Discovering Interesting Plots in Production Yield Data Analytics

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Abstract—An analytic process is iterative between two agents, an analyst and an analytic toolbox. Each iteration comprises three main steps: preparing a dataset, running an analytic tool, and evaluating the result, where dataset preparation and result evaluation, conducted by the analyst, are largely domain-knowledge driven. In this work, the focus is on automating the result evaluation step. The underlying problem is to identify plots that are deemed interesting by an analyst. We propose a methodology to learn such analyst’s intent based on Generative Adversarial Networks (GANs) and demonstrate its applications in the context of production yield optimization using data collected from several product lines.

1. Introduction

Data analytics have been widely applied in design automation and test in recent years. In certain applications, analytics can be viewed as an iterative search process. Such a process comprises three major steps as illustrated in Figure 1: dataset preparation, running an analytic tool, and result evaluation. The dataset preparation and result evaluation are largely domain-knowledge driven. The analytic toolbox comprises statistical or machine learning tools.

One application that can be seen in terms of this view is production yield optimization. Typically, the data to be analyzed are production test data together with e-test data characterizing the effects of process on each wafer. The analytics have two goals: (1) identifying a failure case that impacts the yield, (2) searching to establish a “high” correlation between one or more e-test parameters and the failing case. The analytics can be extended to manufacturing data if data on manufacturing tools are also available.

In the context of production yield optimization, for example, the work in [2] focuses on the analytic toolbox. The study concerns more on what tools are useful or required in the application context for resolving a yield issue. Then, the work in [3] focuses on the dataset preparation. Due to the iterative nature of an analytic process, dataset preparation can be seen as following a particular flowchart for the search. The work [3] concerns how to construct such a flowchart automatically by learning from an analyst’s past experience, i.e. usage log of the analytic toolbox.

This work focuses on the result evaluation and was motivated by the desire to automate an entire analytic process as much as possible. Automation of the toolbox is relatively easy because the input and output of an analytic tool is usually well defined. Hence, developing an analytic tool is more of an algorithmic question. Automation of the dataset preparation and result evaluation can be challenging because these two components are largely domain-knowledge driven. As a result, what it takes to automate them can be fuzzy or even become an open-ended question.

Automation of the result evaluation component can be considered as a standalone problem and essentially means to capture an analyst’s intent regarding the interest of a result. For example, to search for a high correlation, an analyst constructs a set of datasets \( D_1, \ldots, D_{k \times n} \) and runs each with a Pearson correlation tool. Each dataset comprises \( m \) samples. A sample can be defined as either a wafer or a lot. Suppose a sample is a lot. There are also choices to define what each dataset represents. For example, each dataset represents the number of failing dies from a failing bin. Suppose there are \( k \) bins and \( n \) e-tests. Then, after pairing each bin with each e-test, there are \( k \times n \) datasets. In each dataset two values are calculated for each sample: the number of failing dies from the lot and the e-test value. The e-test value, for example, can be the average of measured values across all wafers in a given lot.

Running the tool leads to results \( R_1, \ldots, R_{k \times n} \) as illustrated in Figure 2. Each \( R_i \) can contain two pieces of result, a correlation number and a correlation plot. In this search, the analyst’s intent is to find a “high correlation.” Usually, a script can be written to check the results to see if any correlation number is greater than, say 0.8. This approach essentially is using a fixed rule to capture the intent.

If the analyst’s intent can be captured completely with a fixed rule, then there is no problem to automate it. The issue
is that in many situations, completely capturing an intent is not so easy. For example, when a rule is fixed to search for a correlation number greater than or equal to 0.8, it would overlook any result with the number less than 0.8. More importantly, a low correlation number does not imply the corresponding plot is not interesting to the analyst.

For example, Figure 3-(a) shows a correlation plot that is interesting (the interest will be explained in detail later). While the correlation number is low, the plot shows that increasing e-test value tends to have more fails. Consequently, adjusting the process to reduce the particular parameter value can be a choice for improving the yield.

![Figure 3. Interesting plots not easily described with a fixed rule](image)

Figure 3-(b) shows another example of interesting plot. The plot shows a wafer and the location of its passing dies marked as dark-purple dots. This plot is interesting not only because it shows a cluster of passing dies but also there seems to be three concentrating sub-clusters on the center (the reason will be explained later).

If an analyst knew in advance to specifically look for those particular plots as shown in Figure 3, then presumably the analyst could write a rule to describe what to look for. However, seeing examples of interesting plots does not always imply it is easy for the analyst to write a rule to capture the intent. For example, the work in [4] develops a non-trivial rule in order to automatically recognize wafers with certain class of clustered fails.

