The COTS Parts Toolbox – Evolution & Examples

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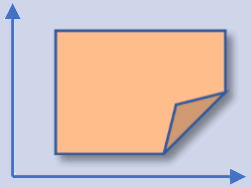
Motivation

- **EEE Parts (both Mil/Aero and COTS) continue to evolve into ever increasing levels of sophistication and complexity**
  - Power regulators w/ adaptive reconfigurability
  - Extensive increase in instruction complexity with each new generation of DDR memory
    - Data bus inversion
    - Temperature controlled refresh, etc…
  - FinFETs, 2.5/3D technologies
- Tools required to correctly understand risk and promote qualification and infusion need to evolve as well
- **Historical Physics of Failure and Statistical Reliability ideas now need to additional concepts like data mining and machine learning**
- Reliability from a system perspective and related levels of abstraction support management of this increase in complexity and provide better assessment of possible risks
  - How to account for variation?
  - Support for prediction
  - Confidence limits vs. single point estimates

Example tool set

Thermodynamic Entropy, Physics of Failure and System Degradation	Shmoo plots	Xapsos RHA Estimate	Bayes Theorem	Cosine Similarity Classification Entropy
$\frac{dS_{Total}}{dt} > 0$ $\Delta U = \Delta Q + \Delta W$		$P_{fail} = \int [1 - H(x)] \cdot g(x)dx$	$P(A\|B) = \frac{P(B\|A)P(A)}{P(B)}$	$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\|\mathbf{A}\|\|_2 \|\|\mathbf{B}\|\|_2}$ $E(S) = -p_i log_2(p_i)$
Comprehensive physics foundation to complex degradation versus “rules of thumb”	Precise emprical mapping of complex part behavior	Robust statistical methodolgy to address variation & unknown in both device and environment	Mathematically axiomatic means to include historical information into outcome possibilities	Transform practical multi-dimensional information into methodology to predict behavior and relationships

Evolution from physics based concepts applied to simple structures to quantitative/empirically based methodologies applied to system behaviors

Thermodynamics and System Ageing

$dU = \delta Q - \delta W$	First Law
$dS \geq 0$	Second Law
$U = \int TdS - pdV + \sum_i \mu_i dN_i$	Internal Energy
$\Delta S_{damage} \geq 0$	Entropy Damage
$\Phi_f - \Phi_i$	Work
$\frac{da}{dt} = \upsilon \cdot \exp(-\frac{\Phi}{kT})$	Arrhenius ageing

- **Degradation is is driven by the tendency of the system/device to come into thermodynamic equilibrium with its environment**
- Entropy damage is a way to measure changes in system performance that can be related to ageing
- **Degradation-Entropy Generation theorem states entropy is generated when the permanent degradation is through an irreversible process, that leads to an increase in disorder in the system**
- This allows the component degradation to be measured by entropy and thermodynamic energy

A. Fineberg, “Thermodynamic Degradation Science: Physics of Failure, Accelerated Testing and Reliability Applications”, 2016

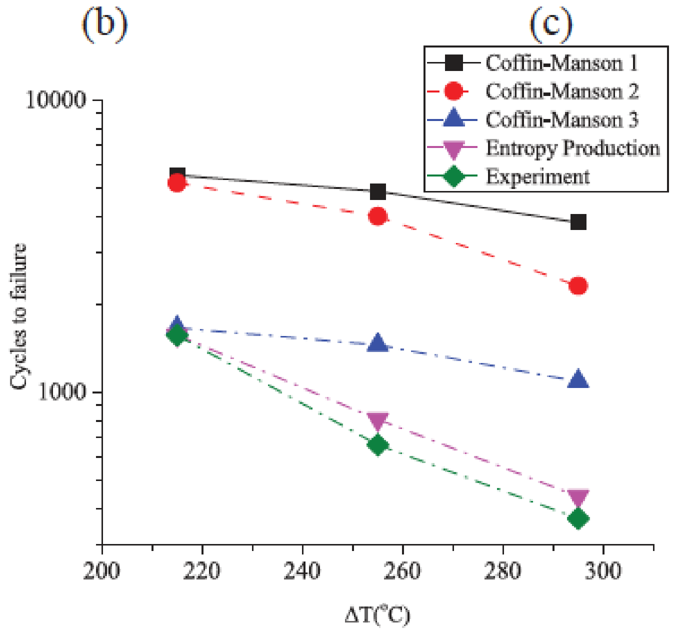
Entropy Ageing Example

- Degradation of Through Silicon Vias (TSV)

