智慧製造與生產線上的資料科學

Manufacturing Data Science

From Predictive to Prescriptive

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Education

- Ph.D, 工業與系統工程, Texas A&M University, USA
  (Major: Operations Research 作業研究/運籌學)
- M.S., 工業工程與工程管理, 國立清華大學
- B.S. & B.B.A., 應用數學暨資訊管理, 國立政治大學

Experience

- 教授， 國立台灣大學資訊管理學系
- 教授兼所長，國立成功大學資訊工程學系暨製造資訊與系統研究所
- 副編輯，IEEE Transactions on Semiconductor Manufacturing(SCI)
- 副編輯，IEEE Transactions on Automation Science and Engineering(SCI)
- 工業工程學會秘書長、工業局新興技術顧問、半導體廠科技顧問、AutoML新創顧問

Award

- 台大管理學院翁肇喜先生講座(2022)、工業工程學會陳樹勛先生講座
- 科技部傑出研究獎(2022)、IEEE Senior Member(2021)
- 呂鳳章先生紀念獎(2019)、美光教師Micron Teacher Award (2018)
- 李國鼎科技與人文講座研究獎 (2018)、科技部吳大猷先生紀念獎 (2017)

Research Interest

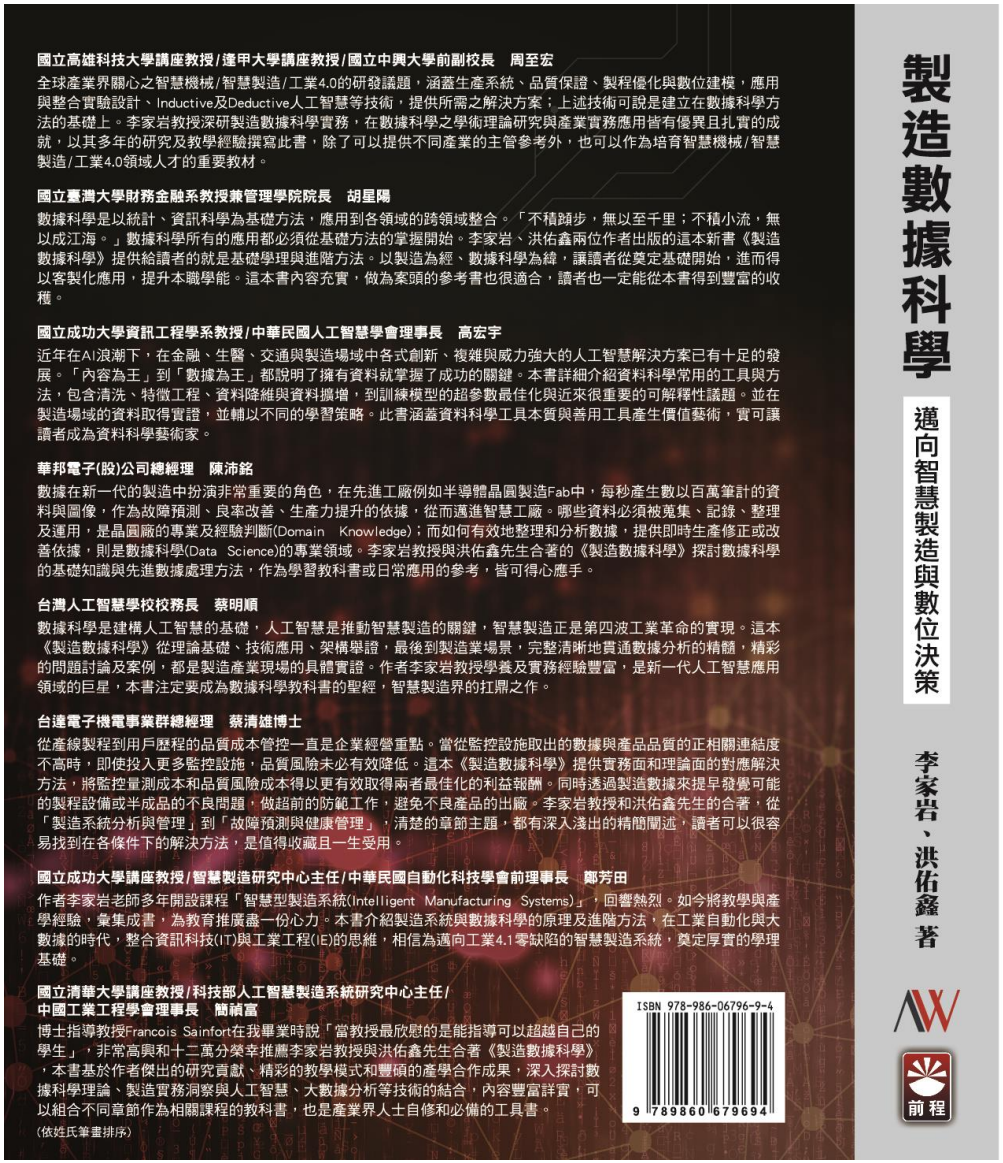
- 製造數據科學、智慧型製造系統、生產力與效率分析、多目標決策、碳抵換與交易

實證案例

POLab

	生產規劃	製程監控	供應協同
作業面	Work Study 現場改善與工作研究	Mechanical Parameter Identification 機構參數估測	Procurement Decision 原料價格預測與採購決策
戰術面	Scheduling Optimization 半自動化生產排程	Metrology Prediction 工程參數篩選與精度預測	Chiller Optimization 冰機節能
	Production Simulation 生產系統模擬	Predictive Maintenance (PdM) 預測保養	Cap-and-Trade 碳抵換與交易
戰略面	Robust Capacity Planning 穩健產能規劃	Equipment Health Monitoring 機台健康監控	Vendor Selection & Order Allocation 供應商評選與訂單配置

Productivity & Efficiency Analysis
生產力與效率分析


國立高雄科技大學講座教授/逢甲大學講座教授/國立中興大學前副校長　周至宏
全球產業界關心之智慧機械/智慧製造/工業4.0的研發議題，涵蓋生產系統、品質保證、製程優化與數位建模，應用與整合實驗設計、Inductive及Deductive人工智慧等技術，提供所需之解決方案；上述技術可說是建立在數據科學方法的基礎上。李家岩教授深研製造數據科學實務，在數據科學之學術理論研究與產業實務應用皆有優異且扎實的成就，以其多年的研究及教學經驗撰寫此書，除了可以提供不同產業的主管參考外，也可以作為培育智慧機械/智慧製造/工業4.0領域人才的重要教材。
國立臺灣大學財務金融系教授兼管理學院院長　胡星陽
數據科學是以統計、資訊科學為基礎方法，應用到各領域的跨領域整合。「不積蹞步，無以至千里；不積小流，無以成江海。」數據科學所有的應用都必須從基礎方法的掌握開始。李家岩、洪佑鑫兩位作者出版的這本新書《製造數據科學》提供給讀者的就是基礎學理與進階方法。以製造為經、數據科學為緯，讓讀者從奠定基礎開始，進而得以客製化應用，提升本職學能。這本書內容充實，做為案頭的參考書也很適合，讀者也一定能從本書得到豐富的收穫。
國立成功大學資訊工程學系教授/中華民國人工智慧學會理事長　高宏宇
近年在AI浪潮下，在金融、生醫、交通與製造場域中各式創新、複雜與威力強大的人工智慧解決方案已有十足的發展。「內容為王」到「數據為王」都說明了擁有資料就掌握了成功的關鍵。本書詳細介紹資料科學常用的工具與方法，包含清洗、特徵工程、資料降維與資料擴增，到訓練模型的超參數最佳化與近來很重要的可解釋性議題。並在製造場域的資料取得實證，並輔以不同的學習策略。此書涵蓋資料科學工具本質與善用工具產生價值藝術，實可讓讀者成為資料科學藝術家。
華邦電子(股)公司總經理　陳沛銘
數據在新一代的製造中扮演非常重要的角色，在先進工廠例如半導體晶圓製造Fab中，每秒產生數以百萬筆計的資料與圖像，作為故障預測、良率改善、生產力提升的依據，從而邁進智慧工廠。哪些資料必須被蒐集、記錄、整理及運用，是晶圓廠的專業及經驗判斷(Domain Knowledge)；而如何有效地整理和分析數據，提供即時生產修正或改善依據，則是數據科學(Data Science)的專業領域。李家岩教授與洪佑鑫先生合著的《製造數據科學》探討數據科學的基礎知識與先進數據處理方法，作為學習教科書或日常應用的參考，皆可得心應手。
台灣人工智慧學校校務長　蔡明順
數據科學是建構人工智慧的基礎，人工智慧是推動智慧製造的關鍵，智慧製造正是第四波工業革命的實現。這本《製造數據科學》從理論基礎、技術應用、架構舉證，最後到製造業場景，完整清晰地貫通數據分析的精髓，精彩的問題討論及案例，都是製造產業現場的具體實證。作者李家岩教授學養及實務經驗豐富，是新一代人工智慧應用領域的巨星，本書注定要成為數據科學教科書的聖經，智慧製造界的扛鼎之作。
台達電子機電事業群總經理　蔡清雄博士
從產線製程到用戶歷程的品質成本管控一直是企業經營重點。當從監控設施取出的數據與產品品質的正相關連結度不高時，即使投入更多監控設施，品質風險未必有效降低。這本《製造數據科學》提供實務面和理論面的對應解決方法，將監控量測成本和品質風險成本得以更有效取得兩者最佳化的利益報酬。同時透過製造數據來提早發覺可能的製程設備或半成品的不良問題，做超前的防範工作，避免不良產品的出廠。李家岩教授和洪佑鑫先生的合著，從「製造系統分析與管理」到「故障預測與健康管理」，清楚的章節主題，都有深入淺出的精簡闡述，讀者可以很容易找到在各條件下的解決方法，是值得收藏且一生受用。
國立成功大學講座教授/智慧製造研究中心主任/中華民國自動化科技學會前理事長　鄭芳田
作者李家岩老師多年開設課程「智慧型製造系統(Intelligent Manufacturing Systems)」，回響熱烈。如今將教學與產學經驗，彙集成書，為教育推廣盡一份心力。本書介紹製造系統與數據科學的原理及進階方法，在工業自動化與大數據的時代，整合資訊科技(IT)與工業工程(IE)的思維，相信為邁向工業4.1零缺陷的智慧製造系統，奠定厚實的學理基礎。
國立清華大學講座教授/科技部人工智慧製造系統研究中心主任/
中國工業工程學會理事長　簡禎富
博士指導教授Francois Sainfort在我畢業時說「當教授最欣慰的是能指導可以超越自己的學生」，非常高興和十二萬分榮幸推薦李家岩教授與洪佑鑫先生合著《製造數據科學》，本書基於作者傑出的研究貢獻、精彩的教學模式和豐碩的產學合作成果，深入探討數據科學理論、製造實務洞察與人工智慧、大數據分析等技術的結合，內容豐富詳實，可以組合不同章節作為相關課程的教科書，也是產業界人士自修和必備的工具書。
(依姓氏筆畫排序)
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製造數據科學
邁向智慧製造與數位決策
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Manufacturing Data Science
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李家岩、洪佑鑫(2022)

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- 第四章 數據科學分析架構與系統運算決策
- 第五章 數據預處理與製造數據特性
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- 第七章 無母數迴歸與分類
- 第八章 決策樹與集成學習
- 第九章 特徵挑選與維度縮減
- 第十章 類神經網路與深度學習
- 第十一章 集群分析
- 第十二章 特徵工程、數據增強與數據平衡
- 第十三章 故障預測與健康管理
- 第十四章 可解釋人工智慧
- 第十五章 概念漂移
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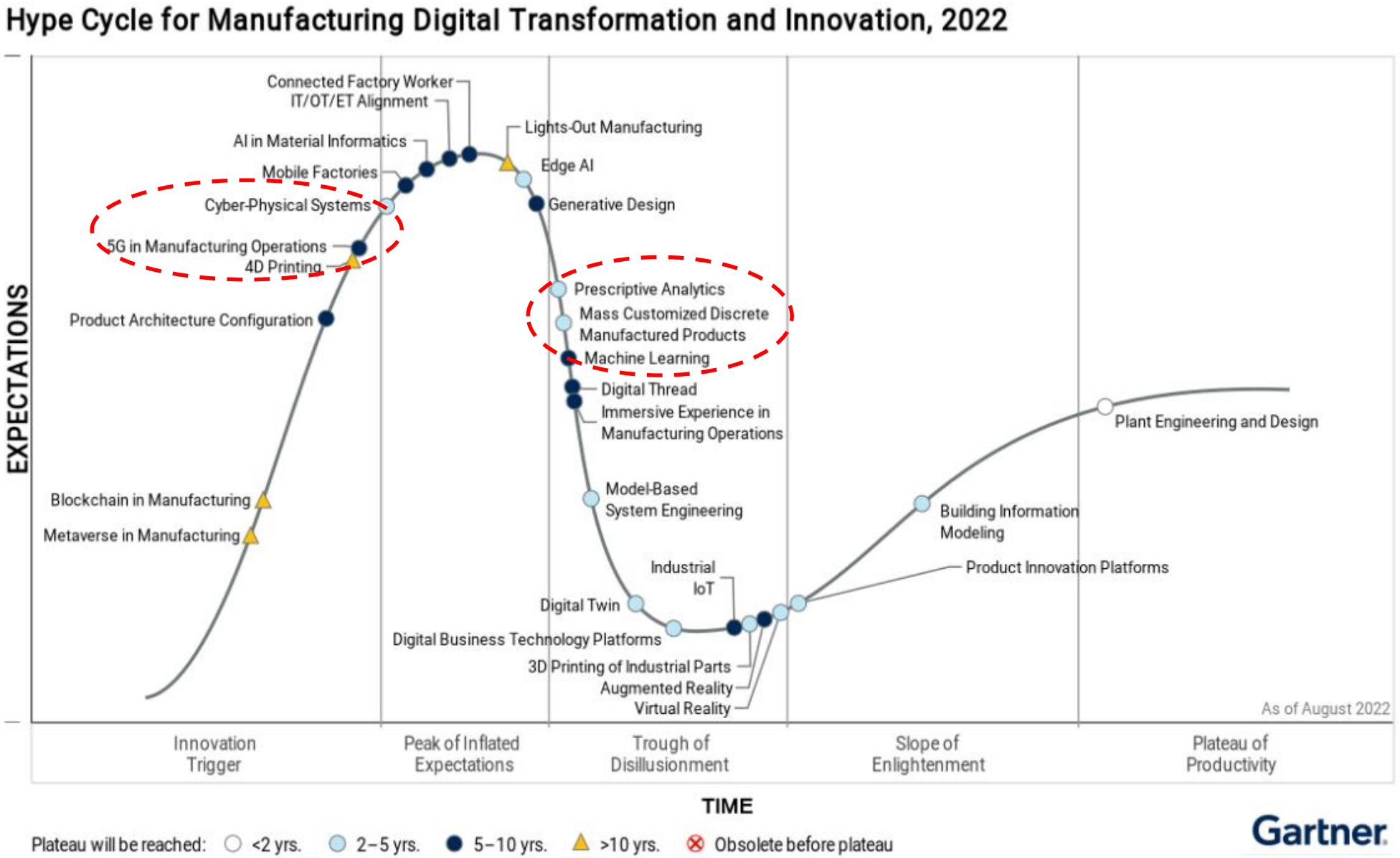
- 附錄D 超參數最佳化

- 應用涵蓋

  產能規劃、瑕疵檢測、製程監控與診斷、機台保養需求預測、 生產排程、電腦視覺、自動光學檢測、原料價格預測與採購等

Hype Cycle 2022 for Digital Transformation



https://stefanini.com/es/gartner-report/gartner-hype-cycle-for-manufacturing-digital-transformation-and-innovation-2022

IBM Watson Health

- IBM 大名鼎鼎的 Watson Health 正考慮出售，人類的 AI 醫療夢該醒了？ (2021/02/22)
  - Watson 在競猜節目上展現的能力，似乎可以移植到醫學領域 — 都是先理解自然語言（患者的電子病歷），然後檢索文本數據庫（治療方案和最新醫學文獻），最終給出答案。 這個方案的價值在於，每天有將近 8000 篇醫療文章發布，醫生一篇篇讀是不可能的，AI 能幫助醫生閱讀最新醫學成果。
  - **花費 40 億收購數據公司，AI 診斷未見起色，合作夥伴也選擇離去**
  - 歸根到底，對 Watson Health 來說致命的問題在於，它的診斷結果不準確 。2018 年 8 月《華爾街日報》報導，沒有任何已發表的研究表明，Watson 提升了患者的治癒率。有十幾位使用過該系統的機構和醫生反饋，其癌症應用成效甚微，某些情況下還會出錯。
  - 在罕見病例研究中，本來應該餵給 Watson 大量的真實數據從而找到新的治療手段， 由於罕見病例數據的極端匱乏，實際上 Watson 被灌了一堆沒什麼用的假想數據，而並不是真正的病人數據 。這種通過假想數據學出來的 AI，準確性可想而知。這就出現了罕見病例中 Watson 的誤診情況。

https://buzzorange.com/techorange/2021/02/22/ibm-sell-watson-health/

亞馬遜無人機送貨 5 年沒成果，高層頻出走被戲稱「老鼠逃離沉沒的船」

亞馬遜最早畫「無人機送貨」大餅，5 年後卻無聲無息？

2016 年 Prime Air 在英國盛大舉辦系列公關活動...無人機送貨將在幾年內和大家見面...更邀請當地學校參觀自家的無人機實驗室...一系列的宣傳影片，在網路上獲得數百萬次的觀看。

在亞馬遜首次執行無人機試飛的五年後，Prime Air 正面臨數據分析團隊被裁員的窘境。...Prime Air 團隊只是縮編並不會退出英國，但他也沒有具體說明未來的工作項目，甚至拒絕確認過去在宣傳影片中出現的無人機送貨，是否能真的進行...