Depending on the experience of an analyst, the analyst might not know what interesting plots to look for in advance or not know how to write a rule to capture a class of interesting plots. In practice, it can be difficult to manually enumerate all classes of interesting plots in advance and describe each with a fixed rule. If this difficulty cannot be overcome in practice for an analytic process, then using fixed rules to implement the result evaluation component can become an ineffective approach.

Motivated by the need to overcome the difficulty, this work pursues an alternative approach than using a fixed-rule. The assumption is that it is easy for a person to judge if a plot, when presented to the person, is interesting or not. Based on this assumption, a machine learning model can be trained to recognize a particular class of plots (interesting or non-interesting). Such a model can be used to capture an analyst’s intent based on learning from the example plots.

Developing a plot recognizer can be seen as an unsupervised learning problem. The training data can comprise only one particular class of plots. Recent advances in unsupervised learning based on Generative Adversarial Networks (GANs) [5] provide a good underlying technology to implement such a recognizer. In this work, we therefore investigate how to build a plot recognizer using GANs. With such recognizers, we develop a methodology to apply them in practice. In particular, the methodology is applied to analyze production data from several product lines. Its usefulness will be explained through several findings that led to an improvement on the yield.

Note that the recognizer-based methodology is not proposed as a replacement for the fixed-rule approach. It is an alternative that can be applied when developing a fixed-rule is practically difficult. The degree of this difficulty, however, can vary from analyst to analyst. Hence, one cannot say that it is impossible for any fixed-rule approach to capture what being captured by a recognizer. Can a well-trained very intelligent analyst to develop a sophisticated rule to also capture an intent captured by a recognizer? Possibly. But this is not the question studied in this work.

It is also interesting to note that very often the end result of an analytic process shown in Figure 1 is a PowerPoint presentation containing slides of interesting plots. The proposed methodology is a way to improve the efficiency for discovering those interesting plots. Applying the methodology results in three sets of plots: non-interesting plots, known interesting plots, and unrecognized plots. The idea is that the number of known interesting plots and unrecognized plots are small enough for the analyst to inspect carefully, and select some to be included in the presentation.

The rest of the paper is organized as the following. Section 2 introduces the GANs approach for learning a plot recognizer. Section 3 describes two product lines and their data used in most of the study. Section 4 focuses on discovering interesting wafer plots and discusses another application scenario. Section 5 focuses on correlation plots and discusses an application scenario. Section 6 focuses on box plots and discusses another application scenario. Section 7 concludes.

2. Developing a GANs-based Recognizer

Generative Adversarial Networks (GANs) [5] are methods to learn a generative model. Given a dataset, a generative model is a model that can synthesize new samples similar to the training samples. A GANs architecture consists of two neural networks. The generator network G is trained to produce the samples. The discriminator network D is trained to differentiate the training samples from the samples produced by the generator. Figure 4 illustrates the design of GANs. While the main goal of GANs is to learn the generator, after the training, the discriminator can be used as a recognizer for future samples similar to the training samples. Hence, in this work, our interest is in training a discriminator to be a recognizer for a class of plots.

1. Please note that this part is not intended to reiterate the materials in [5][6]. Instead, the focus is more on the key aspects to which attention should be given for implementing a GANs-based plot recognizer in practice. We apologize for not including all the detail regarding GANs.
To train a recognizer, a class of plots are used. Suppose there are \( m \) plots and denoted as \( D_1, \ldots, D_m \). These are our training data. Without loss of generality, assume each plot is a square image. For training, the generator produces some \( l \) images, denoted as \( G_1, \ldots, G_l \). Each generated image is produced according to a random vector \( \vec{v} \). Each variable of \( \vec{v} \) can be thought of as a latent input. These variables define a latent space where each vector in this space represents an image produced by the generator.

The training process is iterative. Each iteration has two stages and each stage of training can use the common stochastic gradient descent (SGD) approach. In each iteration, two classes of samples \( D_1, \ldots, D_m \) and \( G_1, \ldots, G_l \) are used. From iteration to iteration, the samples \( D_1, \ldots, D_m \) remain the same, but \( G_1, \ldots, G_l \) are re-produced by the generator for each iteration based on the weights learned in the previous iteration.