$$\gamma_f = \int_0^t \left(\frac{f(t)\Delta w_p}{T(t)}\right) dt$$

$f(t)$ = fraction of work per temp cycle

$\Delta w_p = strain\ energy\ per\ cycle$



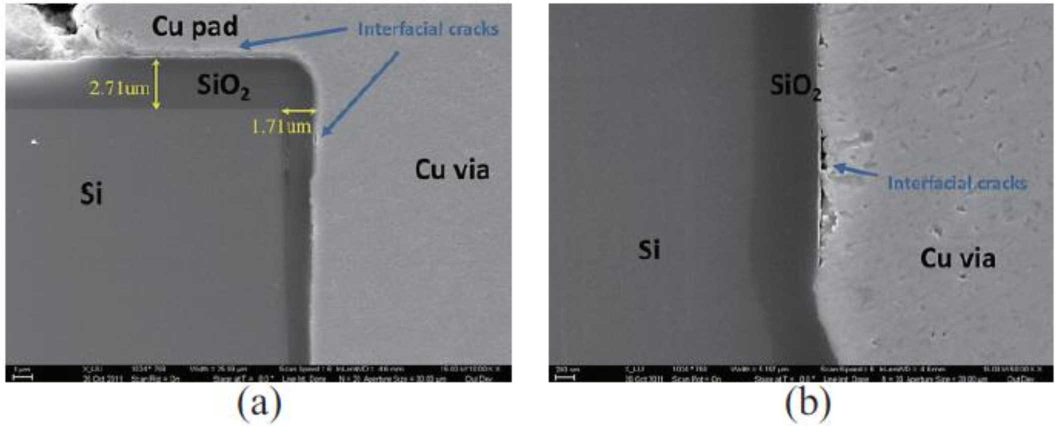


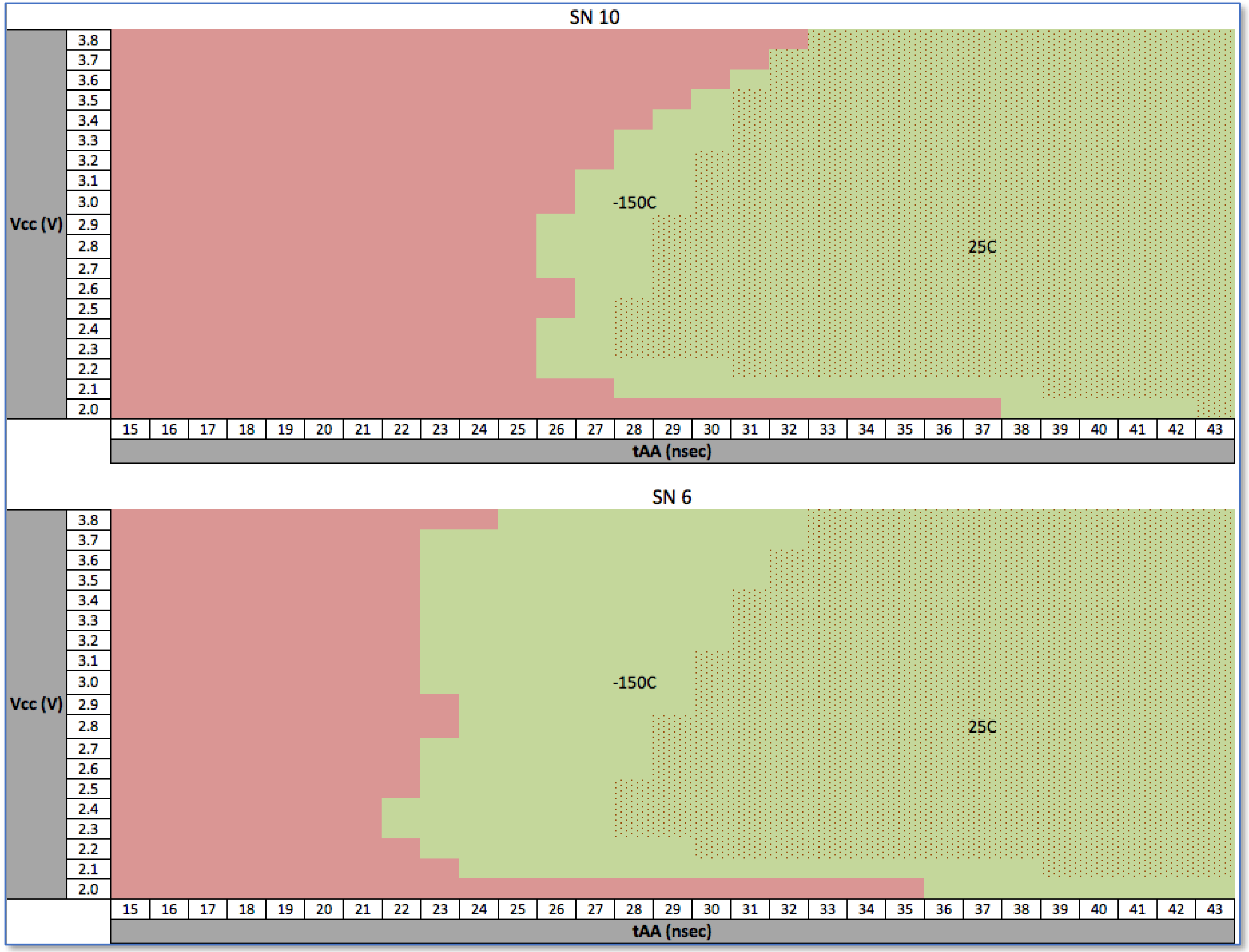
Fig. 1. SEM images of: interfacial cracks (a) under Cu pad and (b) on the TSV side wall [6].

- **Coffin-Manson is shown to be a special case of general entropy expression**
- Able to address complex materials and structure without having to resort to arbitrary estimations of parameters and acceleration coefficients