...Prime Air 團隊在 2019 年底，從初階員工到經理一直不斷有人員變動...讓其他人戲稱這種現像就如「老鼠逃離沉沒的船」。...不只人員變動頻繁，許多新任命的經理專長都是物流或倉儲營運管理，對無人機的技術性工作幾乎一無所知。有一前員工分享，在專案上遇到任何技術性的問題，他們也無法向經理求助。

「落地最後 2 公尺」成為跨不過的最後一哩路

究竟 Prime Air 團隊在無人機送貨的執行上遇到什麼難題？內部的工程師表示，當其他無人機公司都是使用降落傘，將包裹從幾公尺高進行投放，亞馬遜則執著於想辦法讓無人機在人們的家門口降落，並從幾乎貼近地面的高度放下包裹。但是，想建立這樣一個系統，是相當大的工程和機器學習挑戰...

何泰霖(2021)，亞馬遜無人機送貨 5 年沒成果，高層頻出走被戲稱「老鼠逃離沉沒的船」，科技橘報。https://buzzorange.com/techorange/2021/08/06/amazon-drone-delivery-fail/

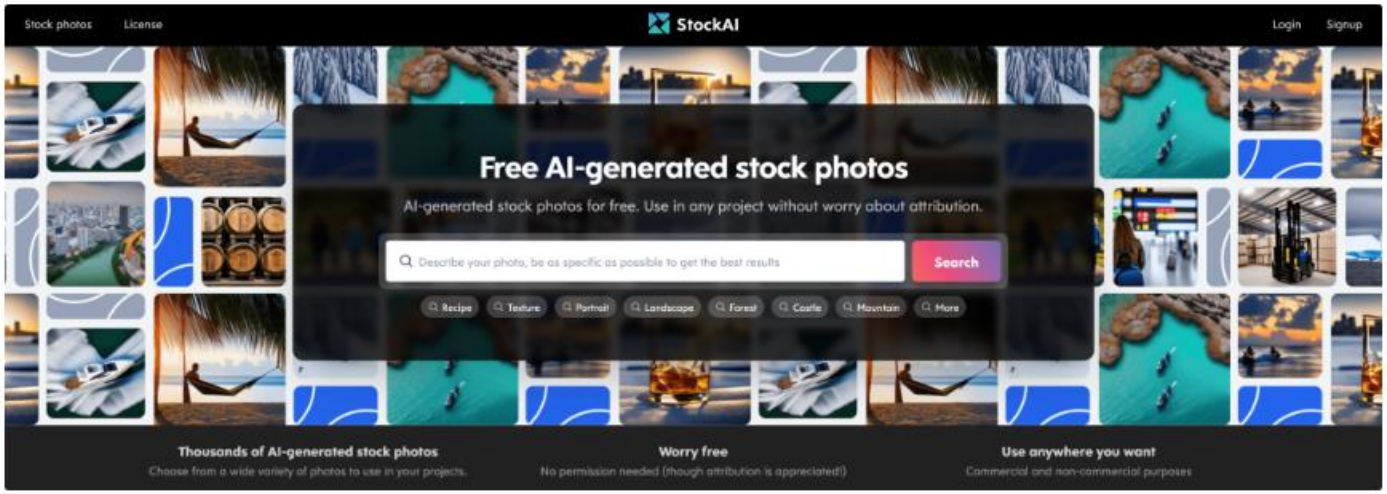
第一家瀕臨倒閉的AI繪畫創業公司出現了，創始人：根本賺不到錢

2022 年的AIGC 創業，可以說是冰火兩重天。
有人融了1.01 億美元，兩年時間就打造了一家獨角獸公司，估值近10 億美元。
有人創立公司僅四個月，就已經預感到了「倒閉」的危險。
就在前幾天，一家提供免費AI 生成圖庫的創業公司Stock AI，
發布了一封CEO 致用戶的公開信

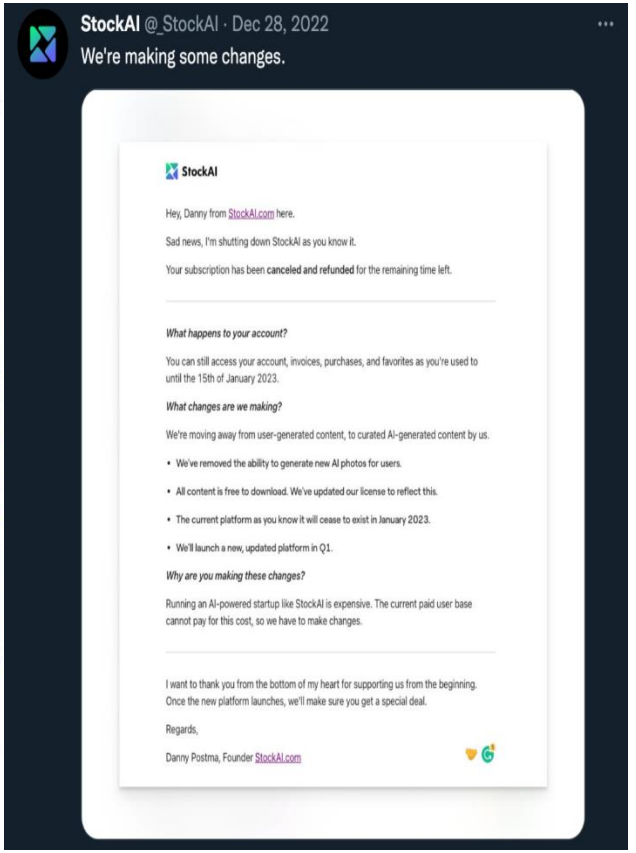
創立於2022，結束於2022

在關閉業務平台的消息傳開之後，很多人才關注到，這是一家成立僅四個月的創業公司。

2022 年9 月，StockAI 發布了開通官方賬號之後的第一條推特：「StockAI 是一個由AI 驅動的庫存照片庫和生成器，準確找到您需要的圖像。如果它不存在，我們會立即為您創建。」



但StockAI 創始人Danny Postma 坦承：「像Stock AI 這樣以AI 為動力的創業公司是成本高昂的。目前的付費用戶群無法覆蓋這些成本費用，所以我們不得不做出改變。」



https://www-36kr-com.translate.goog/p/2077383212732681?_x_tr_sl=zh-CN&_x_tr_tl=zh-TW&_x_tr_hl=zh-TW&_x_tr_pto=wapp

新創公司WeWork聲請破產保護

- 2023年11月7日 週二 下午1:24 （中央社紐約6日綜合外電報導）軟體銀行集團投資的共享辦公室產業WeWork歷經大起大落，重塑全球的辦公室產業，在押寶企業會使用更多共享辦公空間的豪賭黯然收場後，今天在美國聲請破產保護。
- 路透社報導，WeWork聲請破產，意謂投入數十億美元且擁有WeWork約60%股份的軟銀（SoftBank Group）承認WeWork無法繼續生存，除非在破產流程中重新協商價格昂貴的租賃契約。
- 由於租金昂貴，加上企業客戶因員工在家上班而取消訂單，WeWork獲利困難，2023年第2季，其營收就有74%用於支付租金。
- 根據破產聲請，WeWork申報資產債務估計為100億至500億美元。
- 在創辦人紐曼（Adam Neumann）領導下，WeWork一度成長為美國最有價值的新創企業，估值470億美元。它吸引包括軟銀和創投公司Benchmark在內的藍籌投資人挹注資金，也受到摩根大通（JPMorgan Chase）等華爾街銀行歡迎。

https://tw.news.yahoo.com/曾為美國最有價值新創公司-wework聲請破產保護-052452077.html

Outline

1. 智慧製造與資料預處理技巧
   Intelligent Manufacturing and Data Preprocessing
2. 實證個案分析
   Empirical Case Studies
3. 自動化生產排程與演算法
   Automatic Production Scheduling Algorithms
4. 從預測性思維到處方性決策
   From Predictive to Prescriptive

智慧製造與資料預處理技巧

Intelligent Manufacturing and Data Preprocessing

Manufacturing is …

- What is “Manufacturing”?

Manus (hand) Factus (make)

Manufacturing is the realization (具現化) of product.

Swann, J., 2003. Manufacturing Systems, Course Lecture Notes, Georgia Institute of Technology.

Intelligent is…

Shutterstock (www.shutterstock.com)

Knowledge

DATA

詮釋的觀點

Information

思辨的過程

Knowledge

客觀

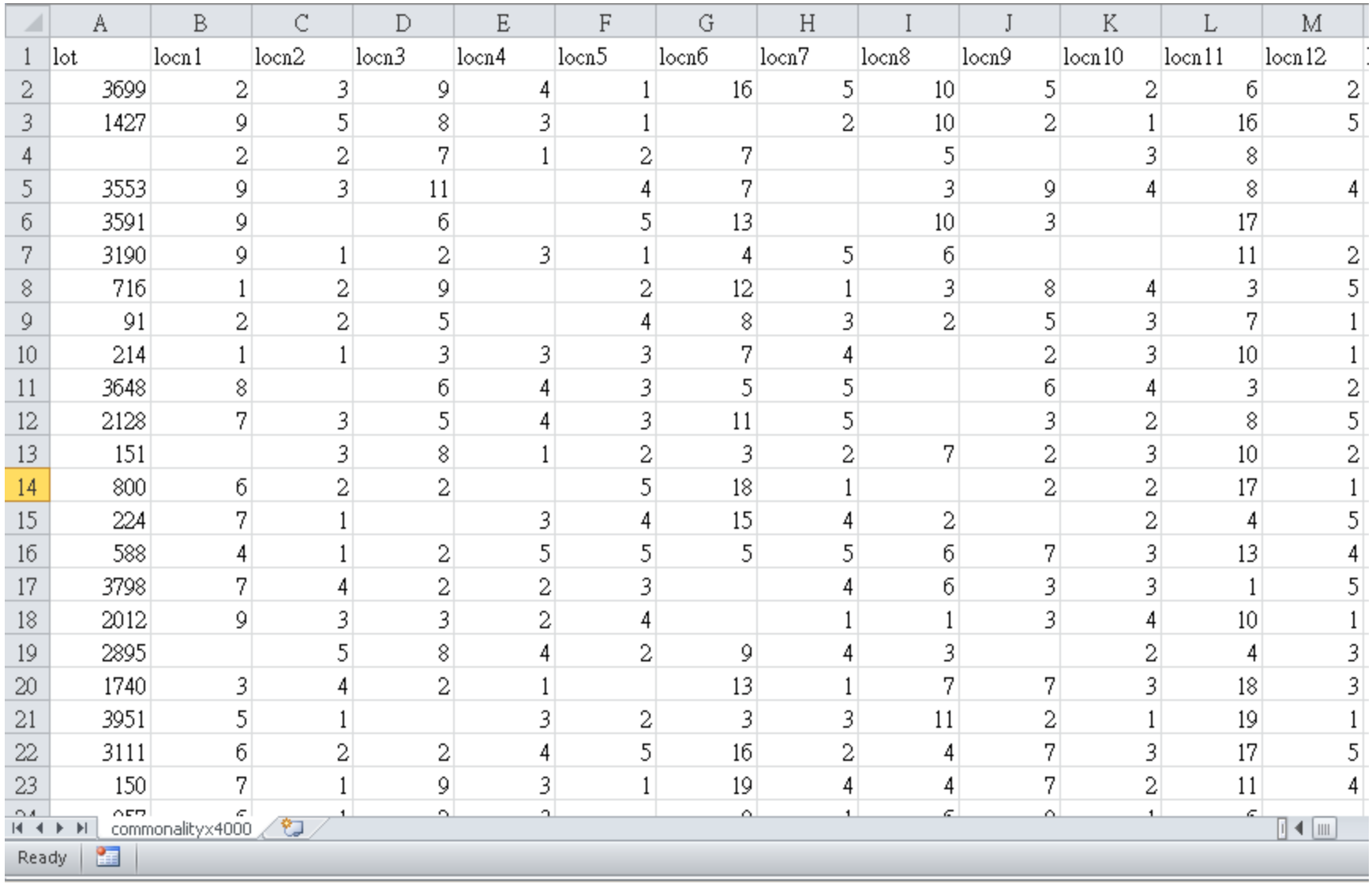
事實

解釋

主觀

科學的原理

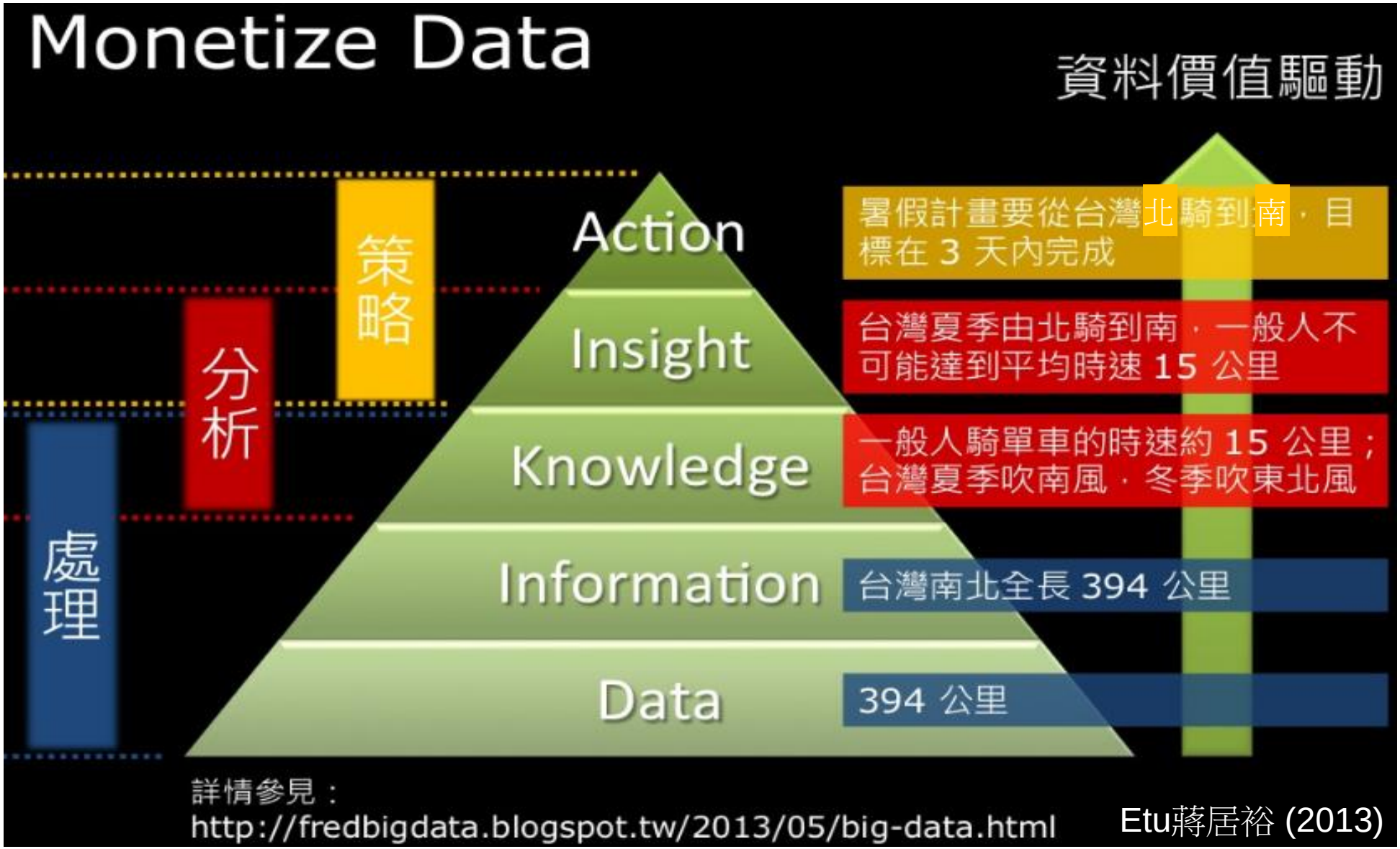
迷思: 資料？資訊?