In the first stage of training, the goal is to learn the weights in the \( D \) network in order to separate \( D_1, \ldots, D_m \) from \( G_1, \ldots, G_l \) as much as possible. During back propagation, the gradients are computed backward from the output of \( D \) to its inputs. In the second stage, weights in \( D \) are fixed. SGD is applied to learning the weights in \( G \). The gradients calculated on inputs of \( D \) are further back propagated to the inputs of \( G \). The optimization objective is to have \( G \) adjust the generated samples such that their output labels by \( D \) are as close as possible to the output labels of the training samples \( D_1, \ldots, D_m \).

The idea of training \( D \) and \( G \) can be thought of as playing a game where the \( D \) network learns to beat the \( G \) network by discriminating the samples generated by \( G \) from the training samples \( D_1, \ldots, D_m \). On the other hand, the \( G \) network learns to generate samples to fool the discriminator \( D \) as much as possible. Over iterations, the generated samples become more like the training samples and it becomes harder for \( D \) to separate them.

2.1. The CNN architectures

For computer vision applications, convolutional neural networks (CNNs) have shown remarkable performance in the context of supervised learning in recent years. Using CNNs for unsupervised learning had received less attention until the GANs approach was proposed. In this work, our implementation of GANs is based on two deep CNNs, following the ideas proposed in [6] which suggests a set of constraints on the architectural topology of Convolutional GANs to make them stable to train.

Figure 5 shows our CNN architecture for the discriminator. This architecture is used for training all types of plot recognizers studied in this work. The leftmost block shows our input assumption. Each input is an image with 48-by-48 pixels. Each pixel has three values: -1, 0, and +1. These three values indicate negative color, no color, and positive color, respectively. Before a plot can be used as an input sample to this CNN, preprocessing is required to convert the plot into this representation.

The CNN has three convolutional layers (Conv1 to Conv3) where after Conv2 and Conv3, there is a Max pooling layer denoted as MaxPool1 and MaxPool2, respectively. After the MaxPool2 layer, there are three fully-connected layers (FC1 to FC3). The size and number of channels after each layer are denoted in the figure. For example, after Conv1 the image is transformed from 1 channel of 48×48 to 64 channels of 48×48, using 64 2×2 filters (In our CNNs, the filter size is always 2×2). After Conv2/MaxPool1, the image size is reduced to 24×24 with 128 channels.

The fully-connected layer FC1 has 256 perceptrons (artificial neurons) each receiving inputs from all the 12×12×256 perceptrons in the previous layer. The FC2 has 512 perceptrons. The last layer FC3 has one perceptron which outputs a classification probability. As suggested in [6], Leaky ReLU is used as the activation function for all perceptrons in the CNN. Each perceptron also includes a bias parameter. The total number of parameters (weights) in the CNN is 9,734,592.

Figure 6 shows the CNN architecture for the generator. There are two fully-connected layers, FC1 and FC2, and four transposed convolutional layers, T.Conv1 to T.Conv4. Like the discriminator CNN, Leaky RuLU and bias parameter are used for all perceptrons. The generator CNN can be thought as the reverse of the discriminator CNN. For the generator CNN, the number of parameters (weights) is 24,333,009. Together, the total number of parameters to be trained in the GANs is 34,067,601.
2.2. Implementation detail

For training GANs, attention is required to ensure two aspects: the convergence of the training iteration and the output quality of both CNNs. The work in [6] suggests several architectural guidelines to improve quality. Among them, we found that the performance of the CNNs is sensitive to whether or not we chose to use (1) the Batchnorm in both generator and discriminator CNNs, and (2) the Leaky ReLU activation function for all perceptrons. For convergence, we found that the feature matching technique proposed in [7] is crucial. Otherwise, it is difficult for the training to converge.

Although the Leaky ReLU is used for all perceptrons, in the discriminator CNN, the Sigmoid function is used to convert the output of the last perceptron into a value between 0 and 1. Similarly, a Hyperbolic Tangent function is used in the generator CNN for adjusting the output value.

The CNNs are implemented with Google TensorFlow [8] and run with the nVidia GTX 980Ti GPU. The optimizer used for the training is ADAM optimizer [9]. We had tried others such as regular SGD and AdaDelta but they did not allow convergence as fast as the ADAM optimizer.

Two things to note regarding the CNNs in Figure 5 and Figure 6 are: (1) It is important to include the fully-connected layers for training a good-quality recognizer (the discriminator). (2) It is important to implement a Dropout strategy in FC2 [10], the largest layer in each CNN.