T. Wang, et. al., "Novel Entropy Production Based Full-Chip TSV Fatigue Analysis", ICCAD 2015

Cryogenic 8Mb SRAM Capability

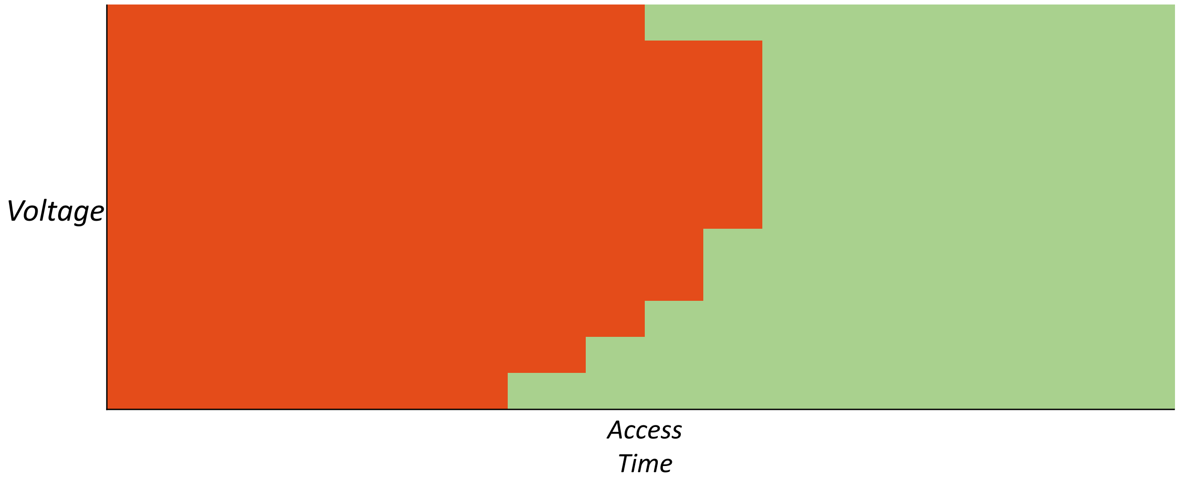
- **Access time (tAA) vs. Vcc (V) for two different parts from the same lot/date code**
- SRAM will continue to operate at cryogenic temperatures
- **Access time is reduced at cold temperatures**
- One part has significantly more margin and operational robustness at cryogenic temperatures than other device



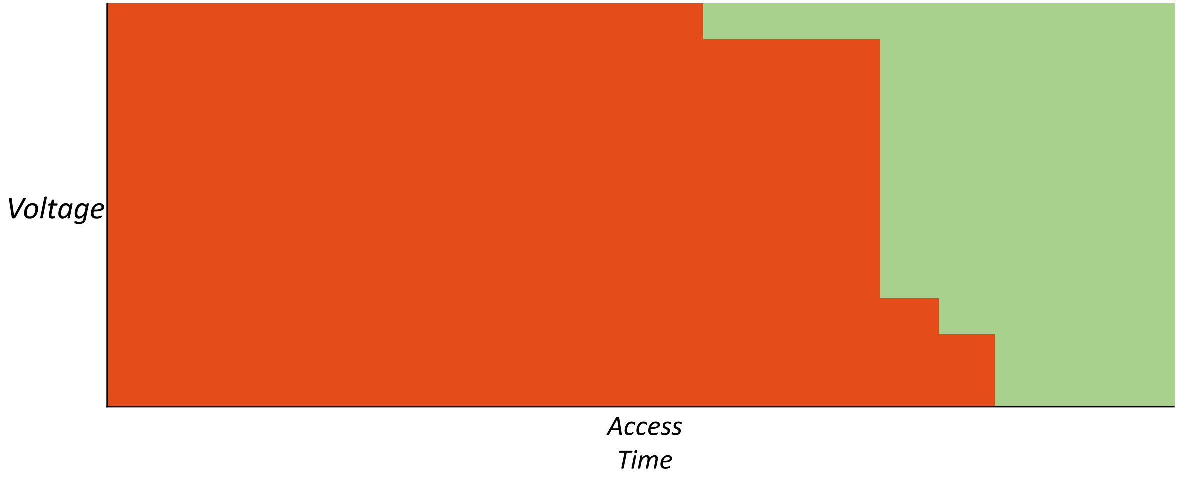
Shmoo plot for Parametric Failure Definition & Reliability Evaluation

- **Identify non-linear degradations in parameters**
- Provide clear insight into complex interactions between voltage, timing, process variation, design marginalities
- **Provide more accuracy to WCA/Fault Tree system reliability**
- Bridge Margin, De-rating, and Tolerance concepts