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	lot	locn1	locn2	locn3	locn4	locn5	locn6	locn7	locn8	locn9	locn10	locn11	locn12
2	3699	2	3	9	4	1	16	5	10	5	2	6	2
3	1427	9	5	8	3	1		2	10	2	1	16	5
4		2	2	7	1	2	7		5		3	8	
5	3553	9	3	11		4	7		3	9	4	8	4
6	3591	9		6		5	13		10	3		17	
7	3190	9	1	2	3	1	4	5	6			11	2
8	716	1	2	9		2	12	1	3	8	4	3	5
9	91	2	2	5		4	8	3	2	5	3	7	1
10	214	1	1	3	3	3	7	4		2	3	10	1
11	3648	8		6	4	3	5	5		6	4	3	2
12	2128	7	3	5	4	3	11	5		3	2	8	5
13	151		3	8	1	2	3	2	7	2	3	10	2
14	800	6	2	2		5	18	1		2	2	17	1
15	224	7	1		3	4	15	4	2		2	4	5
16	588	4	1	2	5	5	5	5	6	7	3	13	4
17	3798	7	4	2	2	3		4	6	3	3	1	5
18	2012	9	3	3	2	4		1	1	3	4	10	1
19	2895		5	8	4	2	9	4	3		2	4	3
20	1740	3	4	2	1		13	1	7	7	3	18	3
21	3951	5	1		3	2	3	3	11	2	1	19	1
22	3111	6	2	2	4	5	16	2	4	7	3	17	5
23	150	7	1	9	3	1	19	4	4	7	2	11	4

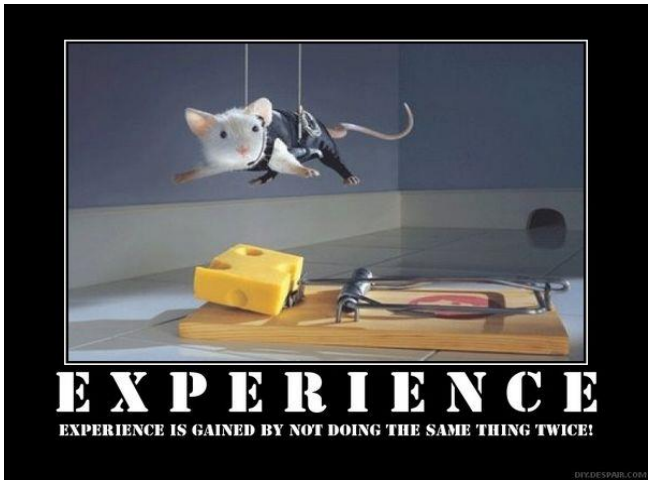
Advanced Analytics – Intel: SETFI: Manufacturing data: Semiconductor tool fault isolation. Causality Workbench Repository, http://www.causality.inf.ethz.ch/ repository.php (2008)

Transformation from Data, Information, to Knowledge



Experience…

Problem → 權衡的觀點 → **Decision** → 失敗的藝術 → **Experience**

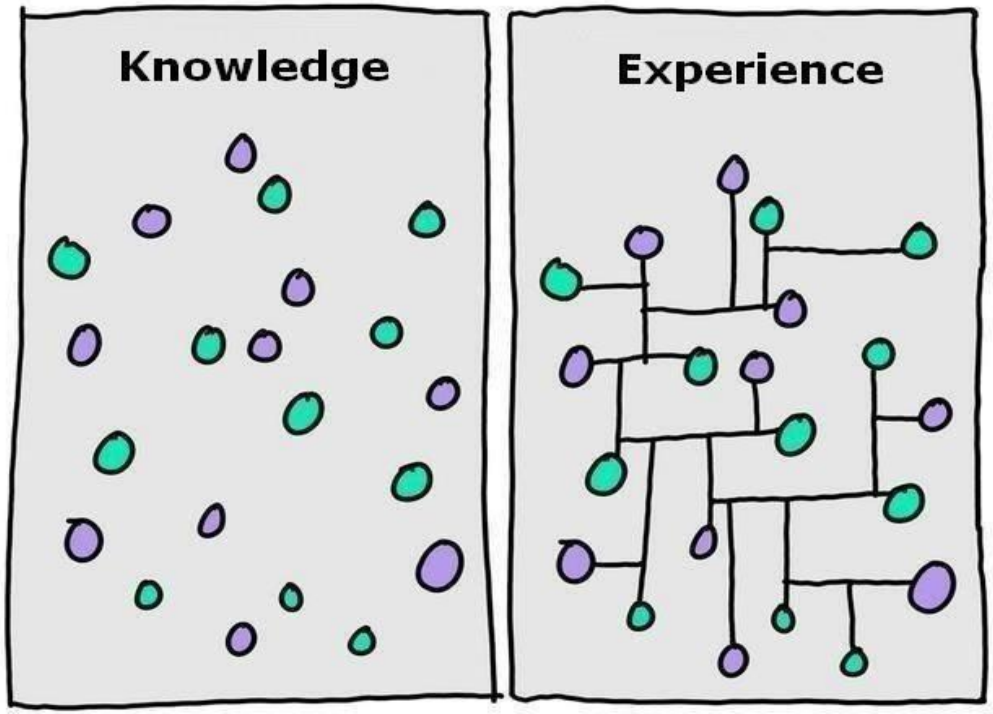


Gap = |預期— 實際|

人生的歷練

Wisdom is…

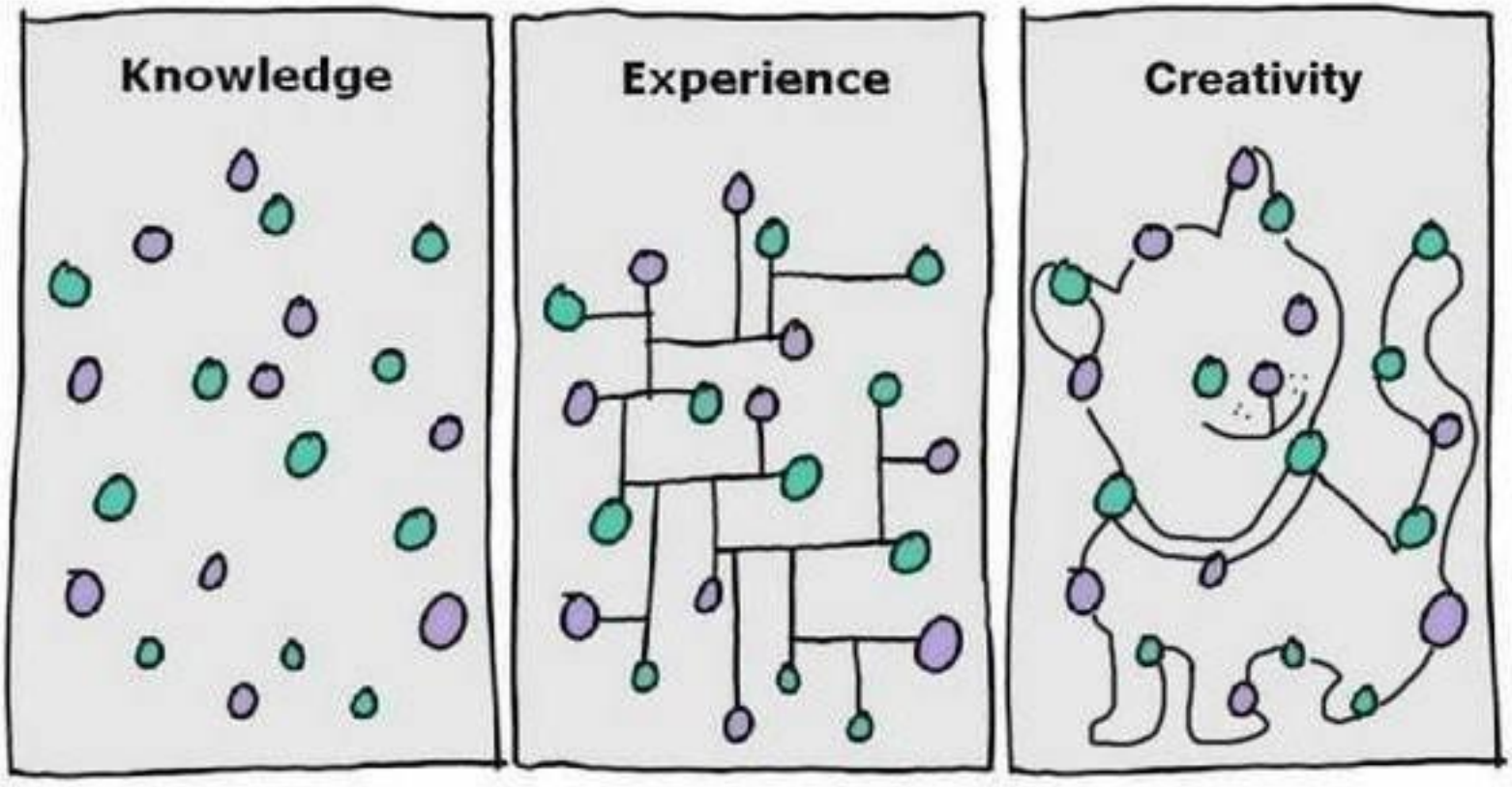
知識 與 經驗
之
融會貫通
（思辨與討論）



http://www.herogamingjobs.com/2014/01/07/experience-vs-knowledge/

Wisdom is…

- The most important skill in the future will be the ability to "connect the dots" in your own way! (Moioli, 2019)



Moioli, Fabio (2019). The most important skill in the future will be the ability to "connect the dots" in your own way!. https://www.linkedin.com/pulse/most-important-skill-future-ability-connect-dots-your-fabio-moioli

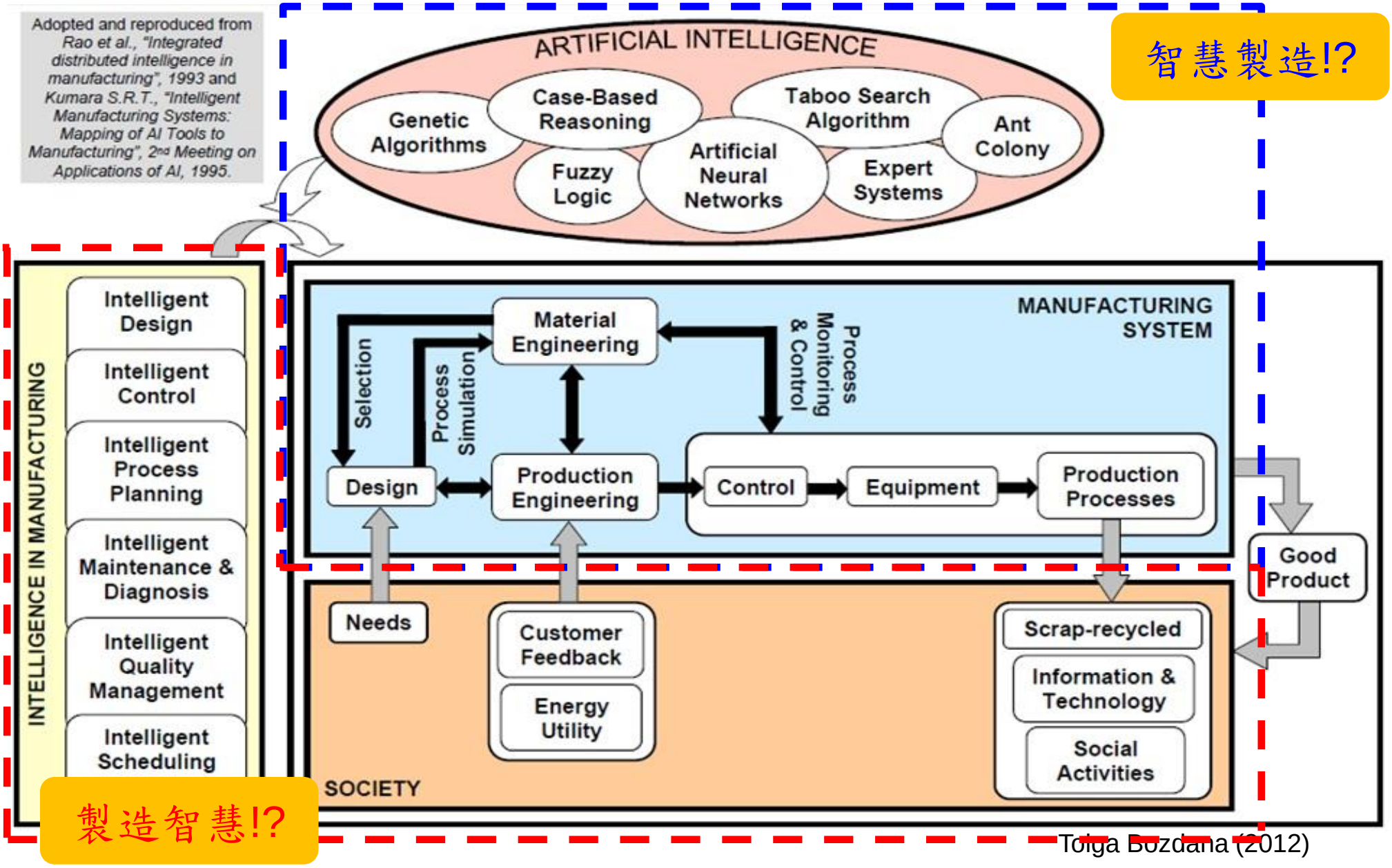
Smart Factory

Smart Factory is a **decision-oriented** system which has the computational intelligence and self-learning ability to optimize the manufacturing process.

計算智慧 → Based on Data (資料處理與分析)

自我學習 → Real-time Feedback Control (回饋控制)

Smart Factory

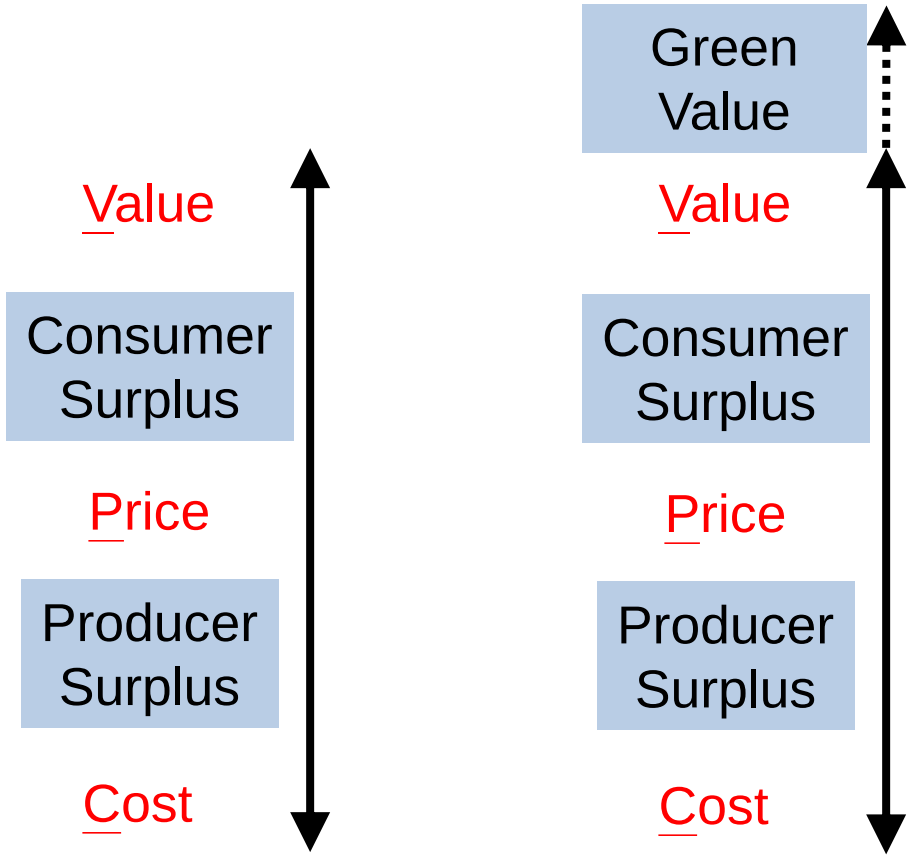


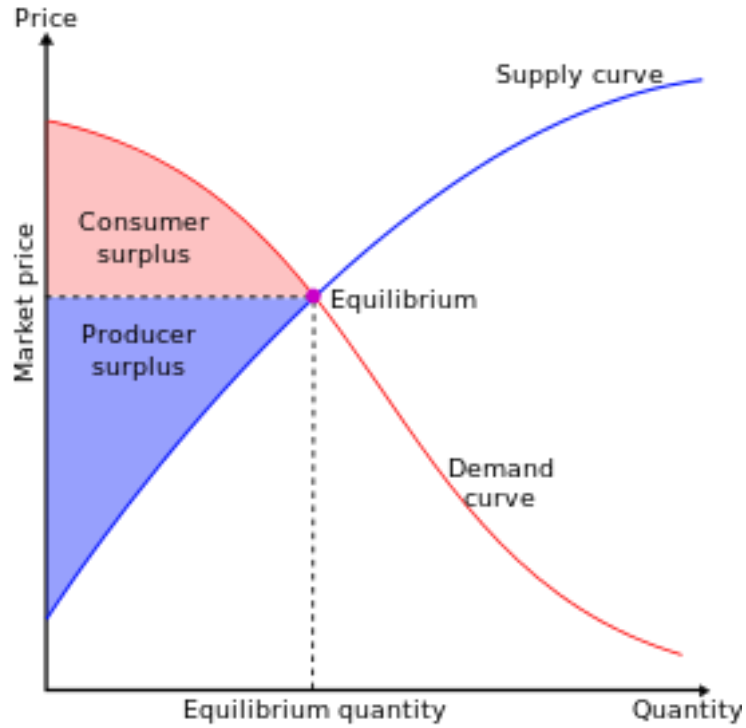
Tolga Bozdana (2012)