2.3. An example recognizer for a wafer pattern

To train our GANs, we need a dataset divided into a training dataset and a validation dataset. Because it is an unsupervised learning, the validation dataset alone cannot fully determine the stopping point. The validation dataset is used to ensure the discriminator does not over-fit the samples in the training dataset, by ensuring that all samples in the validation set are also classified correctly. In our experiments, the stopping point in the training is assisted by inspecting the samples generated by the generator. If these samples show features similar to the training samples, then we stop. If not, the training is resumed for more iterations.

Because our focus is on the discriminator (used as a plot recognizer), we concern more about the quality of the discriminator than the quality of the generator. If the latter is our concern, we might need to train with more iterations until the generator is capable of producing plots close to the training samples. This in turn might require additional techniques in the implementation to ensure convergence.

What we found is that the GANs usually do not require a large number of samples to train if those samples share some common features. To illustrate this, Figure 7 shows five training samples used for training a recognizer for this class of wafer pattern. The yellow dots represents failing dies. To enhance the training dataset, each sample is incrementally rotated to produce 12 samples in total. Then, overall we have 60 samples for training.

Figure 8 shows the five samples used for validation. Similarly, each is rotated to produce 12 samples with a total of 60 validation samples. Note that these samples look alike because these are wafers from the same lot.

The training took about 2 hours with a total of 3650 iterations. After the training, the discriminator (treated as our plot recognizer) is used to recognize similar wafer patterns on 8300 other wafers. The recognizer recognizes 25 wafers and some are shown in Figure 9. On these samples, we see that they all show up with a clear edge failing pattern.

Because the samples generated by the generator are inspected to determine the stopping point, it would be interesting to show the wafer plots produced by the generator. Figure 10 shows five such wafer plots (by giving the generator five random inputs). It can be seen that the generated plots do not look the same as the original plots shown in Figure 7. However, the feature of having many fails on the edge are also present in these generated plots.

2.4. Generality of the plot recognizer

The wafers used in the above experiment each has about 2100 dies. Recall from Figure 5 that input images are in size of 48×48 pixels. One interesting question to ask would be how the recognizer performs on those wafer plots from other product lines where each plot is based on more or has less number of dies.

To answer this question, Figure 11 shows the result of applying the edge pattern recognizer on a 2nd product line. The recognizer was applied to scan 2011 wafer plots and found only 1 recognized plot as shown in the figure. Each wafer for this product line has about 4500 dies, more than twice as many as that in the first product line used for the experiment above. It is interesting to see that the recognized plot also shows a clear edge failing pattern.

Then, the recognizer was applied to a 3rd product line to scan 7052 wafer plots and found 24 recognized wafer plots. Some examples are also shown in Figure 11. For this
product line, each wafer has about 440 dies, much less than that in the first product line. However, each recognized wafer plots also show a clear edge failing pattern.

From the results shown above across three product lines, it is interesting to see that the plot recognizer, trained with a small set of rather similar edge failing patterns as shown in Figure 7, is able to generalize the learning and recognize other edge failing patterns even with some noise in the pattern (Figure 11). These results show that one might not need to re-train a recognizer for every product line even though their numbers of dies per wafer are different. These results also indicate that one can train a recognizer with some higher-level “intent.” For example, in the above, our intent is to capture an “edge failing pattern.”

3. Production Data and Analytics

In the rest of the paper, the results are presented based on data collected from two product lines, one for the medical market (call it product M) and the other for the automotive market (call it product A). Figure 12 illustrates four categories of production data used in our study. Production data refers to all the data, which can further be divided into manufacturing data and test data.

In production, every lot goes through a sequence of tools (manufacturing equipments). There could be more than hundreds of tools involved. Each tool may process one of more stages. A stage has its own recipe name. A stage can be carried out by tools arranged in parallel. Then, two lots may go through two different tools. A tool can have multiple chambers. The chambers can be in sequence and/or in parallel. Hence, two wafers may go through two different chambers if they are arranged in parallel. Each chamber has its own recipe name. Recipe name can change over time. Moreover, many sensors are used to measure properties of a chamber, such as temperature, pressure, etc. Sensor data are associated with the chambers. The sensor data points are incremented over a small time interval.

The manufacturing data is organized at three levels. The first level is organized by lots, showing which tools a lot goes through and when. The second level is organized by wafers, showing which chambers a wafer goes through and when. The third level is organized by chambers, showing the sensor data in terms of waveform signals over time.