Time = 0

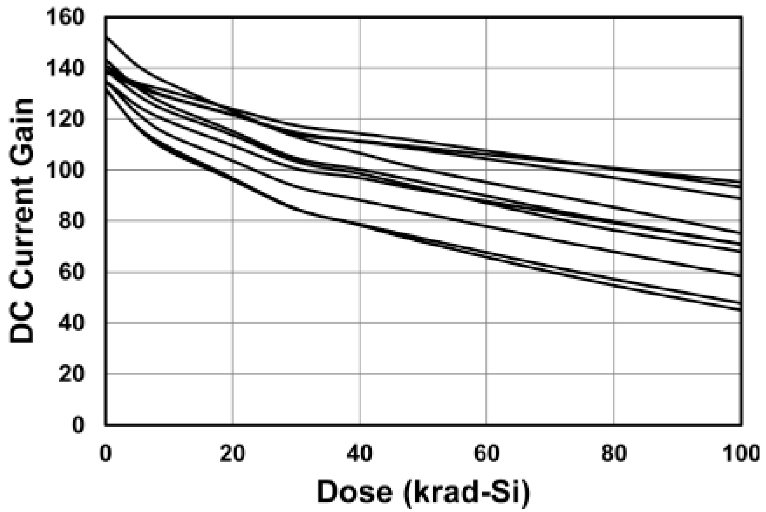


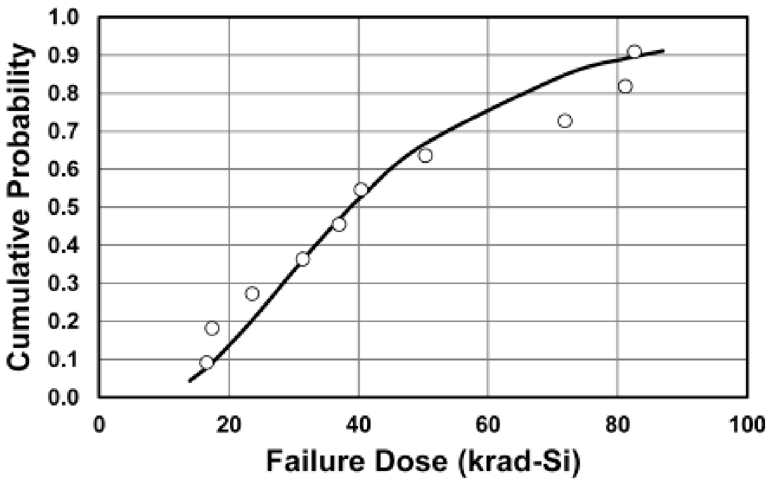
Time = End of Life

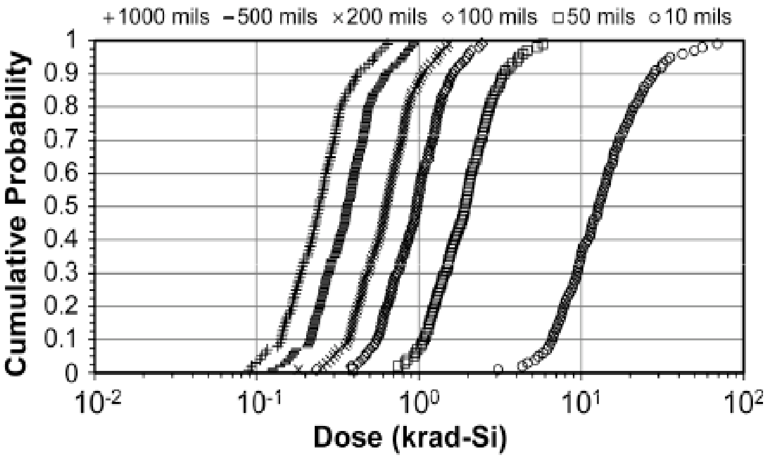


RHA Methodology to include Probabilistic Variation in Device and Environment

- G(x) = CDF (Cumulative Density Function) of devices tested for TID
  - x = dose
  - g(x) = Probability Density Function (PDF)
- H(x) = CDF of dose from space radiation environment
  - AP9/AP8 Monte Carlo , Ver 1.30 – 99 orbital simulations (1 year mission/LEO)
    - Percentile ranking of calculated doses



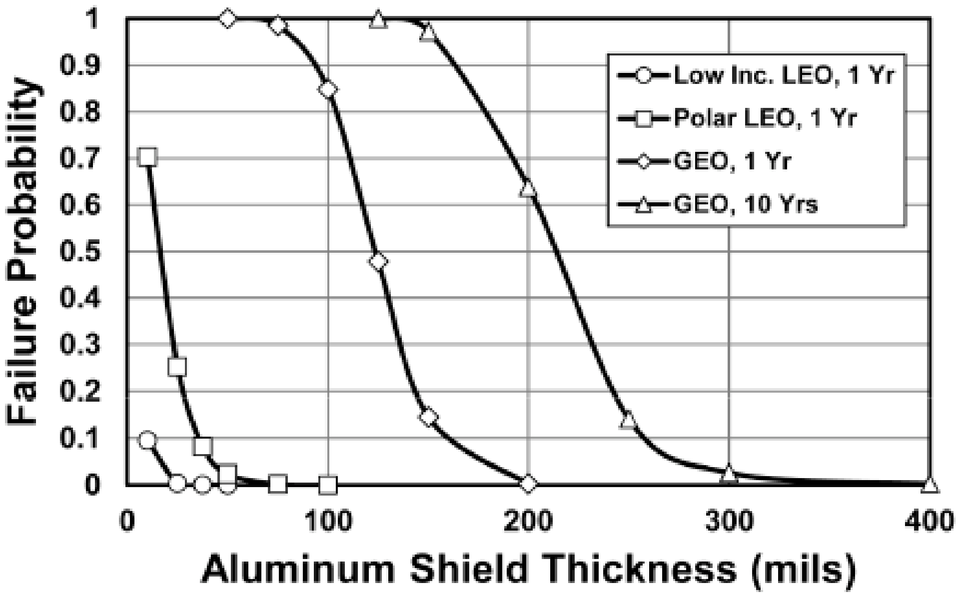




"*Inclusion of Radiation Environment Variability in Total Dose Hardness Assurance Methodology*", M. Xapsos et. al., IEEE Transactions on Nuclear Science, Vol 64, No. 1, 2017

RHA Methodology to include Probabilistic Variation in Device and Environment - 2

- $P_{fail} = \int [1 - H(x)] \cdot g(x)dx$
- Eliminates arbitrary RDF factor approach
- Relate failure probability to reliable circuit operation
  - Improves Worst Case Analysis capability
- Variation in part performance and environmental knowledge is formally accounted for



- Select Mission Lifetime
- Specify Confidence Level

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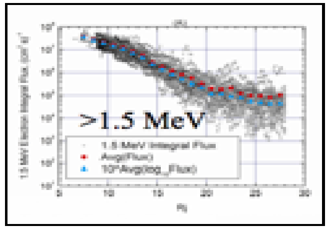

Statistical Environment Model

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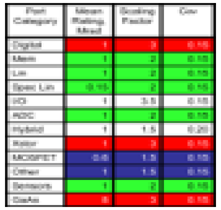

Part Failure Model

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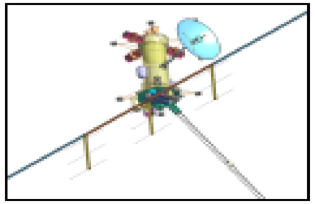