Manufacturing System: VPC Framework

Value

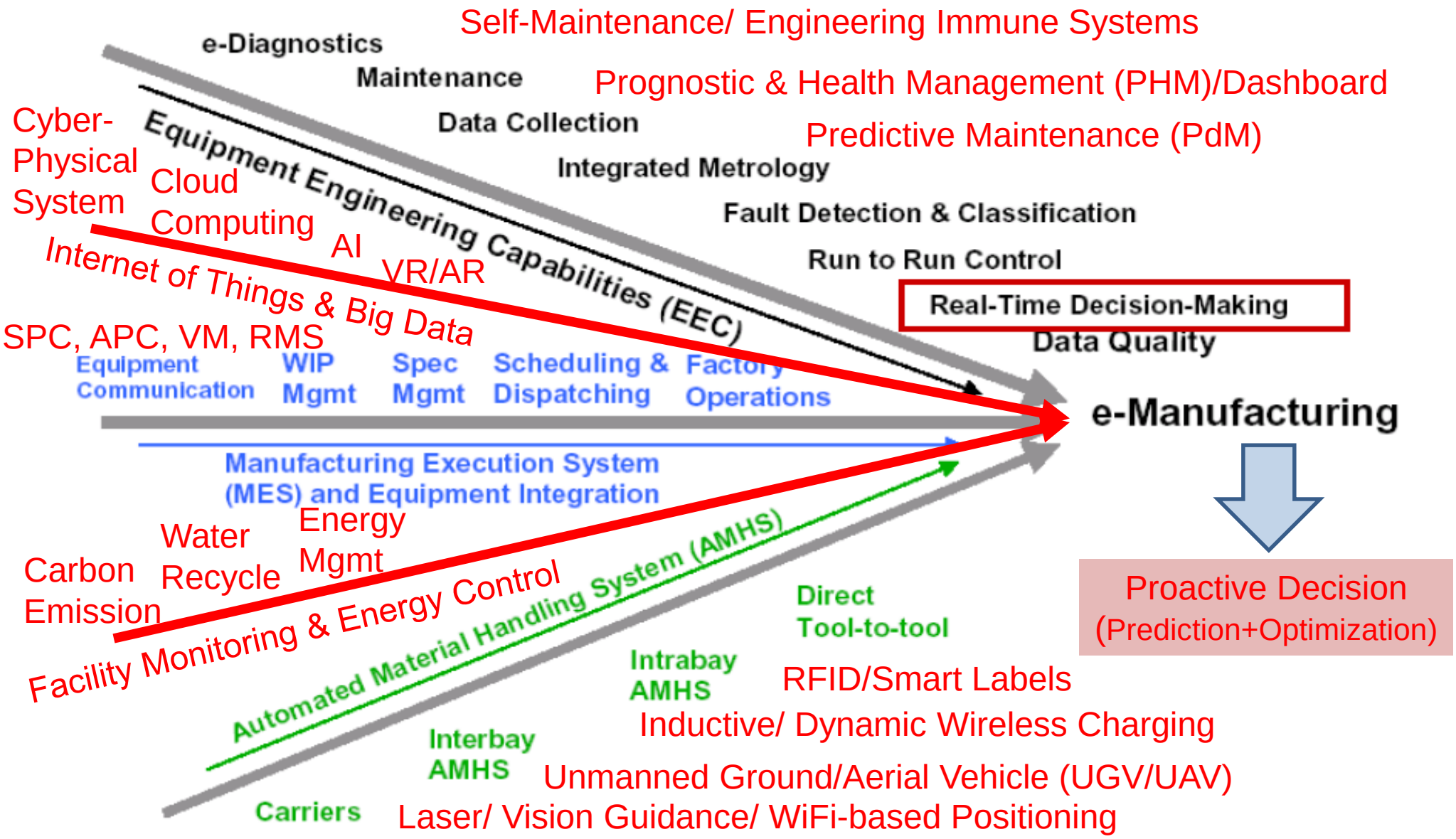
- Manufacturing is value-added process for the realization of the product
- Value – Price – Cost (VPC) framework
- Customer Surplus vs. Producer Surplus





Wikipedia (2016)

製造智慧：決策



Source: International SEMATECH e-Diagnostics and EEC Guidance 2003

Manufacturing system vs. Service system

- Manufacturing system vs. Service system
  - Main difference is “Inventory”!

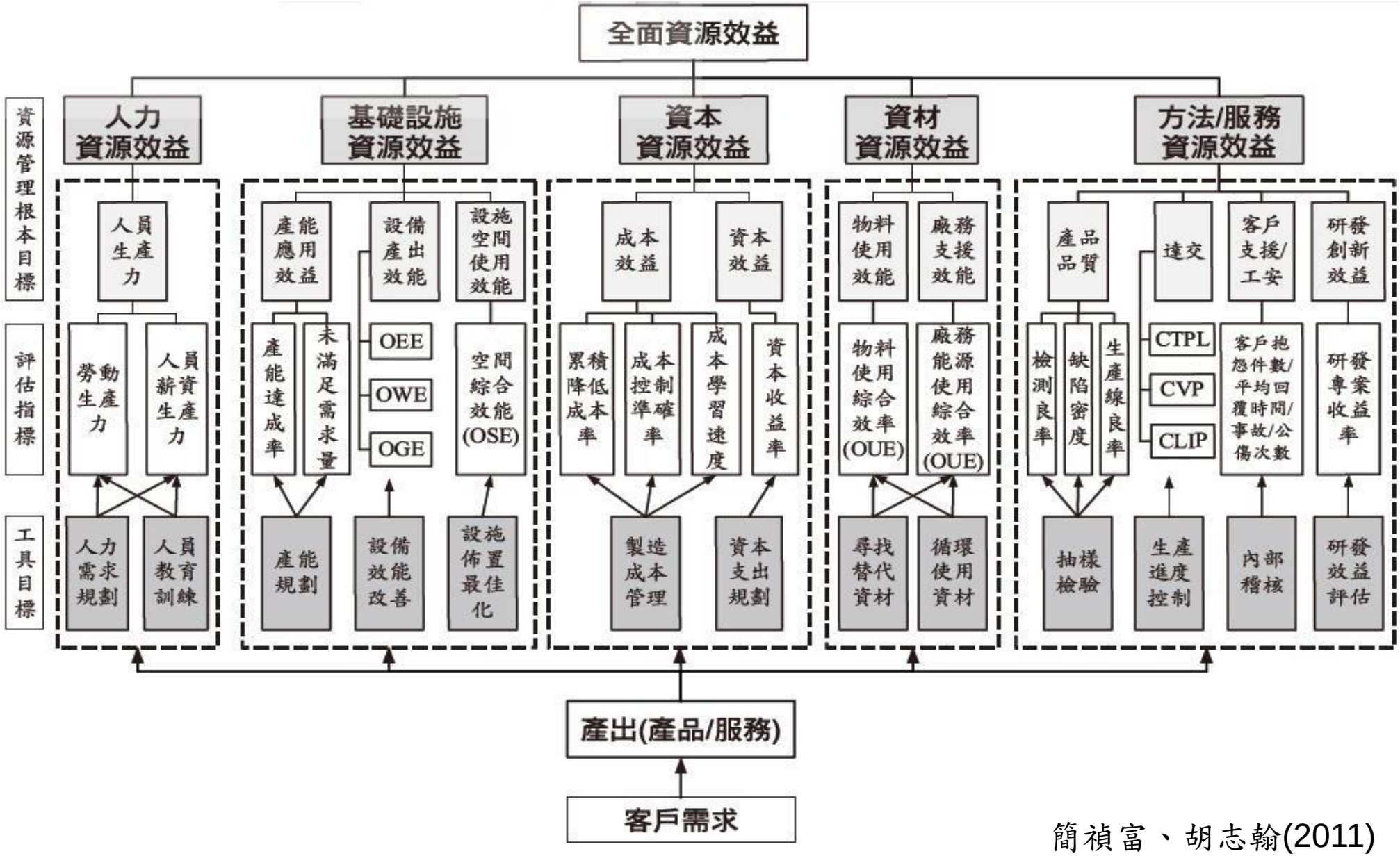
- Inventory
  - Raw materials, Components, Work-in-process (WIP), Finished goods

Capacity + Lead Time + Uncertainty = Inventory

- Inventory Reduction
  - Reduce material and production lead time (includes transport)
  - Reduce information delay times (長鞭效應, Bullwhip effect)
  - Improve quality of information (reduce uncertainty)

Why is it difficult to manage a manufacturing systems?

Diverse Resources and KPIs (資源與KPI的多樣性)

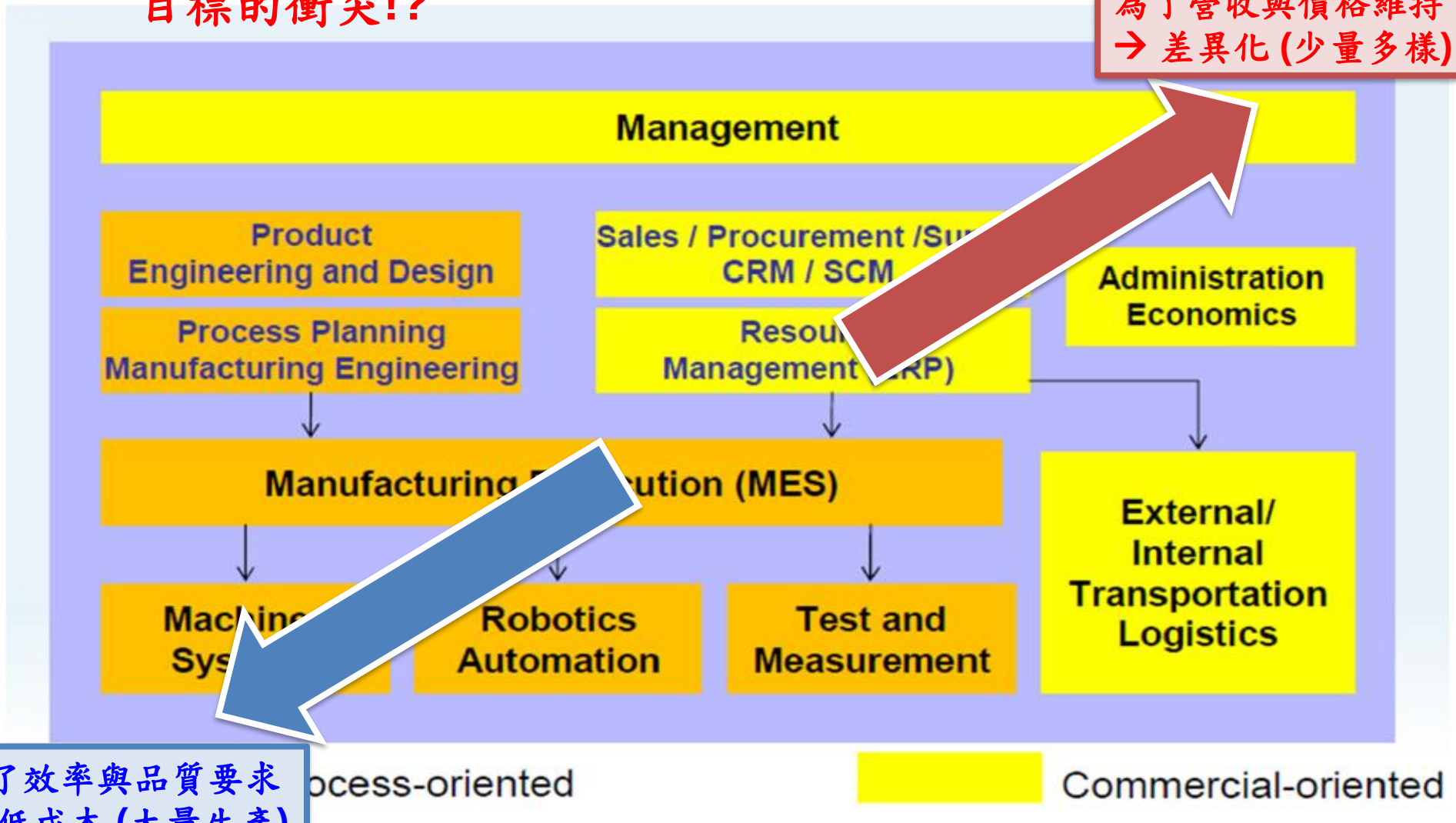


簡禎富、胡志翰(2011)

管理階層與製造現場間目標的衝突 (ICT 系統導入的挑戰)

目標的衝突!?

為了營收與價格維持
→ 差異化 (少量多樣)



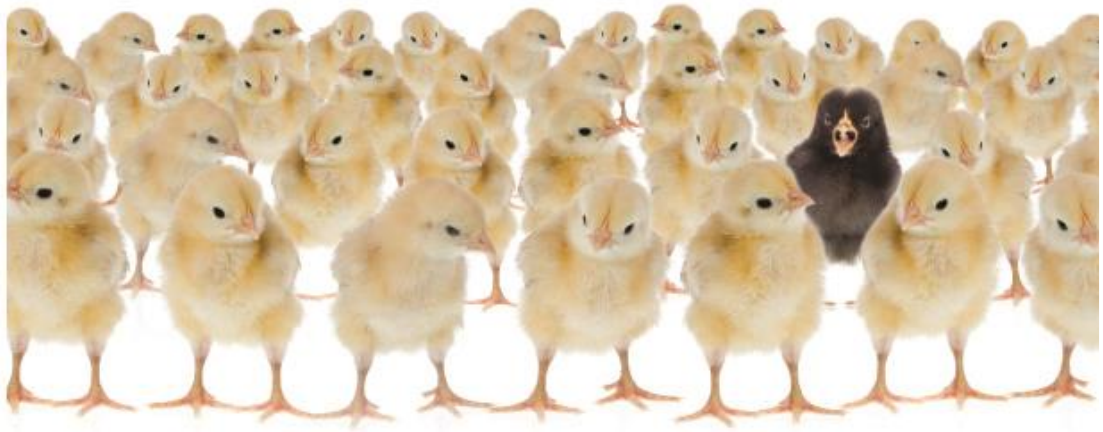
為了效率與品質要求
→ 低成本 (大量生產)

Prof.Dr. Engelbert Westkämper, Fraunhofer IPA Stuttgart, Germany, “Factories of the Future beyond 2013: The role of ICT”
http://cordis.europa.eu/fp7/ict/micro-nanosystems/docs/fof-beyond-2013-workshop/westkaemper-manufuture_en.pdf

Variability (變異)

- Variability is anything that causes the system to depart from regular, predictable behavior.
- Sources of Variability:

setups	workpace variation
machine failures	differential skill levels
materials shortages	engineering change orders
yield loss	customer orders
rework	product differentiation
operator unavailability	material handling



Variability from Resource!

迷思: 變異?不確定性?

現場「變異(variability)」是不好的!!?

但沒有變異，如何「改善」?
就如同考試成績有好有壞，才能對症下藥~

其實...

變異某種程度也代表了「資訊量」!?

