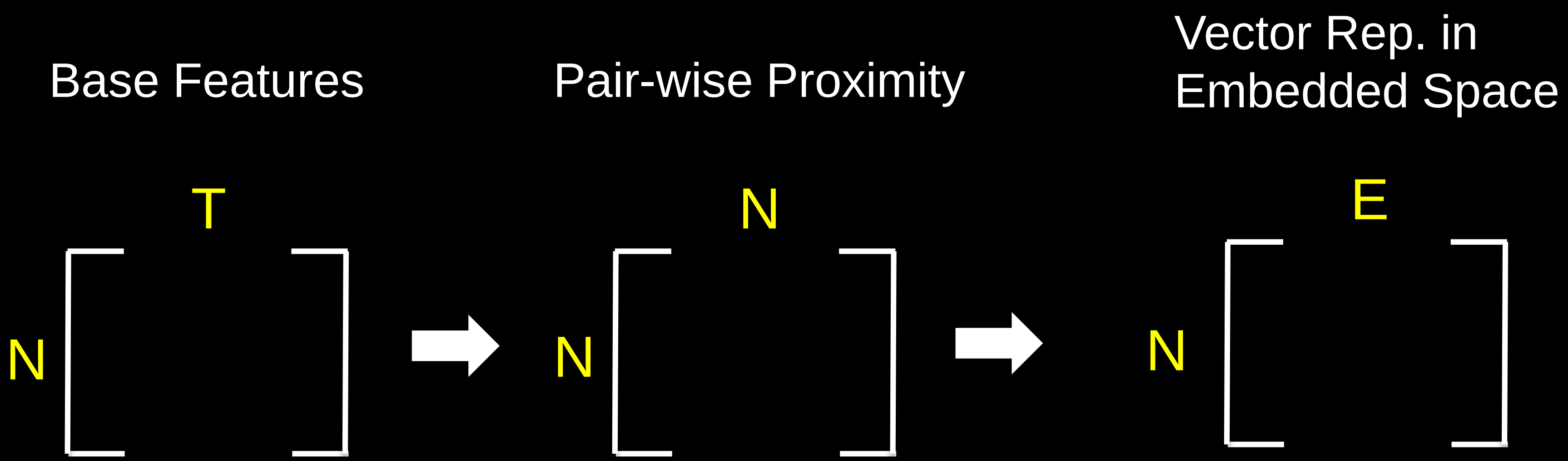
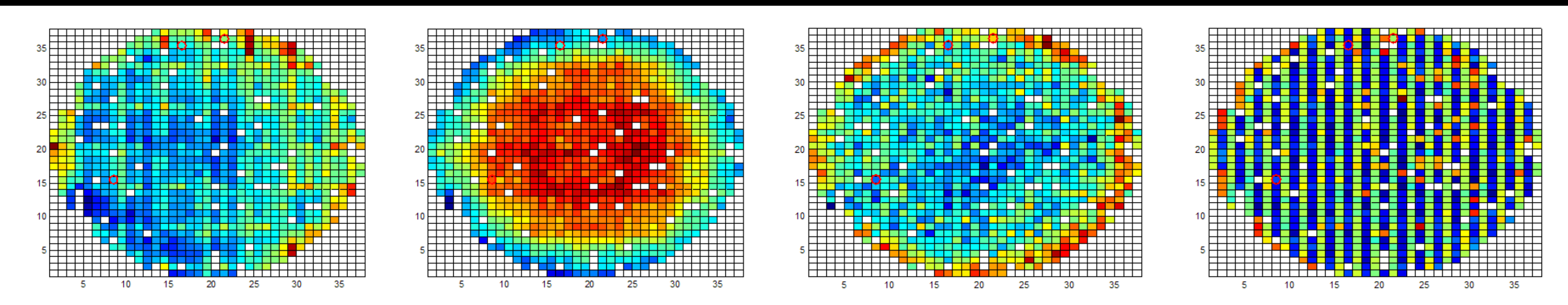