Flight System Reliability Model

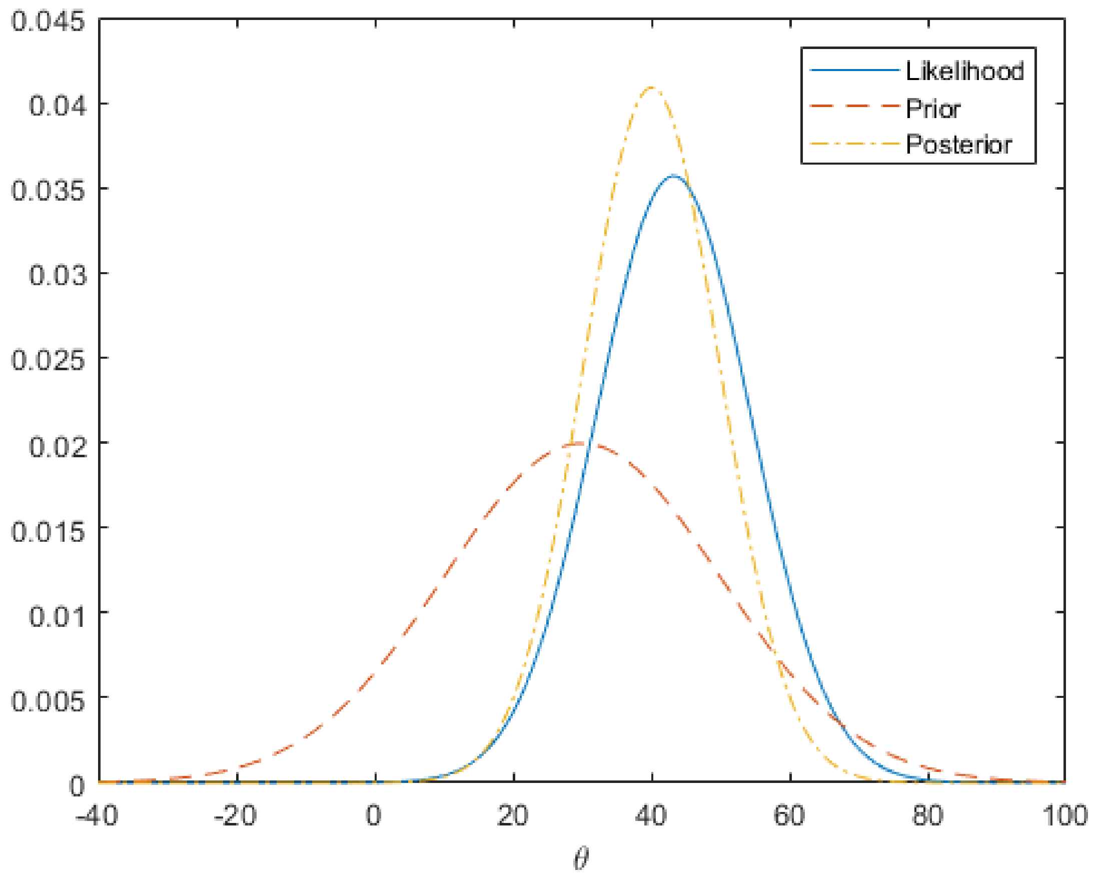
Bayes' Theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad \Rightarrow \quad P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

- Relates probability of a hypothesis before getting evidence, P(H), to probability of the hypothesis after getting the evidence, P(H|E)
  - *H= Hypothesis*
  - *E= Evidence*
  - ***P(H) => Prior Probability***
  - ***P(H|E) => Posterior Probability***
  - ***P(E|H)/P(E) = Likelihood Ratio***
- In Bayesian statistics a parameter is not treated as an unknown constant, but instead has a probability distribution that describes its uncertainty
- The uncertainty about the unknown parameters is quantified using probability so that the unknown parameters are regarded as random variables.
- Before the data is analyzed, the distribution of the parameter is called **prior distribution**, and after the data taken into account, the distribution is called **posterior distribution**.

Bayes Examples

- Many, many examples and they continue to grow as Bayesian techniques catch on:
  - Burn in stratgies – if failures occur, when is it appropriate to not stop but continue with increase samples and demonstrate ppm goals can still be met.
  - High k dielectric film reliabilty – leverage existing SiO2 information and whatever exists in literature and ”best guess” to provide improved confidence levels of long life extrapolation

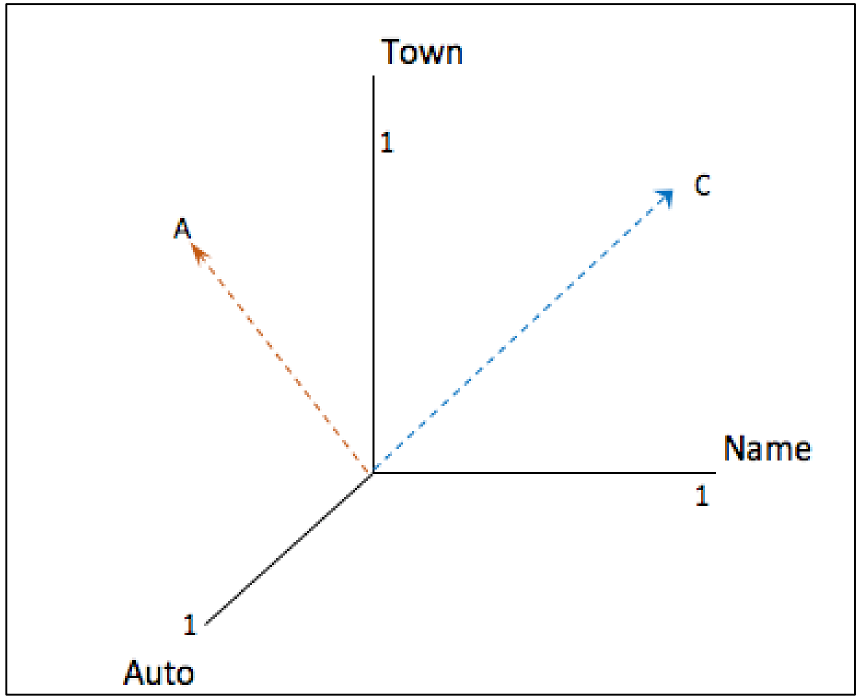


Qualitative to Quantitative Data Conversion

- Much of the information that EEE Parts Engineers deal with is Qualitative
- Need to turn into Quantitative format(s) to leverage many of the new technique
- Variable to Attribute Conversion