	English	Math
Student_A	80	76
Student_B	80	91
Student_C	80	83
Student_D	80	62
Student_E	80	88

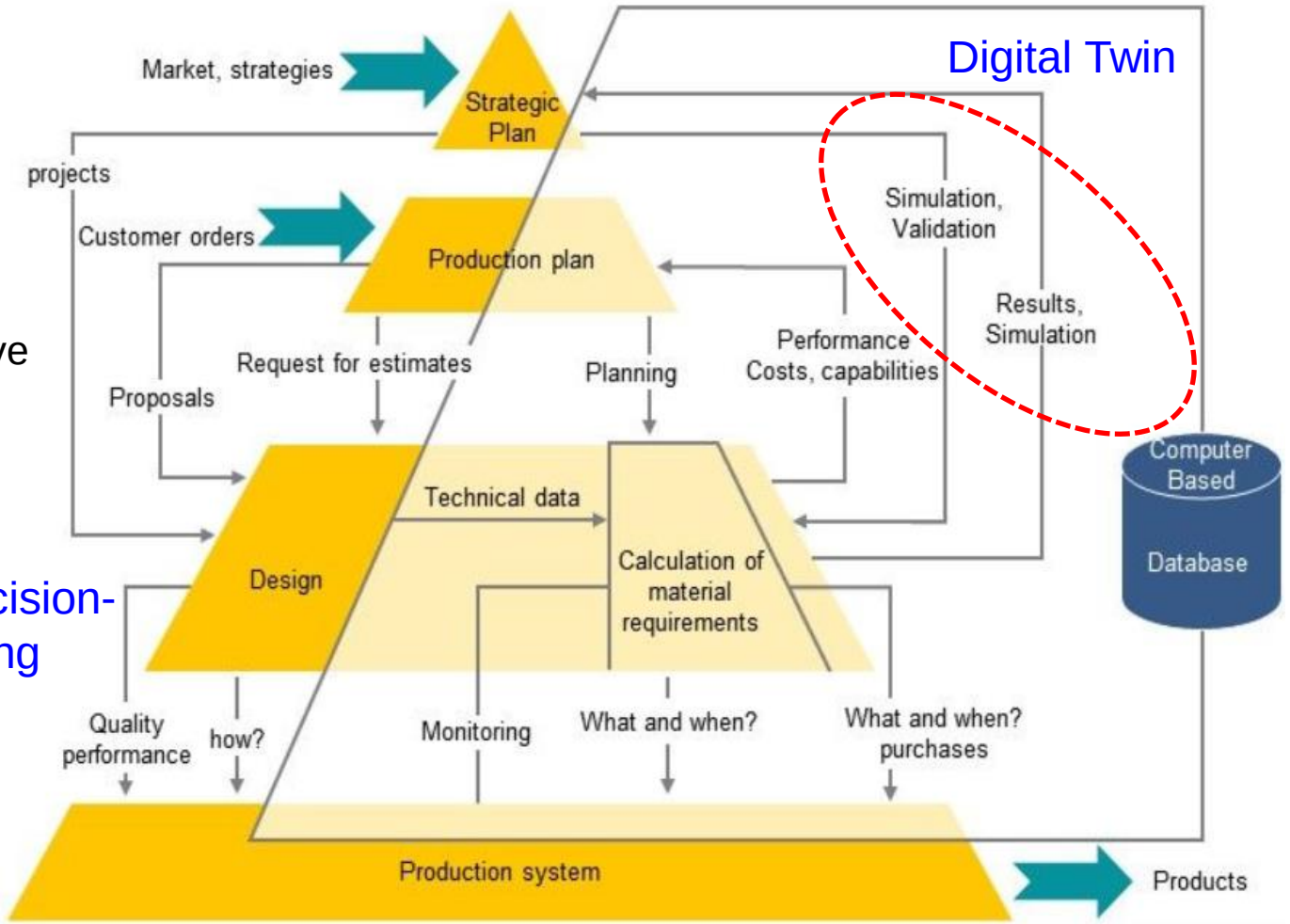
	Layer X	Layer Y
Machine_A	81	76
Machine_B	80	91
Machine_C	79	83
Machine_D	80	62
Machine_E	82	88

Benchmarking! Learn from the BEST PRACTICE.

來自於變異!

CIM and Automation

- Operation Automation
  - Replace Human Efforts
  - Benefits
    - Reduce HR Cost
    - Reduce M/O
    - Improve CT and Improve Productivity,
- Engineering Automation
  - Support Engineer for decision-making or trouble-shooting
  - Benefits
    - Sustain EQ variance
    - Improve quality & Yield
    - Support RD
    - Reduce Engineering Cost
    - Improve Time-to-Market



Waldner, Jean-Baptiste (September 1992). Principles of Computer-Integrated Manufacturing. London: John Wiley & Sons. pp. 128–p132. ISBN 0-471-93450-X.

自動化並不全然意味著大量投資

機器人與設備...

事實上，自動化是製造哲學上的轉變...

透過消除浪費、降低產線不平衡

達到生產標準化且具有彈性的

一種改善過程

Lean Manufacturing

- Lean (identify non-value-added process and remove it)
  - Value and Conflict: Value Stream Mapping (VSM)
  - Waste elimination (8 muda, Womack and Jones, 2003)
    - 1. Transportation
    - 2. Inventory
    - 3. Motion
    - 4. Waiting
    - 5. Overproduction
    - 6. Overprocessing
    - 7. Defects
    - 8. Eschewed Talents
  - Continuous flow
    - Line Balancing
  - Pull production system

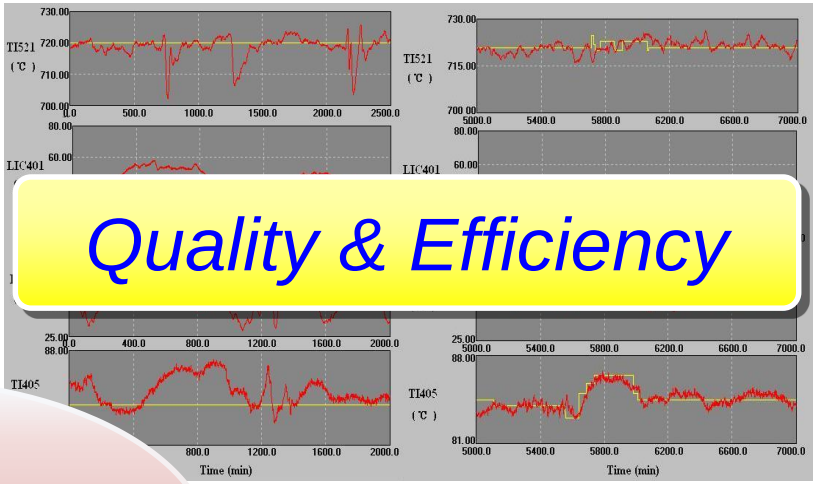
AI並非取代人力…
人機共存、相輔相成

CIM and Automation

MES

On-Time Delivery

APC



Quality & Efficiency

Big Data Analytics

AMHS

Cycle Time Reduction

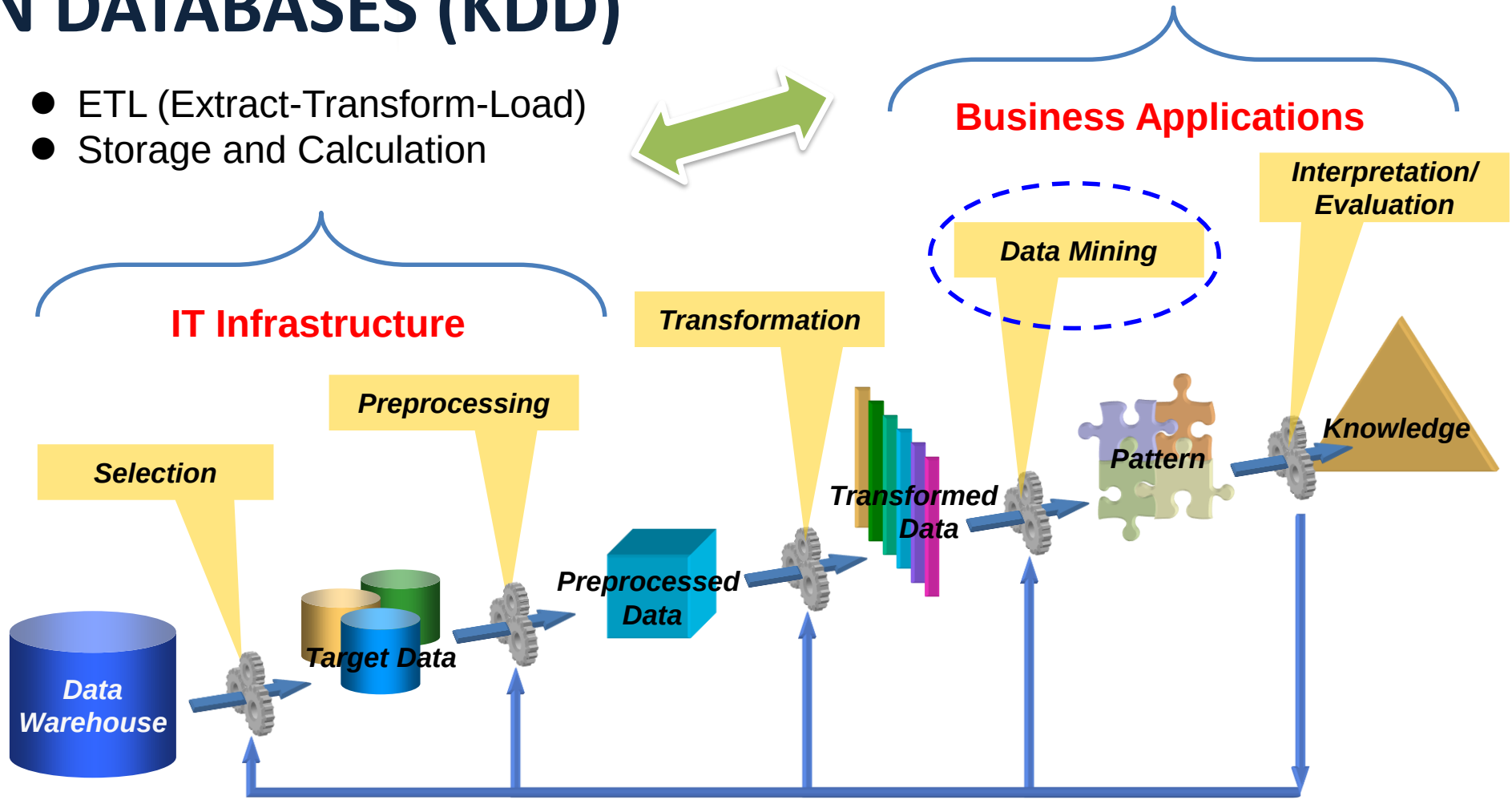
FMEC

Green Environment

KNOWLEDGE DISCOVERY IN DATABASES (KDD)

- ETL (Extract-Transform-Load)
- Storage and Calculation

- Pattern Extraction
- Value Interpretation for **Profitability**



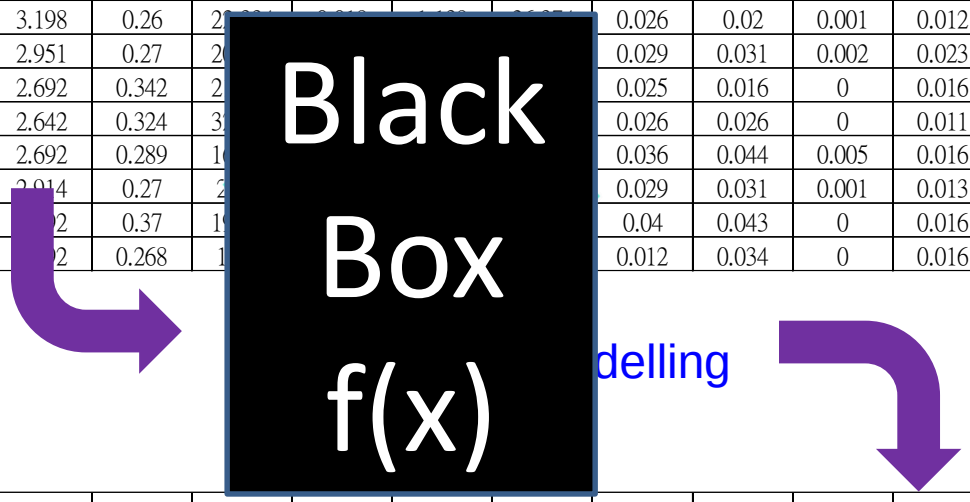
Edge Computing

hadoop Spark python SPSS sas R

Fayyad, U., Piatetsky-Shapiro, G., and Smyth, P. (1996). “From data mining to knowledge discovery in databases”. AI Magazine, 17(3), 37-54.

- Generally, the Prediction of ML/DS…
  - Supervised Learning, Unsupervised Learning, Reinforcement Learning

	Var_1	Var_2	Var_3	Var_4	Var_5	Var_6	Var_7	Var_8	Var_9	Var_10	Var_11	Var_12	Var_13	Var_14	Var_15	Var_16	Var_17	Class
Obs1	-5349	19.8	20.2	0	2.713	0.324	24.069	0.011	2.092	24.301	0.024	0.031	0.002	0.01	6.653	24.478	295.528	1
Obs2	-5597	11.682	28.318	0	2.713	0.319	22.302	0.013	3.949	23.668	0.029	0.032	0	0.01	5.942	23.592	90.394	1
Obs3	-5440.5	22.435	17.566	0	2.713	0.35	21.646	0.016	0.685	23.346	0.023	0.013	0	0.01	3.073	19.719	101.866	1
Obs4	-5614.25	17.163	22.837	0	2.713	0.29	17.521	0.016	1.066	27.508	0.021	0.032	0.002	0.01	2.635	27.749	224.542	1
Obs5	-5534.5	25.457	14.543	0	3.198	0.35	22.798	0.018	1.619	29.305	0.042	0.024	0.001	0.012	3.533	18.54	162.479	1
Obs6	-2649.25	20.551	19.449	0	2.914	0.324	20.481	0.022	1.411	21.722	0.03	0.022	0.001	0.013	2.526	14.507	0	1
Obs7	-5554.25	18.683	21.317	0	3.198	0.38	33.628	0.023	1.641	19.756	0.046	0.034	0	0.012	3.513	24.921	147.607	1
Obs8	-6566	25.443	14.557	0	2.951	0.403	16.265	0.016	1.947	21.162	0.029	0.04	0	0.023	5.361	21.856	0	1
Obs9	-5613.75	17.637	22.363	0	2.914	0.247	20.281	0.031	1.183	16.635	0.039	0.022	0	0.013	7.098	23.817	913.882	1
Obs10	-6546.5	24.351	15.649	0	2.951	0.403	15.373	0.015	4.217	30.47	0.023	0.033	0.006	0.023	4.796	32.937	183.158	1
Obs11	-5652	12.063	27.937	0	2.951	0.27	22.971	0.022	4.47	25.754	0.026	0.029	0	0.023	3.714	24.679	526.739	1
Obs12	-6656.75	9.523	30.477	0	2.914	0.287	20.734	0.02	1.612	13.433	0.026	0.033	0	0.013	5.745	16.663	219.026	1
Obs13	-5681.5	22.925	17.076	0	3.198	0.26	2				0.026	0.02	0.001	0.012	2.813	12.986	163.435	1
Obs14	-5537.5	9.334	30.666	0	2.951	0.27	2				0.029	0.031	0.002	0.023	4.219	24.275	150.967	1
Obs15	-5349.25	12.539	27.461	0	2.692	0.342	2				0.025	0.016	0	0.016	3.356	23.889	168.404	1
Obs16	-5495.75	12.431	27.569	0	2.642	0.324	3				0.026	0.026	0	0.011	7.639	25.813	208.284	0
Obs17	-6518.25	28.636	11.365	0	2.692	0.289	1				0.036	0.044	0.005	0.016	3.703	32.604	329.604	1
Obs18	-4556	8.693	31.307	0	2.914	0.27	2				0.029	0.031	0.001	0.013	3.831	38.056	149.578	1
Obs19	-5432.5	-5.306	25.306	0	2	0.37	1				0.04	0.043	0	0.016	3.584	33.733	977.346	1
Obs20	-5677.75	-8.749	28.749	0	2	0.268	1				0.012	0.034	0	0.016	2.849	23.108	771.212	1



Obs101	-5384.25	2.583	37.417	0	2.828	0.378	33.6	0.012	2.439	19.77	0.018	0.059	0	0.039	4.417	31.293	226.108	?

M. McCann, Y. Li, L. Maguire, A. Johnson, Causality Challenge: Benchmarkingrelevant signal components for effective monitoring and process control,Journal of Machine Learning Research: Workshop and ConferenceProceedings, 6 (2008) 277–288.

Machine Learning

- Find a "Function f(x)"!
- Supervised Learning
  - Data pair (X,Y)
  - Y is label
    - continuous → regression
    - categorical → classification
- Unsupervised Learning
  - Data (x) without label Y
  - Clustering, dimension reduction
- Reinforcement Learning
  - Elements: State, Action, Transition Probability, Rewards, …
  - Optimal Policy: mapping from State to Action

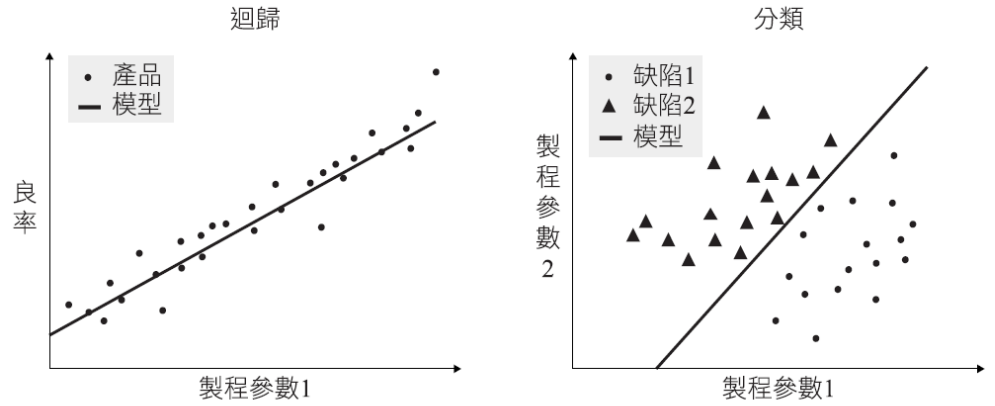


圖 3.4 迴歸與分類

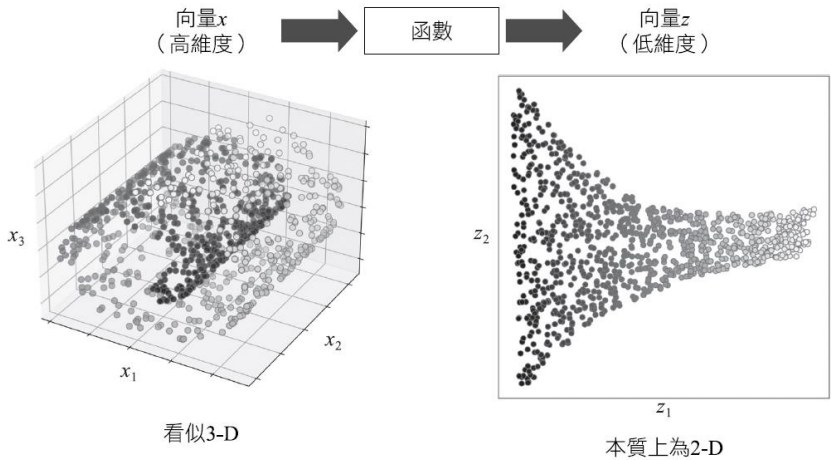


圖 3.6 維度縮減示意圖

Yan et al., 2018. Background Augmentation Generative Adversarial Networks (BAGANs): Effective Data Generation Based on GAN-Augmented 3D Synthesizing. Symmetry, vol. 10, no. 12, 734.