Pairwise Proximity

Test Item 1 | Test Item 2 | Test Item 3 | Test Item 4



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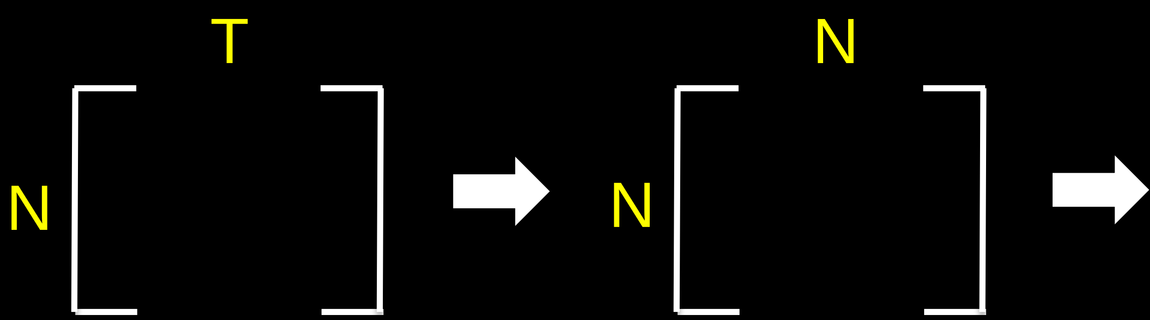
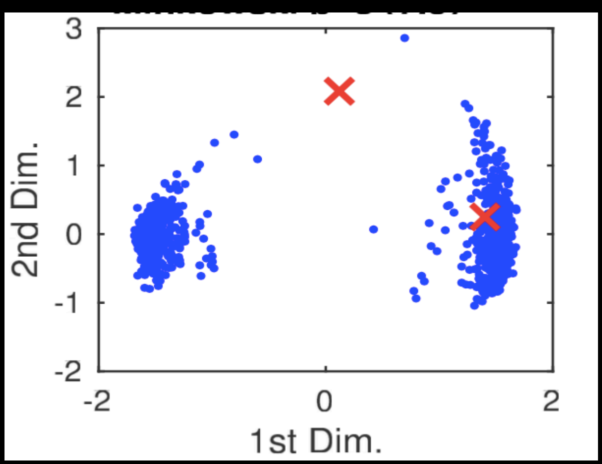
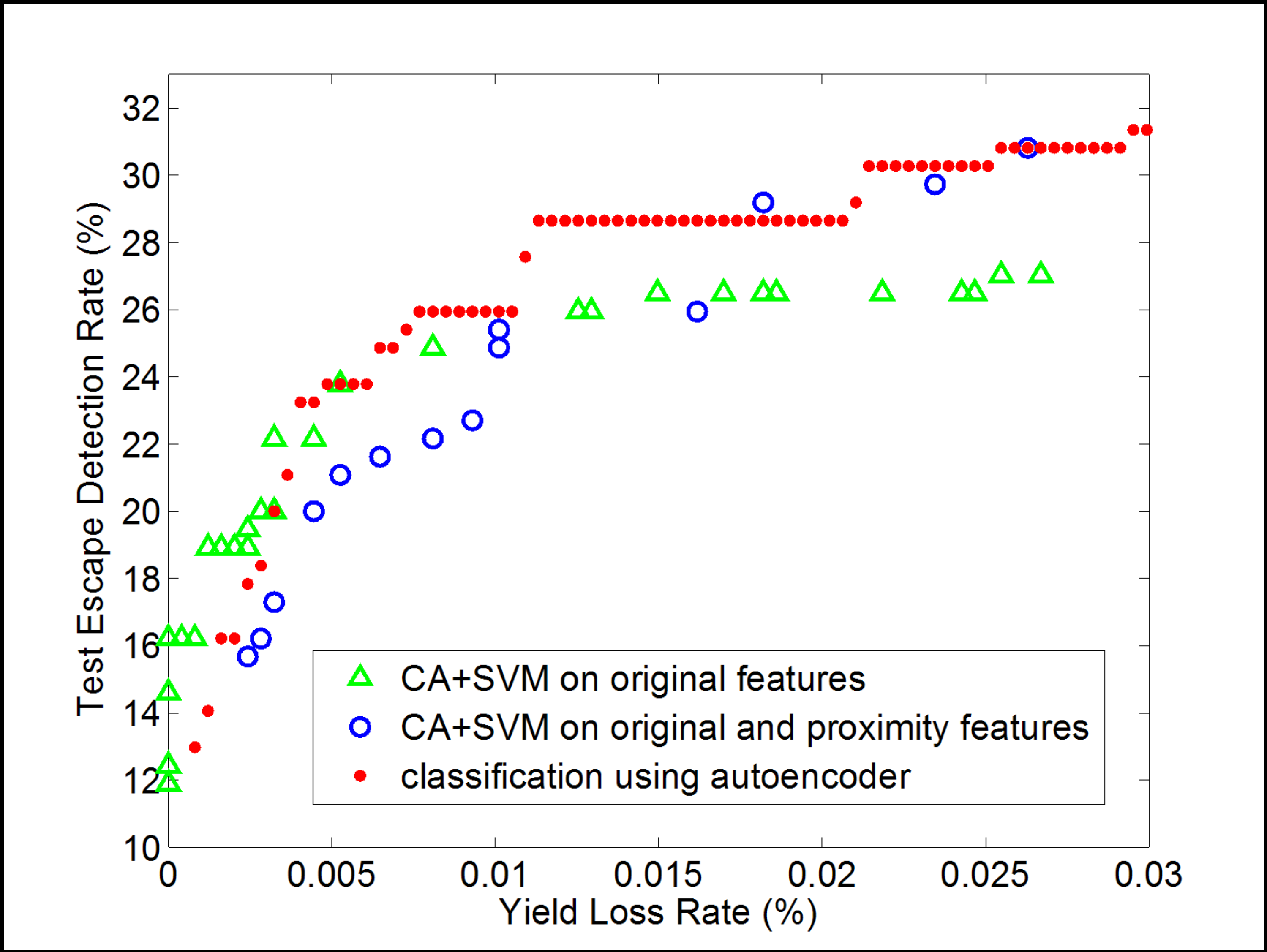
Base Features | Minkowski Distance (p=3) | Vector Rep. in Embedded Space