First Name	Live in Santa Clarita	Drive a Toyota
Doug	Yes	Yes
Lori	Yes	No
John	Yes	No
Jeremy	Yes	Yes

Index	First Name w/ "J"	Live in Santa Clarita	Drive a Toyota
A	0	1	1
B	0	1	0
C	1	1	0
D	1	1	1



How to compare two different attribute vectors - Cosine Similarity

- Calculate the cosine of the angle between the two vectors
- Cosine(0 degrees) = 1 => the vectors are the same.

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}},$$

First Name w/ ”J”	Live in Santa Clarita	Drive a Toyota	Similarity to first vector
0	1	1	1
0	1	0	.7071
1	1	0	.5
1	1	1	.8165

Apply Cosine Similarity to EEE Parts Data

Raw Data

Part Number	Height	Length	Width	Operating Temp Min	Operating Temp Max	Output Voltage Min	Output Voltage Max	Input Voltage Min	Input Voltage Max
LT1965EDD-3.3#PBF	0.8 mm	3.0 mm	3.0 mm	-40.0 Cel	125.0 Cel	3.201 V	3.399 V	4.3 V	20.0 V
LT3090HDD#PBF-ND	0.8 mm	3.0 mm	3.0 mm	-40.0 Cel	150.0 Cel	0.0 V	32.0 V	1.5 V	36.0 V

Vectorized Data

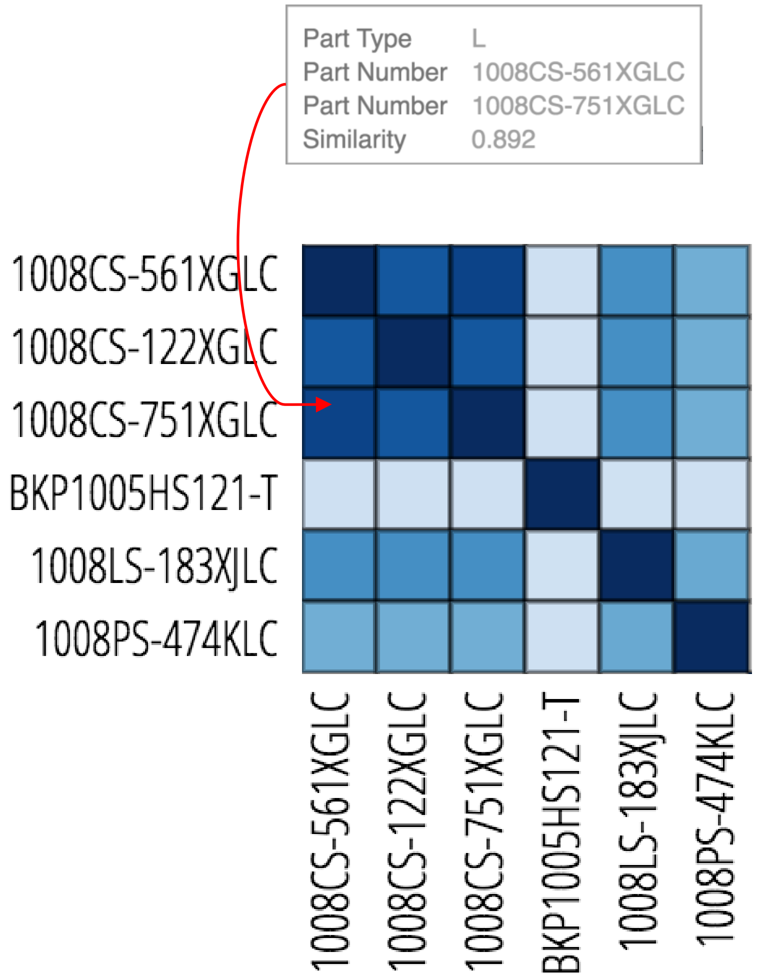
Part Number	Height 0.8 mm	Length 3.0 mm	Width 3.0 mm	Operating Temp Min -40.0 Cel	Operating Temp Max 125.0 Cel	Operating Temp Max 150.0 Cel	Output Voltage Min 3.201 V	Output Voltage Min 0.0 V	Output Voltage Max 3.399 V	Output Voltage Max 32.0 V	Input Voltage Min 4.3 V	Input Voltage Min 1.5 V	Input Voltage Max 20.0 V	Input Voltage Max 36.0 V
LT1965EDD-3.3#PBF	1	1	1	1	1	0	1	0	1	0	1	0	1	0
LT3090HDD#PBF-ND	1	1	1	1	0	1	0	1	0	1	0	1	0	1

Cosine Similarity = 0.44

- **Data from IEEE datasheets360.com via web scrapper**
- *Not hand entered*
- **Using Python API (including Beautiful Soup and pandas)**