How to improve a complex manufacturing system?

Pittsburgh Technology Council (2014). http://www.pghtech.org/media/64942/panoupdated.jpg

數據科學分析架構

人

問題定義

1. 找對的問題
2. 清楚定義問題
3. 問題牽涉範疇

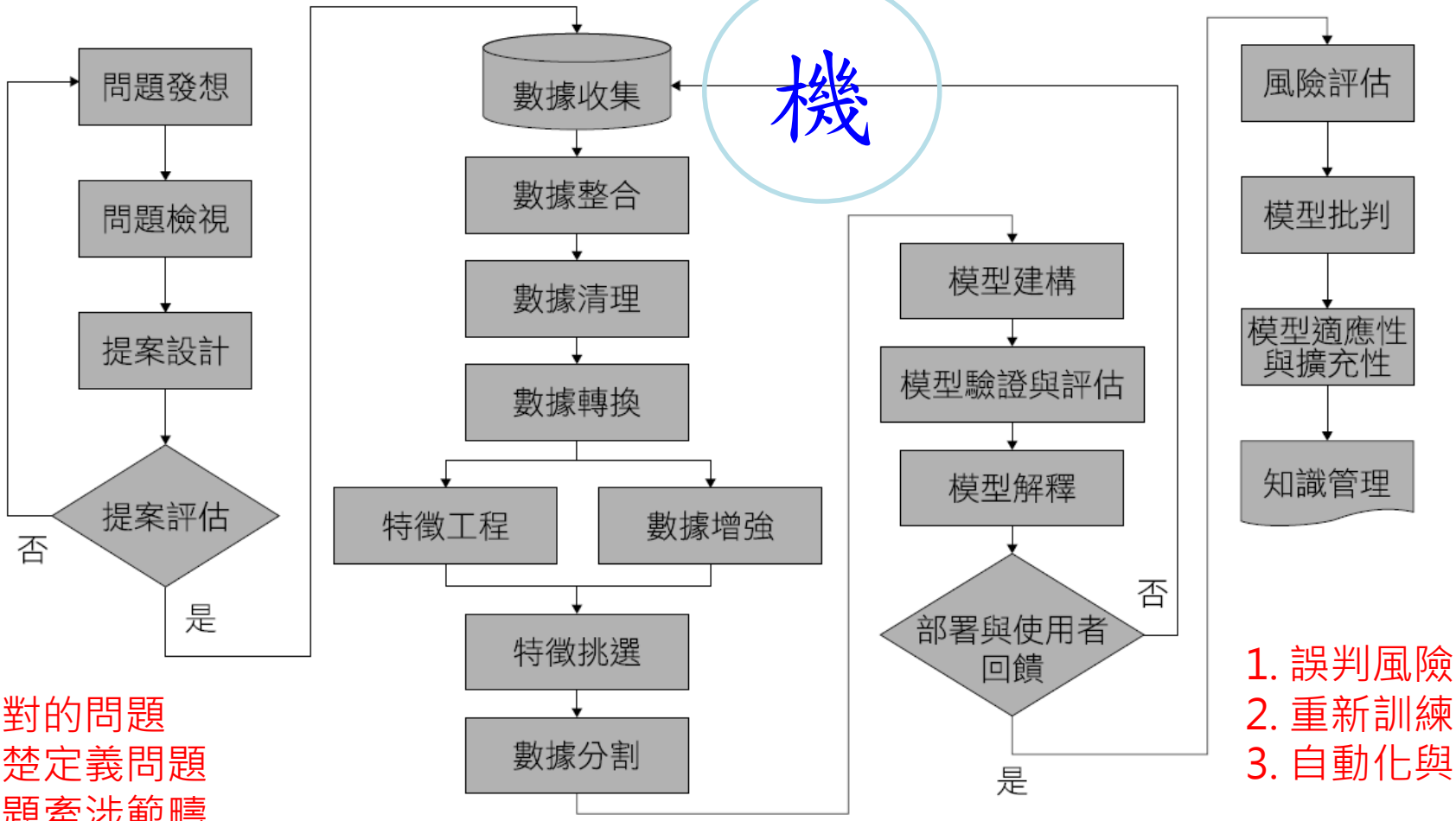
1. 有價值/品質的
2. 異質多元的
3. 場域知識相關

數據分析

1. 假設與背景
2. 使用時機
3. 優與劣

決策支援

人



1. 誤判風險權衡
2. 重新訓練適性調整
3. 自動化與知識管理

問題檢視與定義

- 跨部門業務檢核表 (cross-dept. work checklist)

試想**當前**遇到的問題

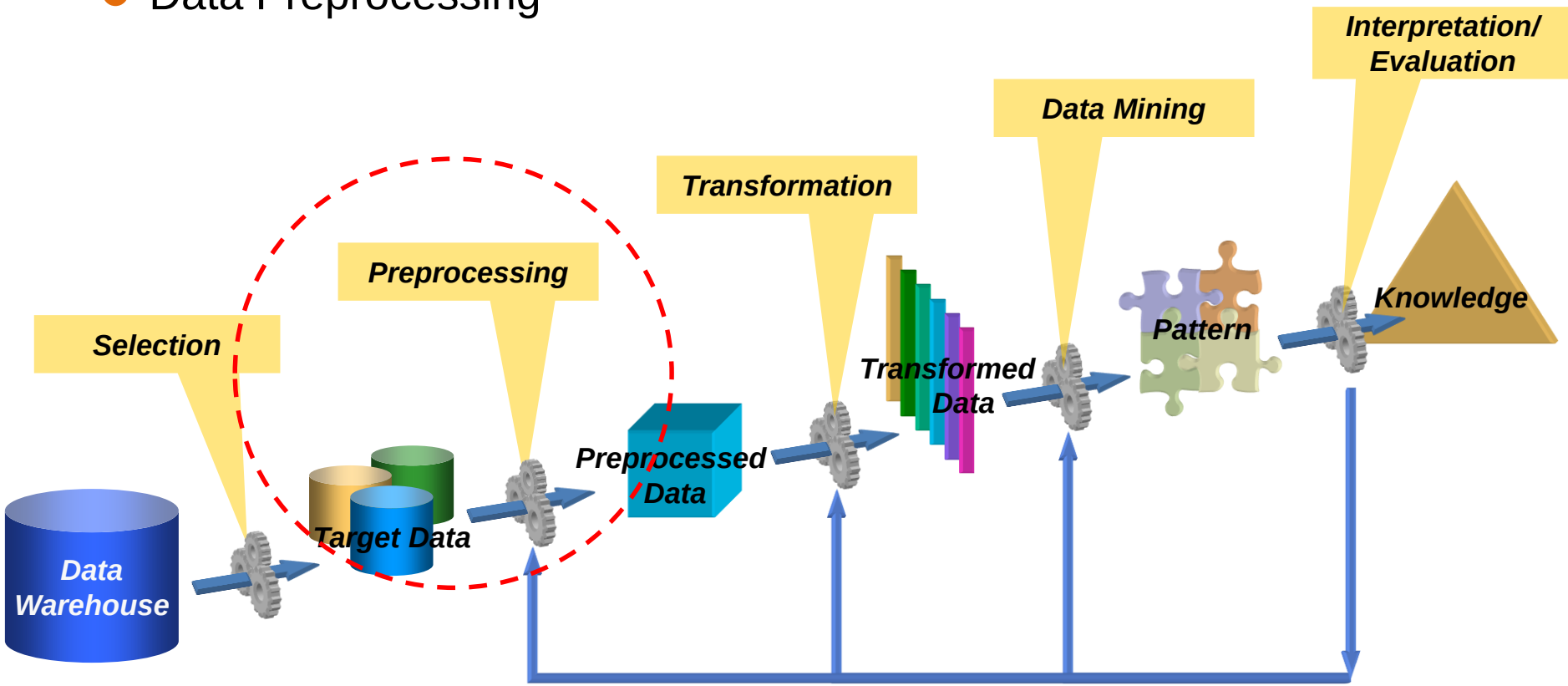
- 這問題是**當下**要做的嗎?
  - 頻率高且重要?
  - 有數據?
  - KPI清楚?
  - OKR可分解?

我所屬 工程 處 部門/課		
與他 品保 部門	As-Is (文字或作圖)	To-Be AI (文字或作圖)
流程業務 (Who/What) 欲改善的業務與流程為何？資源與決策關係人為何？	流程(針對某一業務/功能)： 人工瑕疵檢測 資源(會牽涉到什麼資源)： 技術員、電子顯微鏡...	AOI瑕疵檢測 機台、大數據影像資料庫...
頻率與重要性 (When) 該業務發生的頻率與重要性為何？	頻率(該業務發生頻率)： 高(一分鐘XXXX顆檢查) 重要性(該業務的重要性)： 高(關鍵XXX製程站點品檢)	高(一分鐘可達XXXX顆檢查) 高(關鍵XXX製程站點品檢)
問題 (Why) 目前該業務有什麼問題、困難與挑戰？	問題(目前遇到什麼問題)： 人為誤判率高 問題的問題(根本原因在哪)： 誤判率高的理由是品檢員判斷不一、長時間眼睛疲勞...	AOI可能overkill率高 由於影像數據還在收集中，AI模型訓練仍加強
功能與方法 (How) 目前該業務處理的方法或提供什麼功能？	功能/方法(怎麼做這業務)： 人工操作電子顯微鏡用肉眼觀察量測 投入/輸出(功能投入/輸出)： 投入：技術員、電子顯微鏡 輸出：良品/不良品(bin code)	用AI光學影像自動判斷 投入：光學檢測機 輸出：良品/不良品(bin code)
資料 (Where) 業務中會用到的分析數據從哪裡收集？	資料(欄位名稱與資料來源)： 缺陷影像、FDC數據根因分析 資料品質(資料可靠與否)： 根據機台或光學影像解析度而異 數據跟抽樣頻率有關	檢測員bin code判斷影像與結果、工程師複檢判斷結果 差(尤其隨機defects的狀況人工不易歸類分bin)
績效KPI改善與衝突點(Conflict) 透過To-Be改善自己部門的KPI，是否會造成該業務相關部門他們KPI的惡化	我方：工程處：檢測員誤判率高(false alarm)、分bin錯誤率高、需要複判且時間長 對口： 品保處：「寧可錯殺一百，不可放過一人」	工程處：AOI可協助找出製程根因來源、縮短故障排除時間 品保處：AOI使人力成本降低

Knowledge Discovery in Databases (KDD)

Data Analytics Framework

- Data Preprocessing



製造現場與其資料特性

Characteristics	Data & Management Issues
Batch size（生產批量）	Lot ID decomposition, lot tracing, merge/split
Parallel machine（平行機台）	Missing value, high dimension, multicollinearity
Golden machine（黃金機台）	Utilization, class imbalance → Inference bias
Recipe and parts（處方與零件）	Nominal or categorical variable → too many levels → too many dummy variables → high dimension
Sampling testing（抽樣檢測）	Missing value, multi-response, delay, **figure (AOI)**
Engineering or R&D lot（工程與實驗貨）	Outlier, machine contamination, setup capacity loss, small dataset
Maintenance（維修保養）	When? how (大保養 or 小保養)? capacity loss, reliability, typing error, text, choosing "others"
Changeover（換線、換模）	Sequence-dependent setup time, capacity loss
Bottleneck shift（瓶頸站轉移）	Different treatment, WIP transfer, product-mix
Queue time limit（等候時間限制）	Defects, WIP
Data imbalance（資料不平衡）	Inference bias

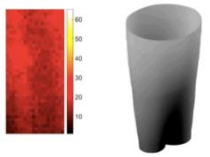
Inventory = Lead Time + Uncertainty

Lee, C.-Y., and Chien, C.-F., 2022. Pitfalls and protocols of data science in manufacturing practice. Journal of Intelligent Manufacturing, 33, 1189–1207.

生產線數據

表 5.3　製造現場不同的數據類型

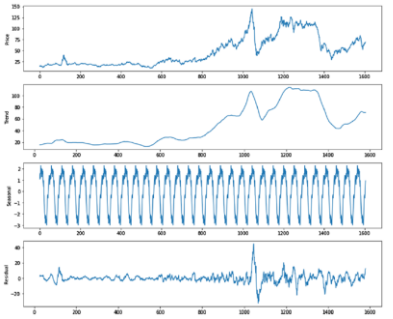
數據種類	特性	主要特徵	常見的特徵工程與分析模型
一般數據	特徵之間相關	領域知識相關特性	• 以領域知識進行的數據轉換與整合 • 統計量（平均值、標準差、偏態、峰態等） • 特徵學習 • 迴歸分析、決策樹、符號迴歸（symbolic regression）
時間序列	• 時間相關（趨勢性、週期性、季節性） • 函數結構 • 低維度	時域、領域知識相關特徵	• 時間標記特徵 • 滑動時窗特徵（sliding window based statistics） • 時間序列分解 • 差分整合移動平均自迴歸模型（autoregressive integrated moving average, ARIMA）
高頻訊號	• 時間相關（趨勢性、週期性） • 振動訊號（高頻） • 函數結構 • 低維度 • 高取樣頻率	時域、頻域、時頻域特性	• 滑動時窗特徵（sliding window based statistics） • 傅立葉轉換（Fourier transform, FT） • 短時距傅立葉轉換、小波轉換（wavelet transform, WT） • 希爾伯特-黃轉換（Hilbert–Huang transform, HHT）
圖片影像	• 空間相關 • 多通道訊號 • 高維度（3D 影像）	影像特性	• 卷積神經網路（convolutional neural network, CNN） • 自編碼器（autoencoder, AE） • 生成對抗網路（GAN）
影片	• 時間與空間相關 • 多通道訊號 • 高維度	上述所有特性	上述所有方法



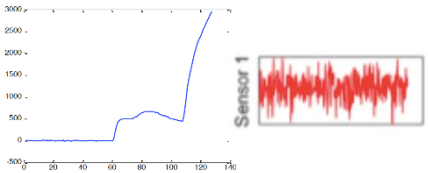
Paynabar, K. (2019). Data science for manufacturing automation: low dimensional learning from high dimensional data. IEEE CASE 2019 Data Science Workshop.

Value x
(one-to-one)

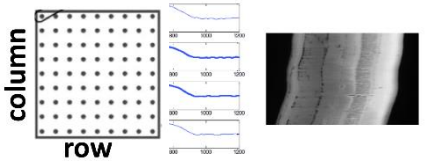
Vector $\boldsymbol{x} = f(t)$
(many-to-one)



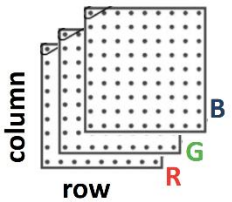
Vector $\boldsymbol{x} = f(t)$
(many-to-one)



Matrix $\boldsymbol{X}$
(many-to-one)

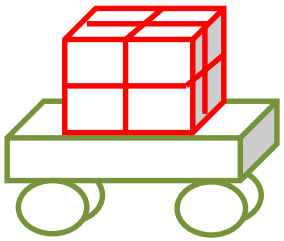


Tensor $\mathcal{X}$
(many-to-one)



Parallel Machine

- Not identical (有機差) → Tool Matching



WS_A_Mach_1

WS_A_Mach_2

Data Preparation

- Missing Value

Lot ID	WS_A_ Mach_1_ Temp	WS_A_ Mach_2_ Temp
Lot001	820	N/A
Lot002	820	N/A
Lot003	N/A	840
Lot004	N/A	840

Lot ID	WS_A_ Temp	WS_A_ Mach_Type
Lot001	820	1
Lot002	820	1
Lot003	840	2
Lot004	840	2

Recipe/ Parts- Nominal (名目) or Categorical (類別) Variable

- Transfer to dummy variable (啞變數, 虛擬變數) (One-hot encoding)

Lot ID	WS_A_Mach_1_Parts
Lot001	PartsA
Lot002	PartsB
Lot003	PartsA
Lot004	PartsC
Lot005	PartsD
Lot006	PartsE
Lot007	PartsB
Lot008	PartsA
Lot009	PartsC
Lot010	PartsE

Lot ID	WS_A_Mach_1_PartsA	WS_A_Mach_1_PartsB	WS_A_Mach_1_PartsC	WS_A_Mach_1_PartsD
Lot001	1	0	0	0
Lot002	0	1	0	0
Lot003	1	0	0	0
Lot004	0	0	1	0
Lot005	0	0	0	1
Lot006	0	0	0	0
Lot007	0	1	0	0
Lot008	1	0	0	0
Lot009	0	0	1	0
Lot010	0	0	0	0

- Given N levels, the method will generate N-1 dummy variables.