Autoencoder Exposes More Test Escapes Than Other Frameworks

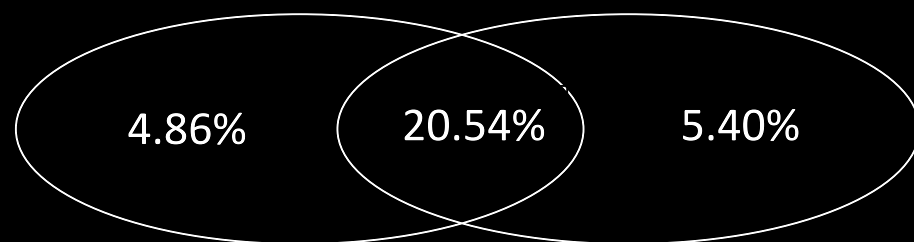


A Closer Look at Identified Test Escapes and Yield Losses

Test escape detection rate

SVM on residual vectors and proximity features

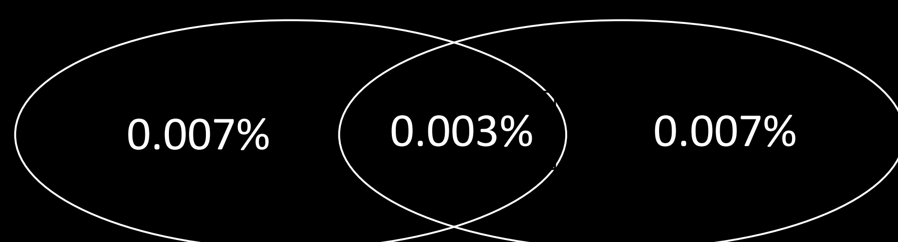
Autoencoder on residual vectors



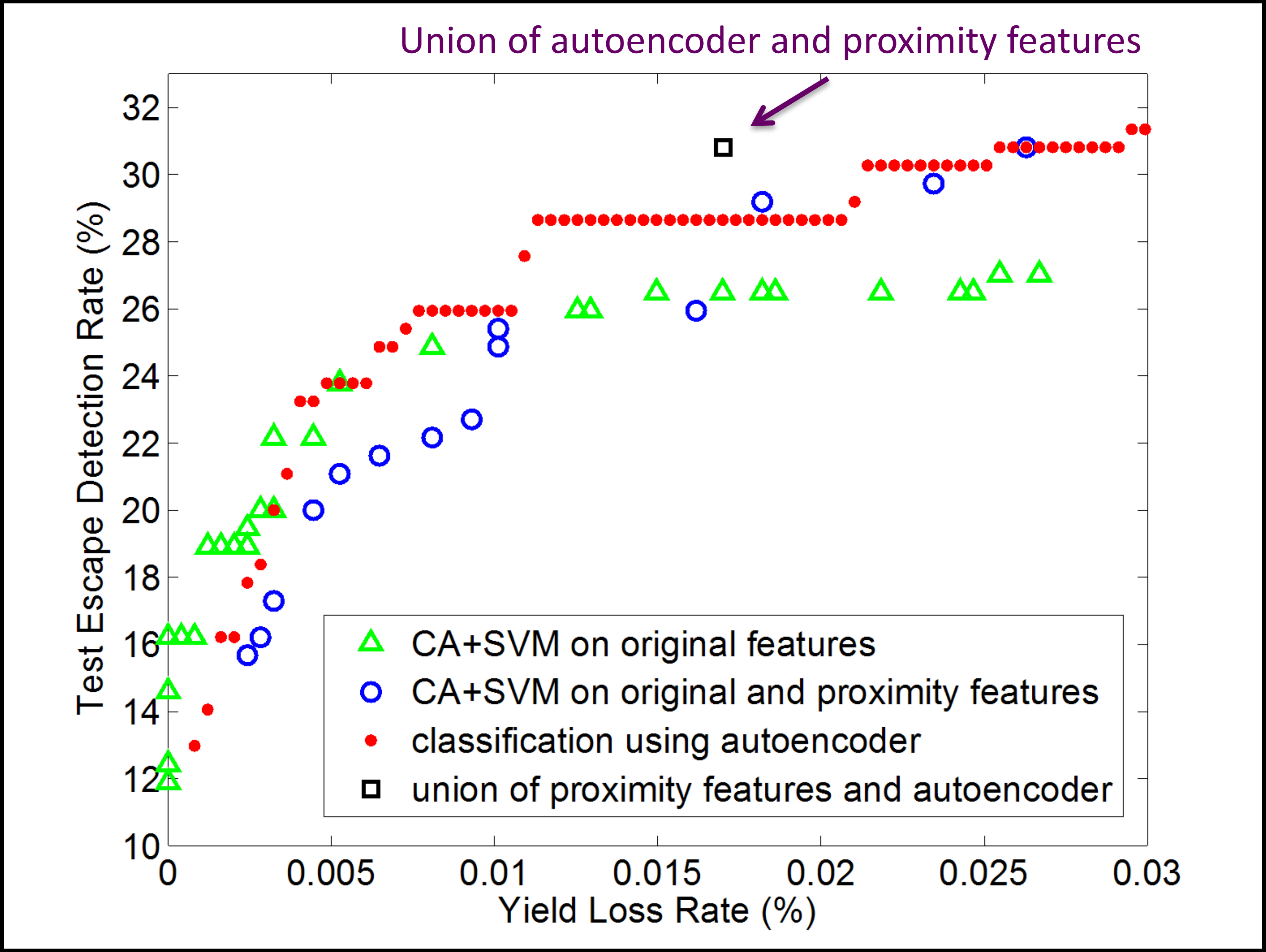
Yield loss rate

SVM on residual vectors and proximity features

Autoencoder on residual vectors



A Hybrid Framework May Improve the Classification Accuracy



Prediction Runtime Improvement

- SVM on base and proximity features
  - 4.6 seconds per wafer
- Autoencoder Configuration
  - Caffe package from UC Berkeley
  - Nvidia GTX 980
  - 0.1 second per wafer
  - 46X speed up

Conclusion

- *Autoencoder* could identify more test escapes than the SVM framework using both base and proximity features, with significant runtime reduction
- Because of the unsupervised training process, a model that fits the training set better does not necessarily lead to a higher test escape detection rate. A validation process is needed to select the best model.
- Proposed autoencoder is a relatively simple ANN structure, several ANN design choices might be further optimized
  - e.g. activation function, cost function, solver for updating weights.