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Structuring Knowledge Using an Example from Texas Instruments

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Abstract: This paper is concerned with the concept of the message as subset of knowledge and not the physical or engineering properties [1] of the signal carrying the message per Shannon. Despite the AI hype, there are vast opportunities for conventional structured decision making. The bonder exception report presented here is an example of a solution with low computational requirements. With availability of good human expertise, Asymmetric Information Resolution (AIR) Models [2] can lead to nominal computational solutions.

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I. INTRODUCTION

In his 1948 paper [1] Shannon stated "Frequently the messages have meaning; that is they refer to or are correlated according to some system with certain physical or conceptual entities. These semantic aspects of communication are irrelevant to the engineering problem."

Shannon was focused on the physics & engineering of data communications, specifically the physical properties of photons and electromagnetic waves in the presence or absence of physical structures, independent of whether the signal carried a message that was meaningful or not. Shannon was not interested in what these messages meant. This paper is not concerned with the physical or engineering properties of the signal carrying the message but the description of the message as subset of knowledge.

Knowledge Constructs [2] are a new approach to structuring knowledge in a manner that lends itself to programmability i.e. machine execution, if necessary. Knowledge Constructs uses knowledge relationships to connect knowledge elements, in a manner to facilitate decision making. Knowledge elements are basic representations of knowledge which cannot or should not be reduced further, for example, knowledge elements can be categorized as states, factors, barriers, and migration strategies depending on how the knowledge structure is constructed [2]. They do have scalar-like and vector-like properties, but more research is required. Knowledge relationships are concepts that are associated with knowledge elements and are related to meaning.

During my 10-years (1983-1992) at Texas Instruments Malaysia, we ran a lot of projects to improve Assembly/Test yields and work-in-progress reductions [2]. This paper is based on my experience at Texas Instruments Malaysia using TI-990 minicomputers with 64k RAM (yield and bonder exception reports) and an Intel 386 PC (factory scheduling which reduced work-in-progress from 5 days to 3 days for a 6,000 SKU operation). The semiconductor Assembly/Test operations consist of several process stages, Die Prep, Die Attach, Bond, Mold, Symbol, Trim/Form, Solder Dip, Visual/Mechanical and Test. Usually, in that order. Our success is evident by our results, having increased average Assemble/Test yields from 85% to 99.9% in less than 5 years. This paper documents one of the Assembly/Test yield-improvement projects, the bonder exception report that traces test failures back to the source, the bonders.

II. MATHEMATICAL FORMALISM OF EXCEPTION REPORTS

There are two cautions, (i) Mathematics has become so sophisticated [3] that it could be used to prove anything. (ii) I infer [4] that both mathematics and language are two of the most powerful types of known syntax, or without a prior knowledge of the meaning of the symbols, the semantics and even syntax is difficult to decipher, i.e. meaning cannot be found in the syntax alone. The Harapan language is a good example [5]. Therefore, caution is required when using mathematical formalism and mathematics to respectively, structure and solve a problem.

The original instructions I was given to develop the bonder exception report was a simple, "Can you find the bonders causing low yields at testing?" This is a far cry from the mathematical formalism presented below in this paper which is an important tool to structure a path to a solution that lends rigor and clarity to the solution discovery process.

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The formalism presented in this paper, ensures rigor and clarity in structuring the problem to be solved,

➢ *Information Rule:*

Information set, R_j, given a set of data, D_i, transformation, Δ_k, and goal, G_l, is given by,

$$\{R_j\} = \Delta_k\{D_i\}|G_l \text{ Information Rule} \quad (1)$$

The transformation, Δ_k, can be any function that operates on what is found. In Assembly/Test operations it a descending order sort of the data D_i, by bonder with worst to best test yields. The goal, G_l, is to find the top few worst bonders. The goal, G_l, is a critical requirement, as without a goal, any transformation of the data is meaningless.

➢ *Non-Randomness Requirement:*

That is, a random set of data, D_i, by itself does not lend itself to the discovery of information that maybe useful to an observer. Otherwise, no useful inferences can be determined as,

$$\{R_j\} = \{D_i\} \quad (2)$$

$$\{R_j\} - \{D_i\} = \{\} \text{ Empty Set Rule} \quad (3)$$

The implicit assumption here is that there are hidden variables or relationships $\{H_M\}$ in the data that can be determined by the transformation Δ_k used.

$$\{D_i\} \supset \{H_M\} \text{ Data is a superset of Hidden Variables} \quad (4)$$

This (1) clearly shows the difference between data and information, and if there are no hidden variables or relationships, there is no information, as the data D_i is truly random as shown by (2).