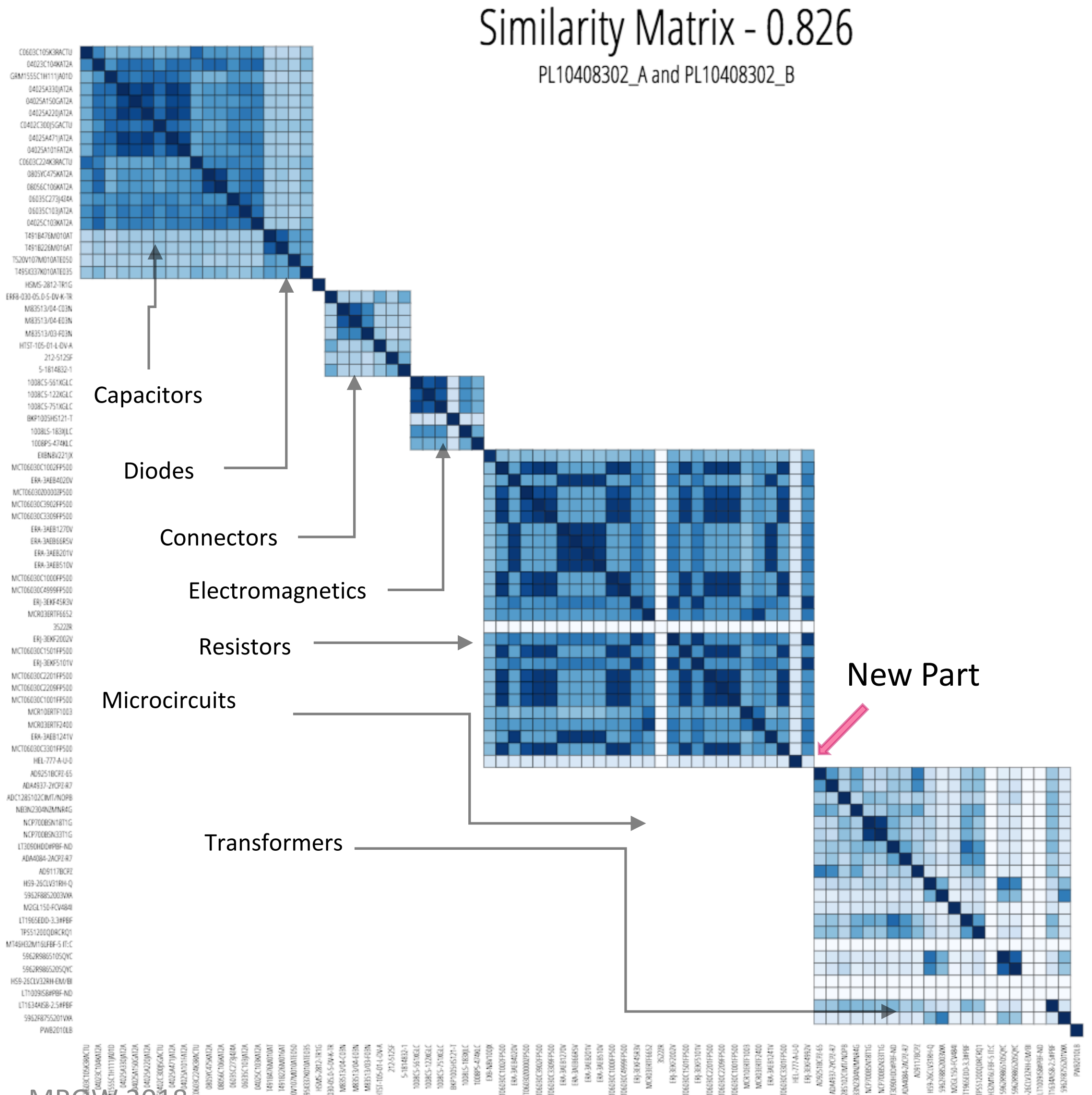
Cosine Similarity – Parts List Revision

- **Similarity matrix for L type parts (electromagnetics)**
  - Similarity calculated between parts of the same type
- **Coloring indicates strength of similarity:**
  - 0 – white (no similarity)
  - 1 – dark blue (identical)
- **Diagonal of 1's is an artifact of comparing different revisions of the same part list**



Cosine Similarity – Parts List Revision

- **Similarity matrix for two part lists**
- **Coloring indicates strength of similarity:**
  - 0 – white (no similarity)
  - 1 – dark blue (identical)
- **Diagonal of 1's is an artifact of comparing different revisions of the same part list**
  - One-off in diagonal indicates addition of a **new part**
- **Distinct regions correspond to part types**
  - Part comparisons are not made between different part types
- **Manage subtle changes in part type, provide an precise definition of "Heritage" as way to reduce risk**



Information Entropy

Manufacturer	Part Number	Function	Topology	Vin (V) Min/Max	Vout (V) Max	Switching Frequency (KHz)	Process Technology	SEL result	SEL Value
Linear Technology	LTC3708	Step Down	Buck	3.2/36	5	240	0.5um BiCMOS	Non-destructive at 11	<11
Intersil Corporation	ISL70002SEHFE			3.2/36				SEL immune	> 75
Linear Technology	LTC3129	Step Up/Down	Buck Boost	1.92/15	1.4	1200	0.5um BiCMOS	Destructive SEL @ 42 MeV	42
Linear Technology	RH3845	Step Down	Buck	4.0/60	8	600	3u Bipolar w/NMOS	Destructive SEL @ 42 MeV	<19.6
Texas Instruments	TPS54821	Step Down	Buck	4.5/17	15	200/1600	0.25 um BiCMOS	Ok	>43
Texas Instruments	TPS54020	Step Down	Buck	4.5/17	5	200/1200	0.25 um BiCMOS	Destructive SEL @ 42 MeV	42
Texas Instruments	TPS54620	Step Down	Buck	4.5/17	15	200/1600	0.25 um BiCMOS	Destructive SEL @ 42 MeV	42
Texas Instruments	TPS562209	Step Down	Buck	4.5/17	7	650	0.25 um BiCMOS	???	???