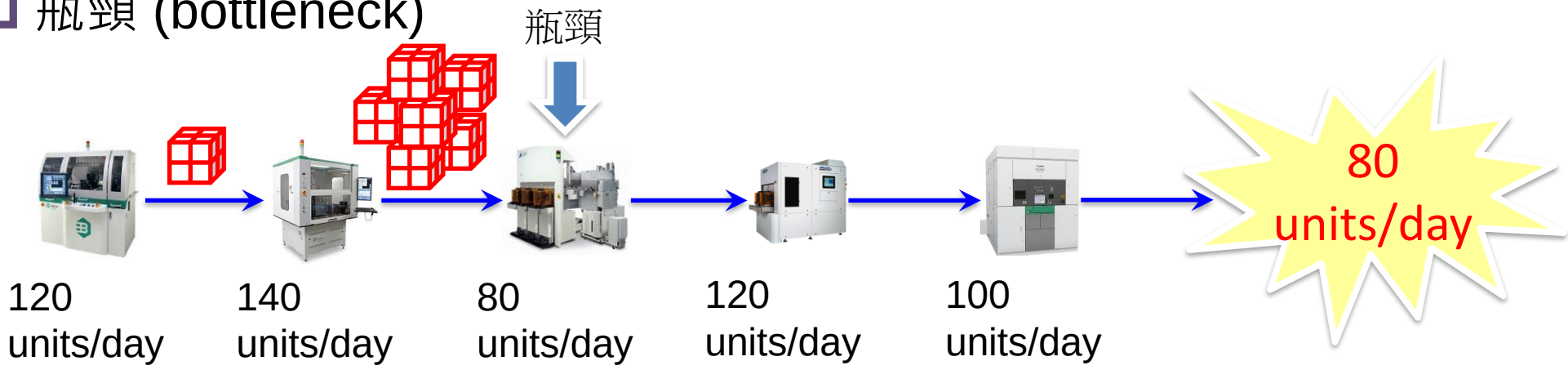
- 某類別變數level過多 (Recipe or Parts數目過多)
  - 轉成Dummy Variables會產生許多新變數
    - Issue: Curse of Dimensionality (維度的詛咒)
  - 建議方式
    - 將部分level整合 (grouping)
      - eg. 產品 → 產品族
      - eg. tool → tool group
    - 選取特定時間區間的資料進行分析
      - 降低該變數level的數目
    - 將某類別中只有出現一次觀測值的level刪除
      - 沒有再現性!

實驗貨工程貨

- 主要是研發產品、或機台測試校正用，資料上有時會呈現Outlier。
- 若針對一般性產品資料分析，需要在分析前先濾掉或移除。
- 一般而言，有特殊的LotID，在收集資料時可先過濾掉，或在預處理中進行。若無給定特殊LotID，那需要在資料中觀察，例如使用特殊機台、特殊recipe，該產品只經過某些特定製程等。

特性 \ 階段	實驗貨工程貨	一般正常貨
資料量	剛起步，較少 (n<<p)	較多 (大量生產) (n>>p)
資料數值	實驗設計，參數較分散	很多參數已成為定值
成本	需要反覆試驗，較高	大量生產，較低
良率	較低	較高且穩定
分析方法	最佳化方法、無母數、實驗設計/田口方法、LASSO、SVM、Forward Stepwise...	有母數、GLM、Random Forests, Boosting, Deep Learning…

瓶頸 (bottleneck)



- 一般來說，瓶頸機台常是利用率高且週期時間長的機台→ WIP堆積多

內部瓶頸

- 特定機台或工作站的產能限制
- 薪資水準或工作環境無法吸引到優秀員工
- 搬運/運輸/物流形成為生產的瓶頸
- 現場管理團隊能力/生產規劃團隊的排程/規劃
- 管理階層對於系統產能不正確假設/認知

外部瓶頸

楊大和(2016)

- 原物料的供應
- 特定區域的人力供給 (勞工和幹部)
- 公司產品的品牌知名度
- 公司產品的配銷通路

資料合併

- 表單串接 – 注意必須為相同的欄位名稱, i.e., KEY
- Key通常為Lot ID, Machine ID等

Event-based record

Time	SVID 1	SVID 2	.....
2/11 00:06:29			
2/11 00:10:41			
2/11 03:41:09			
.			
.			
.			
2/11 23:11:57			

Period-based record

Time	SVID 101	SVID102	.....
2/11 00:00:00			
2/11 01:00:00			
2/11 02:00:00			
.			
.			
.			
2/11 23:00:00			

兩種不同類型的資料紀錄，該如何合併串接呢? Which one could be "Main Table"?

Data Merge

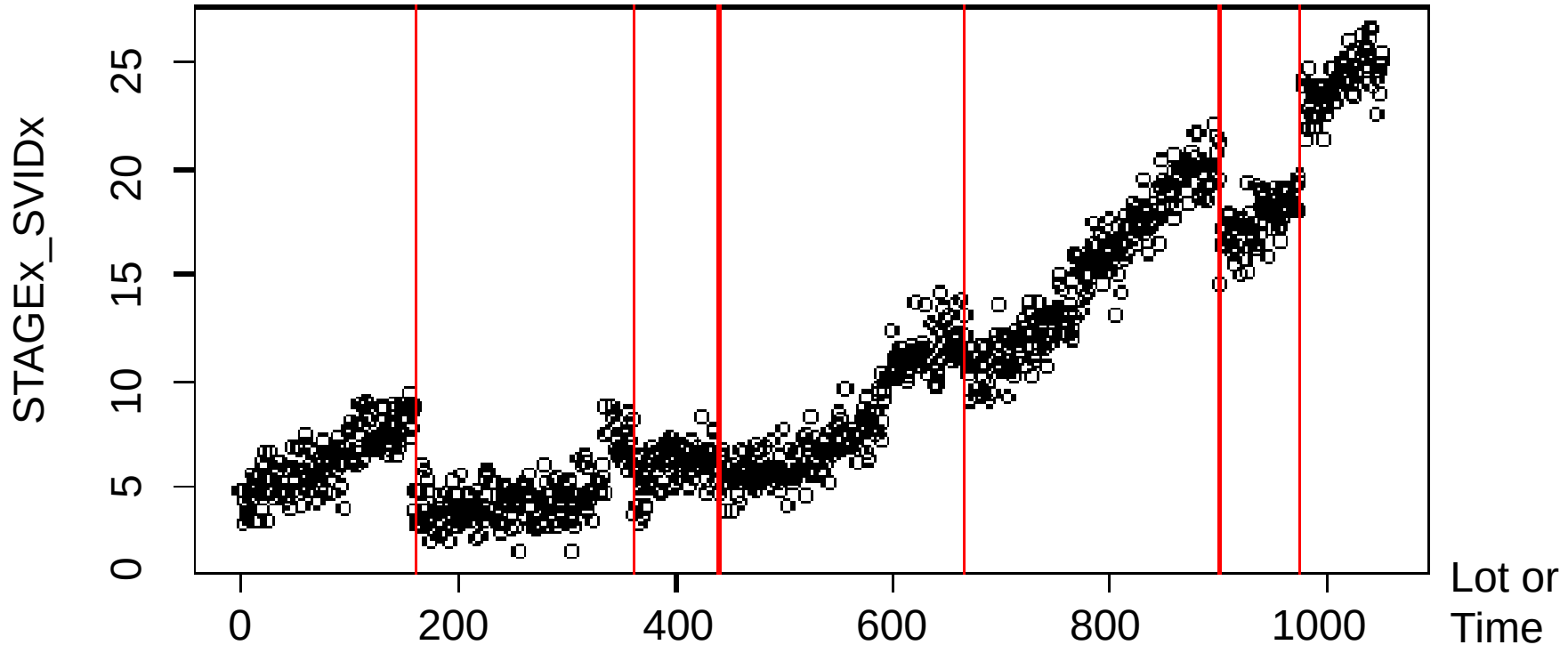
比較表	以 Event 為基準做串聯	以 Period 為基準做串聯
記錄方式	有"事件"才記錄。 例如機台換模、停機、人為調機等	固定"週期"記錄。 例如1小時一次
串接前 表單特性	資料筆數通常較少且稀疏	資料筆數通常較完整
串接後優點	資料較完整 (串接後可能遺漏值較少)	可觀察週期性變化
串接後缺點	可能有某"長"時間區段無資料	資料可能有部分缺失 (串Event會造成大量遺漏值)
建議串接 方法	Rolling Forward Nearest time	Rolling Forward Rolling Backward Nearest time
目的或 使用時機	**Troubleshooting**	**Monitoring**

Lee and Dong (2019)

維修保養(調機)

- 定期保養 (年保、季保、月保、機台生產10,000產品…)
- 若有收集保養資料，可直接找出保養時間點。若無，可藉由推估
  - 機台up與down的時間 (Overall Equipment Effectiveness, OEE)
  - 產品的queue time
  - 機台參數(eg. status variable identification, SVID)的監控

再與相關部門(例如設備)進行確認。



維修保養troubleshooting

- 機台故障表單 + MES (含Recipe跟使用的零組件材料) + 良率
- 針對某一機台ID，用"時間"進行資料的合併串接

機台故障表單 | MES | 良率

Time	Down code	Repair		Recipe	Part	Material		Yield
2017-05-07 14:05:28	Run	No或NA		Recip18	Part01	Mater05		94.3%
2017-05-07 16:12:14	Run	No		Recip18	Part01	Mater05		93.1%
2017-05-07 17:41:30	Down04	Part19 (換零件)	…	Recip18	Part19	Mater05	…	82.5% 或內插
2017-05-07 19:22:43	Run	No		Recip18	Part19	Mater05		82.5%
2017-05-07 20:18:17	Run	No		Recip02	Part19	Mater10		76.7%

$$\frac{93.1\% \times [(17:41:30) - (16:12:14)] + 82.5\% \times [(19:22:43) - (17:41:30)]}{(19:22:43) - (16:12:14)}$$

Data/Class Imbalance原因

- # of qualified product extremely dominates the # of defective product
- 資料不平衡大多發生於類別型態的資料上(一般泛指兩類)，若以連續分佈的資料來說，資料不平衡代表資料可能集中在某些區段，而這些區段也可以稱作"群/類別"。
- 資料不平衡的情況可能出現在獨立變數或是相依變數。

資料多不平衡才算不平衡?

- For the two classes (0 and 1), rule of thumb…
  - 10% vs. 90%? 5% vs 95%? or 1% vs. 99%?
  - It depends… on your industry applications.
- From a theoretical viewpoint, it occurs if it skews the model training for prediction…
- 也就是說，如果你訓練的模型準確率"異常地高"
  - Overfitting? Class Imbalance?

Lot ID	X1	…	X100	Inspection
Lot01				PASS
Lot02				PASS
Lot03				PASS
Lot04				PASS
Lot05				PASS
Lot06				PASS
Lot07				**FAIL**
Lot08				PASS
Lot09				PASS
Lot10				PASS
Lot11				PASS
Lot12				PASS

預測Inspection的結果

- 由於只有1筆FAIL
- 預測模型全部都猜PASS
  - 不需要分析變數X1~X100
  - 準確度可達 11/12 = 91.7%

資料整合與清理

問題	原因	步驟
不正確的資料	資料的值超出合理範圍	資料整合
不一致的資料	不同來源資料整合後所出現的分歧 數值不一致、資料內容不一致、欄位不一致	
重複的資料 (Duplication)	重複記錄的欄位或數值 (data type: single, double…) (同樣的資料卻不同的寫法，“做了36顆”, “打出36粒”, “生產36個”，”左上角區塊有產生defects”, “defects發現於左上方 區域”)	
冗餘的資料 (Redundant)	出現相同意義的資料或欄位 具有相同意義或彼此間存有已知數學關係的欄位，此變數的屬性或意義可由另一變數推導而得 (有些冗餘資料可以經由相關分析偵測到) eg. 地址vs.地區	
遺漏值	量測設備或人為因素所造成的資料遺漏	資料清理
雜訊	資料本身的誤差或資料輸入的偏差	
離群值	資料本身的特性、不當量測或資料輸入錯誤	
資料尺度不適	資料格式不符合挖礦工具的假設	資料轉換 (正規化)
資料太多	資料或維度過高	資料化約

(簡禎富、許嘉裕，2014)

迷思: 補遺漏值?

遺漏值填補是...補「資料」?

	English	Math
Student_A	80	76
Student_B	80	91
Student_C	80	83
Student_D	80	62
Student_E	80	?
Avg.	80	

Max: 91
Min: 62
Avg: 78

迷思: 補遺漏值?

- 填補遺漏值一般會造成部分失真或偏差

- 使用者應根據製造「資料特性」以及「分析目的」，來決定填補遺漏值的方法，以避免忽略原本應有的資訊

- 方法**(補值一定要找關係!!!!)**
  - 忽略變數值 (“N/A” 與 “0” 是不一樣的!!)
  - 移除觀測值 (remove the tuple)：當依變數Y遺漏時
  - 人工填寫遺失值
  - 使用一個全域常數填充遺漏值 (eg. N/A)
  - 使用屬性平均值
  - 使用與給定變數值屬於同一類別的所有樣本之平均值
  - 模型: 簡單/多元線性迴歸、類神經網路、最鄰近估計法K-Nearest Neighbor (KNN)、Random Forest、” MICE”、Inverse Distance Weighting (IDW)…

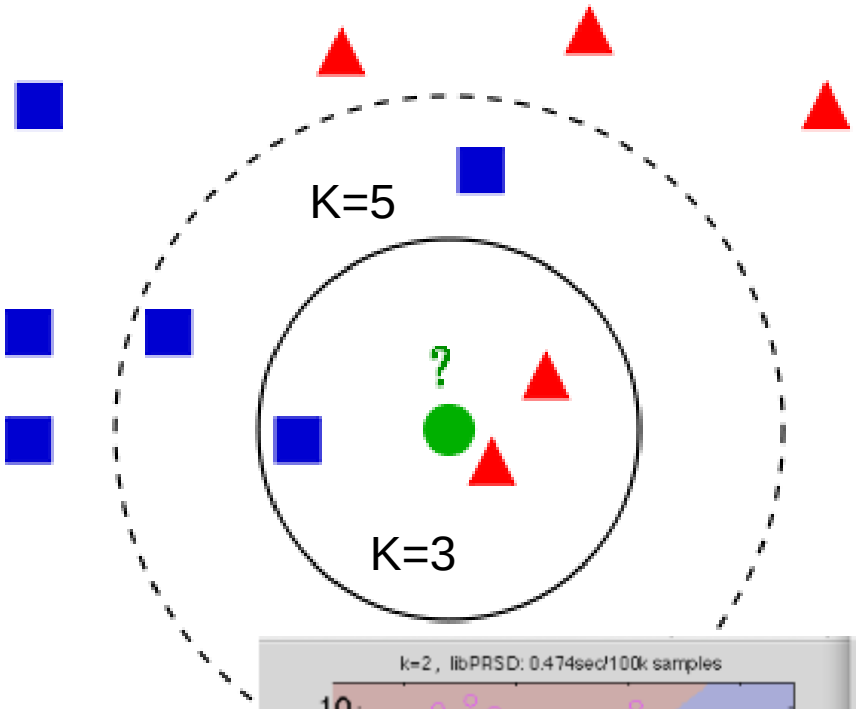
最鄰近估計法 (Nearest Neighbor Estimator)

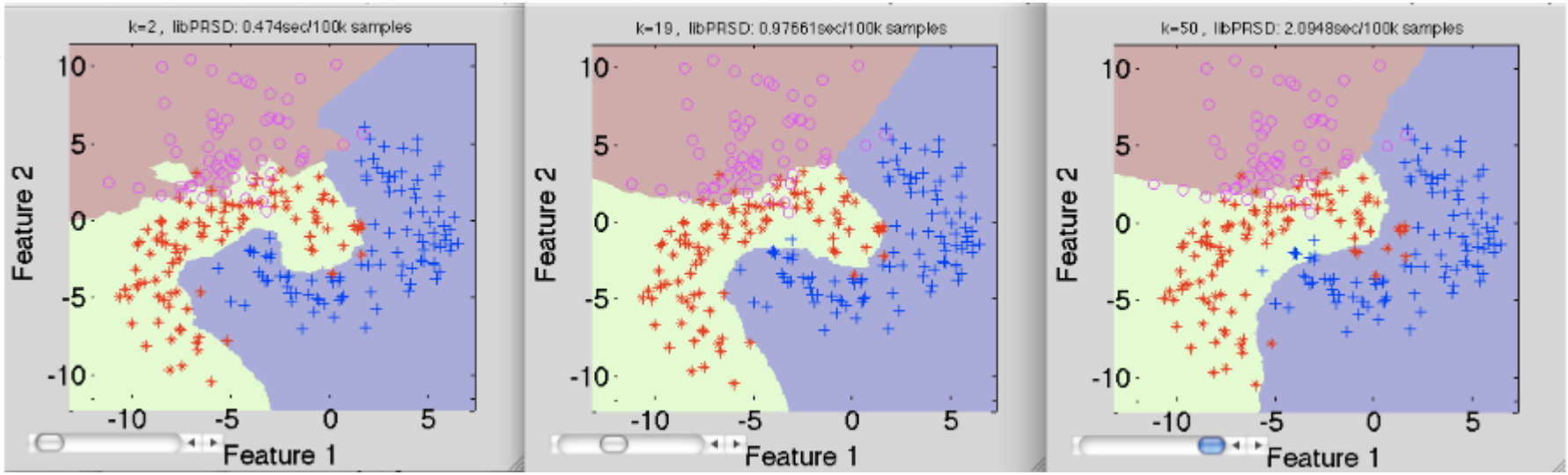
- 補值一定要找關係!!!!
  - 利用其他變數與遺漏值之間的關係來估計遺漏值
  - 補值：可利用其他變數與遺漏值之間的關係來估計遺漏值
  - 例如，若「收入水準」變數發生遺漏值，或許可能用「房子坪數」這變數來做預測

- 假設在現有的資料庫中發現某一顧客其購買反應的態度為一遺漏值

顧客	性別	年齡	薪水	購買反應
A	女	27	$19,000	No
B	男	51	$64,000	Yes
C	男	52	$105,000	Yes
D	女	33	$55,000	Yes
E	男	45	$45,000	No
F	女	45	$100,000	?