The test data is organized in three groups: e-tests, wafer tests, and final tests. For e-tests the data contains information regarding the measurement sites and also the equipment used to measure them. For wafer and final tests, the data contains a list of failing bins including the test a die fails on. The data also contains information regarding the test equipment. The test data are indexed so that one can organize the information in terms of die, wafer, or lot for an analytic task. It is possible to arrange the data over a time index so that a particular result can be tracked over time.

| Product | Wafers | E-tests | Probe Tests | Final Tests | Total # of Bins |
|---------|--------|---------|-------------|-------------|-----------------|
| M       | 8300   | 501     | 140         | 400         | 289             |
| A       | 7052   | 596     | 2367        | >10k        | 132             |

Table 1 shows some numbers regarding the test data. Our experiments use mostly the test data and one experiment uses part of the manufacturing data.

4. Types of Analytics (Plots)

In production yield analytics, an analyst can apply many different types of analytics to examine the data described above. In this work, we focus our discussion on three basic types of analytics generating three types of plots: wafer plots, correlation plots, and box plots. We use these three types of plots to illustrate our recognizer-based methodology which can be applied to other types of plots as well.

In section 2 many examples of wafer plots are already shown. A typical wafer plot has two colors, one to show the failing die locations and the other to show the passing die locations. A wafer plot can be based on all the failing dies, or only those collected in a particular test bin, due to a particular test, or at a particular test value range. Wafer plots are useful in production yield optimization because a plot may show an unusual failing pattern. If this pattern persists over time, it may become a strong indicator for an issue with a particular process tool, stage, or chamber.

Correlation plots are often used to assist in correlation analysis. For a plot, the analyst decides what variable to use for the x-axis and what variable to use for the y-axis. For example, x-axis variable can be an e-test and y-axis variable can be the yield based on a selected test bin. On a plot, typically the analyst is interested in discovering a “trend,” for example “large y values tend to imply large x values.” Correlation plots are often used to relate a failing case to a process parameter.

Recall from Figure 5 that our plot recognizer assumes the input image size is $48 \times 48$. Hence, internally a recognizer sees the plot differently from that seen by an analyst. For example, Figure 13 shows an example where the left correlation plot is what is being seen by a person and the right plot represents what is being seen by the recognizer.
The third type we consider in this work is the box plot. Typically, the x-axis of a box plot includes multiple options. The y-axis is a variable of concern. For example, the left of Figure 14 shows a box plot with three options $X_1, X_2, X_3$. The red line marks the medium data point. The box denotes the 25%-75% quantile range. The two dash lines mark the $\pm 1.5 \times$ the quantile range. Points outside these dash lines are shown as the outliers.

A box plot can be used to examine if an issue is with a particular option. For example, $X_1, X_2, X_3$ can be three tools for the same stage. The y variable can be the % of passing dies from a lot. Each data point represents a lot. What is usually being looked for with a box plot is some unexpected bias associated with an option, for example higher yield loss is associated with a particular tool.

To build a box plot recognizer, a straightforward way is to convert an entire box plot into a single $48 \times 48$ image. We found that this approach was not as effective. Instead, we convert a box plot into a scatter plot as shown in the middle of Figure 14. Then, for each option we convert the spread of points into a $48 \times 48$ image. Therefore, a box plot with $k$ options would result in $k$ images for the recognizer. The reason for this choice will be discussed in detail later.

### 4.1. The recognizer development methodology

As discussed before, an analytic task results in three groups of plots: non-interesting (usually the majority), known interesting, and novel. A novel plot can be deemed interesting or non-interesting by an analyst. Our methodology to develop the plot recognizers is trying to develop recognizers for non-interesting plots first, followed by recognizers for the known interesting plots. Then, the remaining plots unrecognized by all the recognizers are considered novel.

There are two main reasons for following this ordering. First, there are usually many more non-interesting plots than interesting plots. Hence, to begin with, there are more samples for training a non-interest plot recognizer. Second, in practice an analyst might not have a concrete idea what to look for in advance. It would be easier to randomly pick a few non-interesting plots (because there are many) and ask a person to verify their non-interest. After majority of the non-interesting plots are filtered out, the remaining set is much smaller and easier for a person to select those interesting examples for training an interesting plot recognizer.

### 5. Discovering Interesting Wafer Plots

In this section, the focus is on wafer plots. Discussion on correlation plots and box plots will be in the next two sections. All three sections follow the same methodology described in Section 4.1 above.

#### 5.1. Developing a sequence of recognizers

Recognizers discussed in this section are developed based on wafer plots from the product M shown in Table 1. The training follows the approach discussed in Section 2 where five wafer plots are used as the training samples and five wafer plots are used as the validation samples.