- **Parts community has lots of data like this – how to best turn it into more useable information?**
  - *Will the TI TPS562209 latch up?*
  - Can it be predicted?
- Use information entropy to make decision tree
- **Train the decision with initial dataset and then ”predict” results for new data**

Information Entropy

$$E(S) = \sum_i^c -p_i log_2(pi) \quad \text{[Entropy]}$$

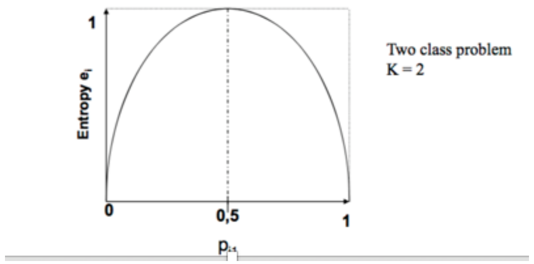
$$IG(A,S) = E(S) - \sum_{t \subset T} p(t)E(t) \quad \text{[Information Gain]}$$

Information Gain = Difference in entropy before and after the set is split at an attribute

- **GOAL - Construct a decision tree that returns the highest information gain (i.e., the most homogeneous branches).**
- Data is partioned into subsets that contain instances with similar values (homogenous).
- **Use entropy to calculate the homogeneity of a sample/subset**
- If the sample is completely homogeneous the entropy is zero and if the sample is an equally divided it has entropy of one.

Sample Dataset

$$e_i = -\sum_{j=1}^{k} p_{ij} \log_2 p_{ij}$$

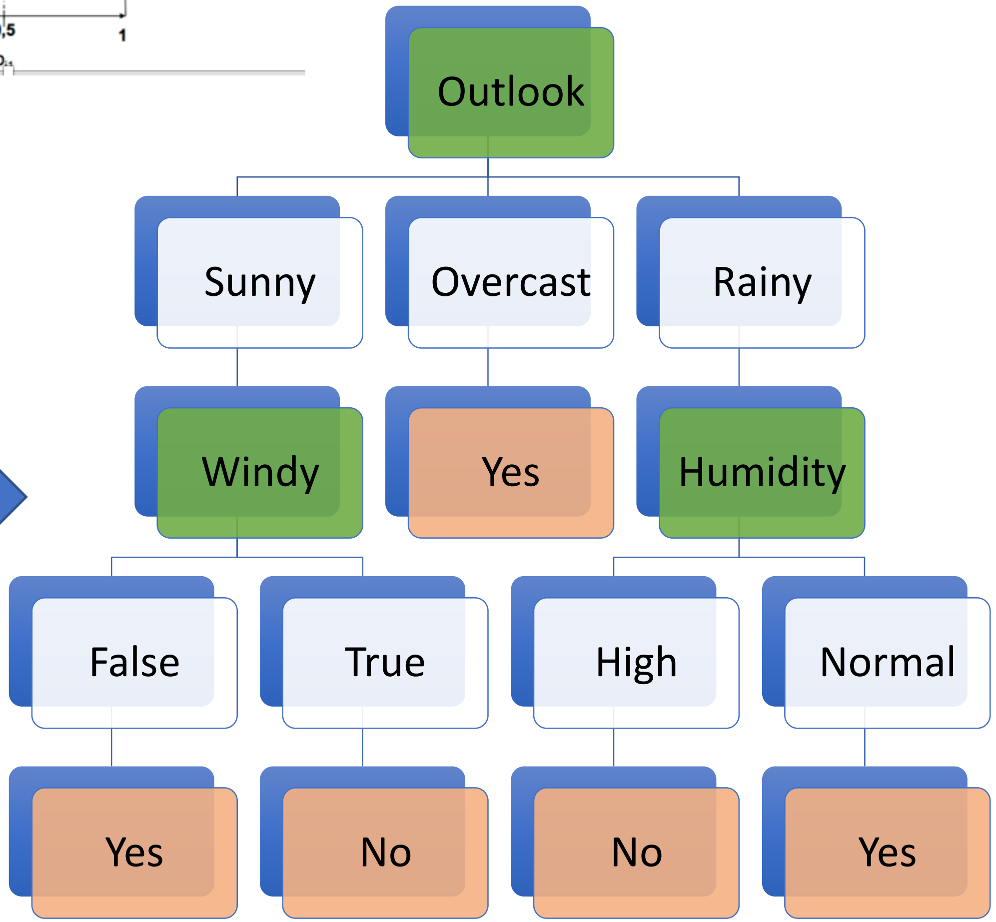


Predictors

Target

Outlook	Temperature	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	Normal	False	Yes
Sunny	Cool	Normal	True	Yes
Sunny	Cool	High	False	No
Overcast	Mild	Normal	True	Yes
Rainy	Cool	Normal	True	No
Overcast	Mild	High	False	Yes
Sunny	Cool	High	False	Yes

ID3 Algorithm



http://www.saedsayad.com/decision_tree.htm

Summary

- **Complexity and sophistication in EEE parts is increasing rapidly**
- Tools used to qualify and manage risk for EEE space parts need to evolve and adapt to meet these constantly changing demands
- **Example tools that might be helpful in this endeavor have been reviewed in this discussion**
  - Entropy – system level degradation and information
  - Shmoo plotting
  - Bayesian Analysis
  - Data Clustering and Decision Tree

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