➢ *New Information Rule:*

Insight, I_j, is the new knowledge element(s) or knowledge set, not present in the original set K_O of knowledge elements,

$$\{I_j\} \notin \{K_O\} \text{ New Information Rule} \quad (5)$$

What we were seeking was new information that would restore bonder performance as we already know the original information set K_O which did not provide a path to solving problematic bonders.

➢ *Constraining the Search Domain Space:*

The Search Domain Space, S_j, is subset of Information, R_j, and satisfies one or more criteria. For example, the test yield Y must be less than a specific value Y_C,

$$\{S_j\} \subseteq \{R_j\} \text{ Search Domain Space Rule} \quad (6)$$

The set $\{S_j\}$ is a proper subset of the information available in set $\{R_j\}$. Where the data set $\{D_i\}$ consists information of the bonder and test equipment used, yields and other manufacturing data by production batch or lot.

$$\{S_j\} = \{R_j|(Y \leq Y_C)\} \text{ Selection Rule} \quad (7)$$

The Selection Rule (7) is also known as an exception report provided by information, R_j and reduces amount of information required to be examined to just the most relevant at that time. Note, weekly runs of this report will show different problematic bonders. For example, a bonder failure report identifies the 10 worst bonders out of 300 because they cause the test operation production batch yields Y that are less than or equal to some critical value Y_C i.e. an exception report. Thereby, constraining the Search Domain Space to a manageable size, from 300 to 10 in this example.

➢ *Attributable Property Rule:*

Given that there are m bonders in an Assembly/Test facility, bonder m, B_m, is associated with M parameters P_M or Hidden variables H_M, that can drift or change, because these bonders have, for example, alignment problems thus causing excessive failures in the test area.

$$\{B_m\} \supset \{P_M\} \text{ Attributable Property Rule} \quad (8)$$

Bonders are a superset on bond parameters. That is, the Attributable Property of the bonders to be investigated are properties that potentially cause the bonders to cause Test failures. Once these are known, these can be investigated to determine and fix these problems.

➢ *Defining the Operating Region:*

The Insight I_j is derived by analyzing the Solution Domain Space by a set of Criteria C_M which defines the Operating Region. In the bonder example P_M are the bonder parameters that should operate within these Criteria C_M of between a lower parameter range $R_{M,L}$ and an upper parameter range $R_{M,U}$ for each Criteria C_M, the Operating Region. This is denoted as follows,

$$\hat{C}_M = R_{M,L} < P_M < R_{M,U} \text{ Compliant Operating Region Set} \quad (9)$$

$$\bar{C}_M \neq R_{M,L} < P_M < R_{M,U} \text{ Non-Compliant Operating Region Set} \quad (10)$$

Of course, there can be other case by case definitions for the Operating Region. In this example, each bonder m, has a combined Compliant Set and Non- Compliant Set of parameters P_M,

$$\{C_{M,m}\} = \{\hat{C}_{M,m}\} \cup \{\bar{C}_{M,m}\} \quad (11)$$

That is, (10) identifies each problematic bonder by its set of non-compliant bonder parameters, the Non- Compliant Set, with respect to their respective Operating Region as defined by Criteria C_M. Thus, the set of new insight I_j are the failed Criteria set for each specific bonder m,

$$\{I_{j,m}\} \supset \{\bar{C}_{M,m}\} \text{ Solution Domain Space} \quad (12)$$

➢ *Intention is Important:*

To fix these non-compliant bonders, the solution is determined by technical expertise, Δ_E, transforming non-

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compliance to a set of engineering solution S_E with the intention or Goal G_M to have a good, reliable working bonder,

$$\{S_E\} = \Delta_E\{\bar{C}_{M,m}\}|G_M \text{ Solution Rule} \tag{13}$$

That is, discovery is a multi-step process, (i) identifying the symptoms (1) and (ii) identifying the cause (10).

This is similar to my recent visit to my doctor, that in the US, initial diagnosis is based on the determination of Non-Compliant Set (10) of blood tests results. Similarly, the doctor uses her expertise Δ_E to prescribe treatment that is derived from this Non-Compliant Set $\bar{C}_{M,m}$.