Figure 15 shows four of the five training samples and four of the five validation samples. After the training, the recognizer is used to scan the rest of the 8300 wafer plots. Four example recognized plots are also shown in the figure.

As seen in Figure 15, the first recognizer is trained to recognize a random and sparse wafer failing pattern. Majority of the wafer plots are of this class. Then, samples shown in Figure 16 are among those not recognized by the 1st recognizer. The left four are among the five samples used to train the 2nd recognizer. The middle four are the validation samples. The right four are example plots recognized by the 2nd recognizer. More than 88% of the plots are recognized by the first two recognizers. As a result, less than 12% of the plots remain after applying the first two recognizers.

Plots recognized by the 2nd recognizer looks similar to those recognized by the 1st recognizer. However, notice that the 2nd class of plots generally contain more failing dies. In theory, the two classes of samples can be combined to train a single recognizer. However, because of the difference in their failing density, it requires more samples and would take
longer to converge. We separate them into two recognizers to simplify the training.

Those plots picked up by the first two recognizers are considered non-interesting. The 3rd recognizer is trained to recognize a high-density failing pattern as illustrated in Figure 17. This class of plots might or might not be interesting, depending on whether they appear randomly or concentrate in the same lot.

Figure 17. Training, validation, recognized samples for the 3rd recognizer

The 4th recognizer is trained to recognize a grid pattern as shown in Figure 18. This class of plots is interesting and may indicate an issue in the test probe. There is also a 5th recognizer which is the edge pattern recognizer already discussed in Section 2 before.

Figure 18. Training, validation, recognized samples for the 4th recognizer

5.2. Six classes of novel plots

After applying the five recognizers, about 5% of the plots remain unrecognized. They include both non-interesting plots and novel plots. About 70% of these plots can be clustered into one of the six novel classes as shown in Figure 19. A class can contain from at least 10 to over 100 plots and hence, not only the patterns are novel, but also they appear "systematically."

Figure 19. Six novel classes of plots discovered

5.3. Detecting an issue with a production tool

As an example, there are a number of wafer plots sharing the same pattern represented by the class B example shown in Figure 19. In fact, this plot is the same as that presented in Figure 19(b) before. Further investigation reveals that the issue was related to the 3 lift bins used by the Gasonics ashers tools. Hence, detecting novel patterns as those shown in Figure 19 proved to be useful in practice. An experienced process engineer could look at a pattern and start forming guided hypotheses to check the related manufacturing equipments. In practice, the recognizers help sort out majority of the wafer plots and bring the attention of an engineer onto those novel plots.

Figure 20. Non-interesting plots missed by the recognizers

5.4. Non-interesting plots missed by the recognizers

Figure 20 shows some additional examples of the plots missed by the five recognizers. These can be deemed as non-interesting plots. Notice that the failing locations look also quite random as those plots shown in Figure 16 but the density of the failing is between those shown in Figure 16 and those shown in Figure 17. These missing plots suggest that a 6th recognizer can be developed to recognize a "medium-density random-failing" plot. The decision to develop an additional recognizer mostly depends on the number of plots available for the the training and validation.

5.5. Generality of the recognizers

As pointed out in Section 2, a recognizer developed for a product line can be applied to the wafer plots from another product line, even though their numbers of dies on a wafer are quite different. The five recognizers above are based on product M. Next, we explain the result by applying these recognizers to wafer plots from product A which has about one fifth of the dies on each wafer.

Figure 21. Novel plots discovered on product A

The result is that more than 84% of the plots are recognized by the first two recognizers, comparing to the 88% number mentioned above for product M. As seen, these two numbers are comparable. After applying the additional three recognizers, similar to the result for product M, for product A also about 5% of the plots remain unrecognized. Figure 21 then shows examples of novel plots found on product A. As seen, these plots show different novel patterns than those plots shown in Figure 19 above.
6. Discovering Interesting Correlation Plots

Recognizers discussed in this section are developed based on correlation plots from product A. Again, the development follows the approach discussed in Section 2 and transformation from a plot to an image is discussed with Figure 13 above.

As shown in Table 1 for product A there are 596 e-tests. For each plot, we assume that the x-axis is an e-test and the y-axis is the number of fails from a test bin. We select the top 9 bins with the most fails, which together account for > 90% of the total fails. The total number of plots to consider is 5364. To train a recognizer, we use about 20 training samples and 20 validation samples.

Figure 22 shows four of the training samples and four of the validation samples. After the training, the recognizer is used to scan the rest of the 5364 correlation plots. Four example recognized plots are also shown in the figure.

![Figure 22. Training, validation, recognized samples for the 1st recognizer](image)

Plots shown in Figure 22 can be thought of as a typical "no-correlation" class in this analysis. Each dot represents a lot. The e-test value is the average of all measured values from all wafers in the lot. It can be seen that the e-test values spread randomly across the range shown with some concentration on the middle of the range. Most of the lots have few fails and hence, more dots concentrate on the bottom of the image. In every plot, there is at least one dot close to the upper edge, i.e. the maximum number of fails. Because of that dot with a large failing number, the rest of the dots are pushed down in the picture.

Then, samples shown in Figure 23 are among those not recognized by the 1st recognizer. Examples of training and validation samples are shown for training the 2nd recognizer. Again each plot contains a dot close to the upper edge of the image, resulting in pushing down further the rest of the dots. Hence, those plots can also be thought of as another class of "no-correlation."

![Figure 23. Training, validation, recognized samples for the 2nd recognizer](image)

The right four are example plots recognized by the 2nd recognizer. Note that more than 94% of the plots are recognized by the first two recognizers.

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6.1. Two classes of interesting plots

Among the remaining plots, two classes of interesting plots are found as illustrated in Figure 24. Class A shows that a smaller e-test value tends to have more fails. Class B shows that a larger e-test value tends to have more fails. As explained with Figure 5(a) before, the correlation coefficients with such plots are small. Hence, a search constrained by a high correlation coefficient would not have found these interesting plots.

![Figure 24. Two classes of interesting plots discovered](image)

6.2. An application scenario for improving yield

Figure 25 illustrates an application scenario. The figure shows the lot-based yield fluctuation over time. As seen, some lots have noticeably lower yield than others.

![Figure 25. Yield fluctuation over time on product A](image)

One analytic task is to find an e-test parameter that correlates to the number of fails from a test bin. The correlation plots used in the experiment above were generated for this task. Therefore, e-test parameters found with the plots in Figure 24 are all candidates for further analysis.

After further investigation based on the e-test parameter with the class B plot and the e-test parameter with one of the class A plot, it was found that after a change of recipe in a tool, the class B parameter drifted toward larger values and the class A parameter drifted toward smaller values. After the recipe was rolled back to the previous version, those drifts disappeared and the yield was improved.

6.3. Plots missed by the recognizers

There are non-interesting plots missed by the two recognizers. Figure 26 shows some examples. Those plots are not interesting because they reveal little correlation between the e-test value and the number of fails.

![Figure 26. Examples of other plots missed by the two recognizers](image)
6.4. An adversarial example

The recognizers above are developed based on the definition that y-axis is the number of fails in a test bin. If we change this definition to be the test values from a test and produce new plots, then an interesting question would be whether or not the above recognizers can still be used to filter the non-interesting plots with the new y-axis definition.

Based on five selected tests and the 596 e-tests, 2908 new plots are generated. When the recognizers are applied to those new plots, most of them are not recognized. Figure 27 shows some examples of those unrecognized plots. As it can be seen, the new plots look quite differently from those shown in Figure 22 and Figure 23 above. The patterns in those new plots appear to be more diverse and random.

Suppose we train a new recognizer specific to the new plots. Figure 27 shows some of the training and validation samples. We use 100 training and 100 validation samples. These numbers are larger than before because there is no clear systematic patterns observed on the new plots. Hence, we expect it is more difficult to train a recognizer.

![Training Samples](image1)

![Validation Samples](image2)

Figure 27. Examples of training/validations samples for the recognizer

After the training (with 5 hours training time), most of the plots are recognized with only 110 plots remaining. Figure 28 shows examples of the recognized and unrecognized plots. For some recognized plots, it appears that we can find a similar training or validation plot in Figure 27 to explain why they are recognized. However, the rightmost unrecognized plot also looks the same as the 2nd training sample from the left (they are actually slightly different).

![Recognized Plots](image3)

![Unrecognized Plots](image4)

Figure 28. Recognized and unrecognized example plots by the recognizer

The rightmost unrecognized plot is called an adversarial example [11], a slightly perturbed example that can fool a neural network (NN) model. This is a well-known issue concerning the robustness of a NN model [11]. For training other recognizers before, the training plots share some similar features and hence, we did not observe such an adversarial example. In contrast, the samples in Figure 27 are much more diverse and random. As a result, the recognizer is less robust and it is easier for adversarial examples to exist. In this work, we acknowledge this well-known issue in NN [11] but will leave it to future research.