III. DISCUSSION: INFERENCES

➢ *Several Inferences Arise from this Mathematical Formalism,*

- Hidden Variables H_M: Hidden variables, and, therefore, new information is evident if (2) or (3) are not true and a null finding is not the same as no hidden variables. Only a better understanding of the problem can distinguish between the two.
- Transformation Δ_k: If (2) or (3) are true then the problem maybe due to the use of an incorrect transformation Δ_k. Therefore, (2) or (3) are a means to determining better transformations.
- Criteria Set $\{C_{M,m}\}$: Changing compliance (9) and (10) to improve compliance metrics by shifting elements of non-compliance set $\bar{C}_{M,m}$ to the compliance set $\hat{C}_{M,m}$ does not solve the manufacturing problem even though the metrics looks better.
- New Knowledge $\{I_j\}$: If a system can generate new knowledge $\{I_j\}$ then (5) must be true, and this cannot be just the perception of old knowledge $\{K_O\}$ presented as new and (5) is the test for this.

➢ *Discussion: A Comparison to AI*

"Inference engines apply logical rules to knowledge bases through iterative cycles of rule matching, selection, and execution until no new rules can be matched. 29 Deep learning inference engines focus on parsing model graph structures and parameters …" [6]

Therefore, one could propose that current AI models, such as LLMs, are statistical inference engines S_{eng} given the topic context $\{K_Q\}$ derived from the questioned asked, with the information provided by the answer R_{AI},

$$\{R_{AI}\} = \{S_{eng}\}|\{K_Q\} \tag{14}$$

The architecture of inference engines is designed to separate the knowledge base $\{D_{mega}\}$ from the reasoning mechanism [6] $\{\Delta_i\}$. However, inference engines [6] apply logical rules to the knowledge base, parsing model graph structures and parameters, Bayesian networks, forward chaining, backward chaining, and hybrid approaches i.e. a set of transformations $\{\Delta_i\}$. Thus, given the vast quantity of data $\{D_{mega}\}$ used to build LLMs, and similar AI products, (14) can be rewritten as,

$$\{R_{AI}\} = (\{\Delta_i\} \cup \{D_{mega}\})|\{K_Q\} \tag{15}$$

Note, no new information exists if (16), and it maybe that $\{K_Q\}$ provides the perception that $\{R_{AI}\}$ is different or new.

$$\{R_{AI}\} \subseteq \{D_{mega}\} \text{ No New Information Rule} \tag{16}$$

Compare (15) with (1). The first difference is the much more computational power is required of $\{\Delta_i\}$ in (15) compared to Δ_k in (1). The second difference is the context $\{K_Q\}$ in (15) as opposed to the goal G_l in (1). The context $\{K_Q\}$ is a more sophisticated version of the goal G_l but there is a goal G_k buried in the context $\{K_Q\}$. The third difference is the amount of data $\{D_{mega}\}$ required of (15) compared to a simpler data requirements D_i of (1).

That is, AI models cannot be hosted on much simpler computational platforms than structured decision-making can. Therefore, there are vast opportunities available for simpler, cheaper, structured decision-making if managed well within the corporate environment.

➢ *Discussion: Knowledge Constructs*

Asymmetric Information Resolution (AIR) Models [2] is the only known model for the structure of knowledge based on knowledge constructs, because this field is new and other models have not yet been invented.

An AIR Model A_i consists of a set of Maps M_i (usually 3 or 4) depicting a structured relationship between knowledge elements,

$$A_i \supset \{M_j\} \tag{17}$$

A Map M_i consists of a set of Frameworks F_k (usually 5) constructed from knowledge elements, depicting how different Frameworks interact with each other within the Map,

$$M_j \supset \{F_k\} \tag{18}$$

And each Framework F_k consists of 4 states S_l, showing how each state allows or blocks migration between states depending on the outcome of the neighboring states, such that, each Framework is a set of constrained-conditional-transition-states.

$$F_k \supset \{S_l\} \tag{19}$$

The purpose of evaluating an AIR Model is to find a path R_{AIR} to a better set of states given that for each iteration one can only move to an allowed neighboring state. A path consists of change from a set of old states $\{S_{old}\}$ to set of new states $\{S_{new}\}$ or, $\{T_{n,n\pm1}\}$,

$$\{R_{AIR}\} = \{T_{n,n\pm1}\} \tag{20}$$

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Note, if no change is required then $S_{new} = S_{old}$. Usually, a few iterations are sufficient. That is, there is nominal computational requirements. Many time a visual inspection will provide the required transitions $T_{n,n\pm 1}$. This nominal computational requirement is consistent with the human brain operating at 111 Watts, versus AI at mega- or giga-watts. However, the hard part of AIR Models is the building of a consistent and reliable AIR Model.

IV. CONCLUSION

This paper has proposed and presented 3 approaches to find a path to a solution $R_?$ given that a problem exists. Each approach has it pros and cons. The selection of which approach is to be taken is dependent upon the context in which the problem exists. Therefore, careful evaluation of the context is a necessary first step.

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