7. Box-Plot Based Recognizers

When a box plot is used by a person, the plot usually includes a small group of options for the convenience of visualization. However, for a recognizer it can process all box plots together as long as they have the same y-axis definition. For example, suppose y-axis is the yield. Then, if an option shows no bias, the vertical distribution should look similar to the original yield distribution. Hence, regardless of what each option means, as long as the y-axis is fixed, many of their vertical distributions should look similar. This is why in our methodology, we follow the idea explained in Figure 14 before. In this way, each option is associated with an image. After the transformation, all options are considered collectively by a recognizer to recognize the “normal behavior.” An unrecognized image then tells that the corresponding option behaves differently from others.

7.1. Monitoring production tools

To show how such a “box-plot” recognizer can be useful, we apply the idea to monitor production tools for product A (because of the yield fluctuation issue shown in Figure 25). The goal is to detect if any tool behaves unexpectedly as comparing to other tools for the same stage. In the production process, there are more than 790 stages with two or more tools. For each tool, an image is extracted and yield distribution is represented as the spread vertically (i.e. y-axis). The horizontal spread is artificially randomized and has no particular meaning. Each dot represents a lot.

Three recognizers are trained in sequence following the same methodology used above. Figure 29 shows some training samples for training the recognizers. For training one recognizer, 20-40 samples are used. After applying the three recognizers, only 29 plots are left. Figure 30 shows examples of those plots.

![Training Samples](image5)

Figure 29. Examples of training samples for the three recognizers

Figure 29 tells that most of the tools follow three classes of typical “behavior” in term of the resulting yield (i.e. recognized by the three recognizers). Then, the remaining images in Figure 30 tells that those corresponding tools are used by much fewer lots and hence, their images look different. Together, the result show that no tool has a strong bias in terms of the yield. Note that the same approach can be applied to monitor chambers and other process options.
7.2. Monitoring testers

The approach can be applied to monitor testers and compare their statistical behaviors. For example, in Figure 31, each image represents a wafer. A dot represents a part from the wafer. The y-axis is the test value of a final test, measured on tester#1. This is also based on product A. One recognizer is trained for tester#1, with 20 training samples and 20 validation samples. Figure 31 shows some examples. The recognizer recognizes all plots derived from tester#1 except for 32 plots deemed non-interesting after inspection.

Figure 31. Training, validation, recognized samples for the one recognizer

Similar plots are obtained for tester#2 and tester#3. The recognizer is applied on those plots. For tester#2, all plots are recognized except four of them. These four plots are shown in Figure 32. Because most of the plots from tester#2 are recognized, we can say that tester#1 and tester#2 behave “statistically” similarly (and also across time because different wafers of parts can be tested at different times).

For tester#3, the situation is quite different. More than 50% of the plots are not recognized. Some examples are also shown in Figure 32. A careful look on those plots can tell the reason why they are not recognized - the dots tend to be vertically lower and have a wider spread than those shown in Figure 31. This suggests that tester#3 behaves differently from the other two testers. Further investigation confirms that tester#3 does have six times more failing parts (in the test bin containing the final test) than that from the other two testers combined. This signals an issue with tester#3. After the issue was resolved, the yield was improved.

Figure 32. Unrecognized images each corresponding to a tool

8. Conclusion

In this work, we use two deep CNNs to implement GANs for training a plot recognizer. Multiple recognizers can be trained for a particular type of analytics in order to recognize both non-interesting and known interesting plots in the respective application context. Then, unrecognized plots are novel and their interests can be decided manually. We consider three types of plots commonly used in yield data analytics: the wafer plot, the correlation plot, and the box plot. We use data collected from two product lines to illustrate the development of various plots recognizers. We discuss four application scenarios to explain their usefulness in practice where in three scenarios engineers were able to improve the yield based on the findings, and in one scenario the plot recognizers help ensure that no individual tool as a whole causes a significant shift in the yield.

The proposed plot recognizer based methodology is general and can be applied to other types of plots and in other application scenarios. However, the effectiveness and the generality of a recognizer can largely depend on the classes of images to be trained with. If a single recognizer is trained to recognize images with very diverse and/or random features, this might demand a large training set, a carefully-selected validation set, and/or a longer training time. This might also cause difficulty to converge in training or result in a model of which robustness can be in question (e.g. the adversarial example discussed in Section 6.4). As a result, training such a recognizer might become impractical. Further study is required to understand the limitations of the methodology and the scope of its applicability in practice.

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