最鄰近估計法K-Nearest Neighbor (KNN)





Wikipedia, https://zh.wikipedia.org/wiki/%E6%9C%80%E8%BF%91%E9%84%B0%E5%B1%85%E6%B3%95

perClass, 2017. kb16: Visualize the effect of a change of parameters in a trained classifier. http://perclass.com/doc/kb/16.html

迷思：補遺漏值?

- 不偏估計量 vs.變異程度

觀測值	原始資料值	第 11 筆遺漏	利用平均數估計	利用標準差估計
1	0.0886	0.0886	0.0886	0.0886
2	0.0684	0.0684	0.0684	0.0684
3	0.3515	0.3515	0.3515	0.3515
4	0.9874	0.9874	0.9874	0.9874
5	0.4713	0.4713	0.4713	0.4713
6	0.6115	0.6115	0.6115	0.6115
7	0.2573	0.2573	0.2573	0.2573
8	0.2914	0.2914	0.2914	0.2914
9	0.1662	0.1662	0.1662	0.1662
10	0.44	0.44	0.44	0.44
11	0.6939	?	0.3731	0.6622
平均值	0.4023	0.3731	0.3731	0.3994
標準差	0.2785	0.2753	0.2612	0.2753
誤差值			0.3208	0.0317

平均值補的愈多，資訊量就愈少

(簡禎富、許嘉裕，2014)

數據品質

資料理解就是選取資料、資料異質、資料品質

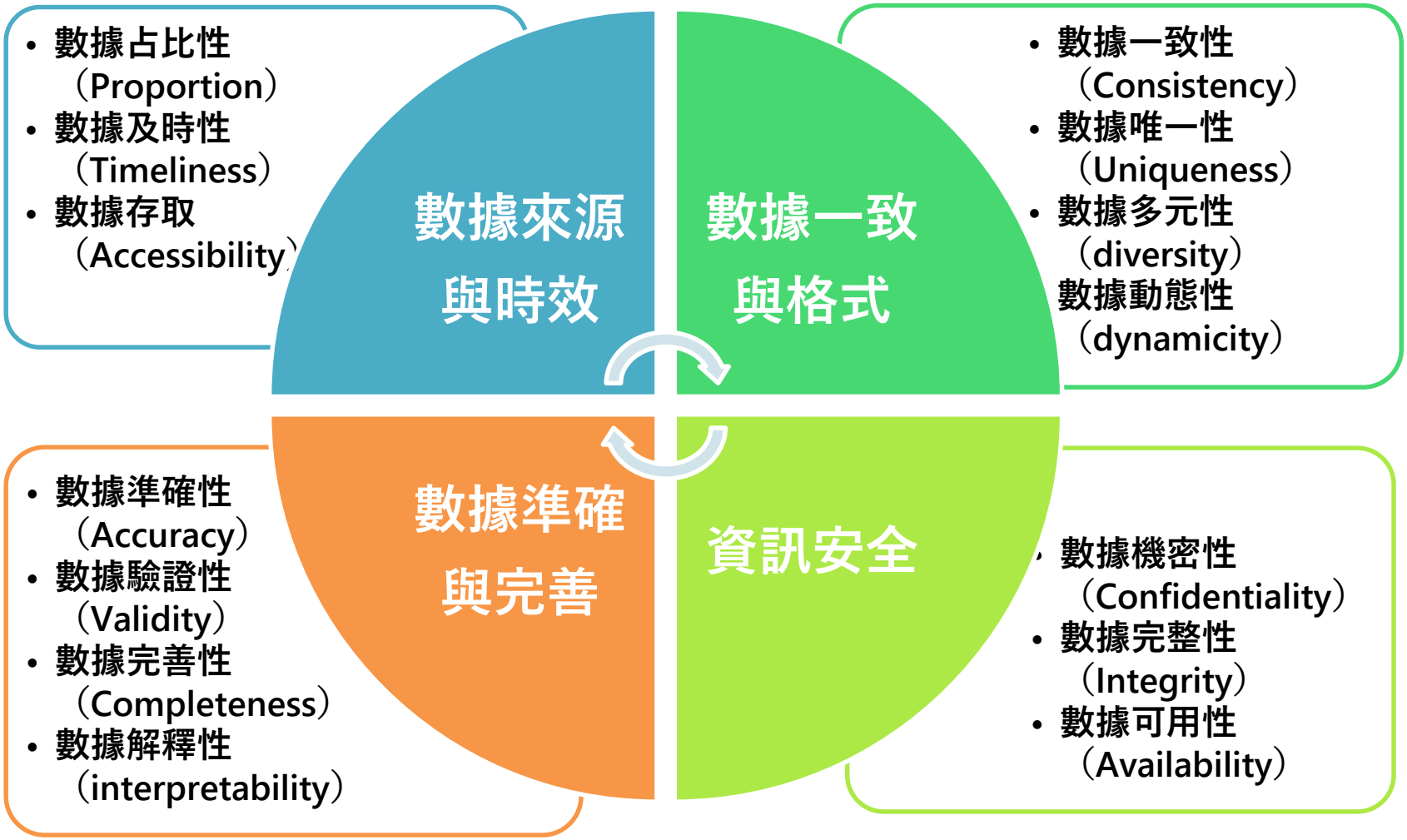
- 從資料庫與檔案中濾出相關的資料，透過魚骨圖篩選資料
  - 選擇適當的獨立相關變數；變數間的獨立性，可降低變數內含資訊的重疊性
- 資料數量
  - 檢視三個維度：樣本個數(n) (代表性)、變數/特徵個數(p)、異質性(資訊量與格式)
    - 一個母體平均數的單尾檢定時，當樣本數佔母體總數的比例R=80%時，顯著水準0.05要調整為0.0001. (馬瀰嘉，2019) (樣本大到接近母體，不需檢定直接敘述統計視覺化)
    - when 1,000,000 SNPs are tested in a genome-wide association study (GWAS), α would be 5×10^{-8} and when expression dysregulation is examined for 20,000 genes on a whole-transcriptome microarray, α would be 2.5×10^{-6} (Jafari and Ansari-Pour, 2019) (變數個數太多會造成維度過高，使得分析時間過長→ 維度詛咒)
- 資料品質
  - Univariate
    - Statistics: mean(median, mode), variance, skewness, kurtosis
    - Visualized plot: missing values, noise, outlier…
    - Regression: $y = \beta_0 + \beta_i x_i + \varepsilon$. Check β_i violating the engineering experience
    - Eg. Milling time (x) and thickness (y) should be with negative β_i .
  - Multiple Column (Validity and Reliability 信度與效度)
    - Correlation or Covariance between two variables
    - Eg. machine temperature vs. utilization is positive.

馬瀰嘉(2019)，巨量資料分析下如何調整顯著水準，智慧科技與應用統計學報，16(2)，19-36.
Jafari M, Ansari-Pour N. Why, When and How to Adjust Your P Values? Cell J. 2019 Jan;20(4):604-607. doi: 10.22074/cellj.2019.5992. Epub 2018 Aug 11. PMID: 30124010; PMCID: PMC6099145.

數據品質

數據品質的評量構面

- 除了透過視覺化(visualize)確認數據集的噪音、離群值、遺漏值等狀況，接著可對數據品質做一整體性的評估

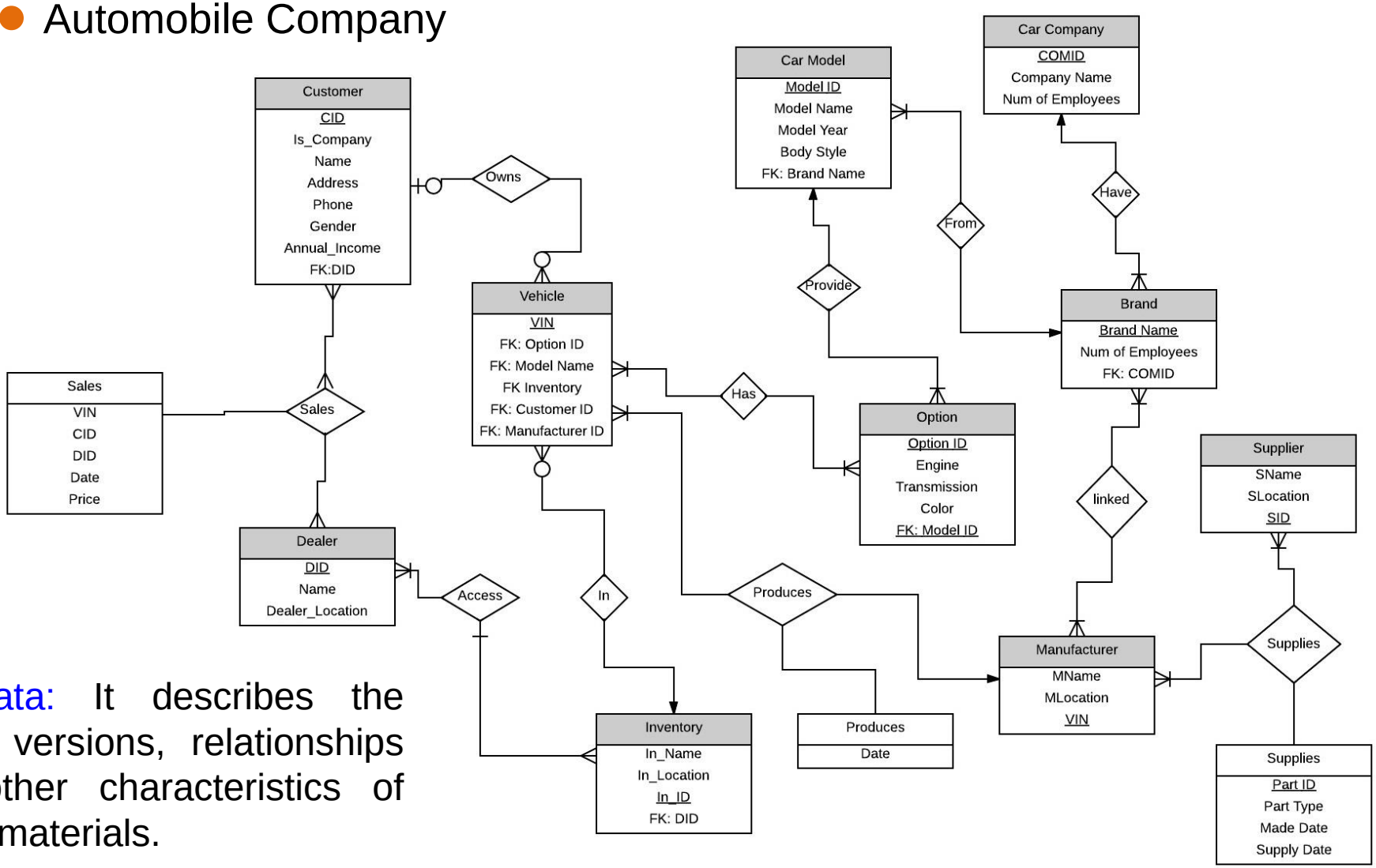


李家岩、楊舒惠、歐子毓、盧宣文, 2022。數據科學分析的土壤：數據品質評估，東華AI通訊報，第三期。

數據品質：企業系統長期累積的積習...

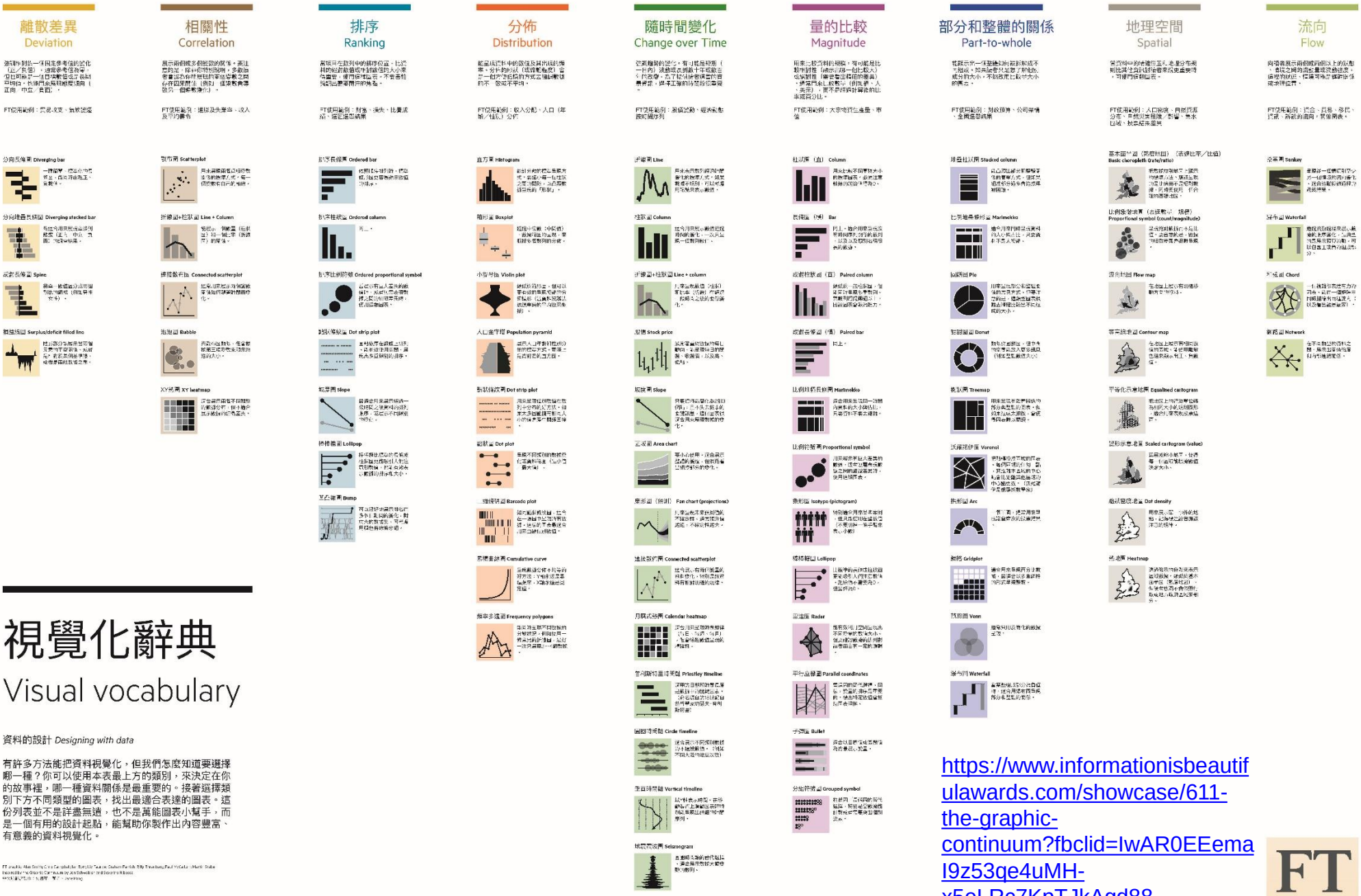
Data Quality Investigation- Entity-Relationship (ER) Model

- Automobile Company

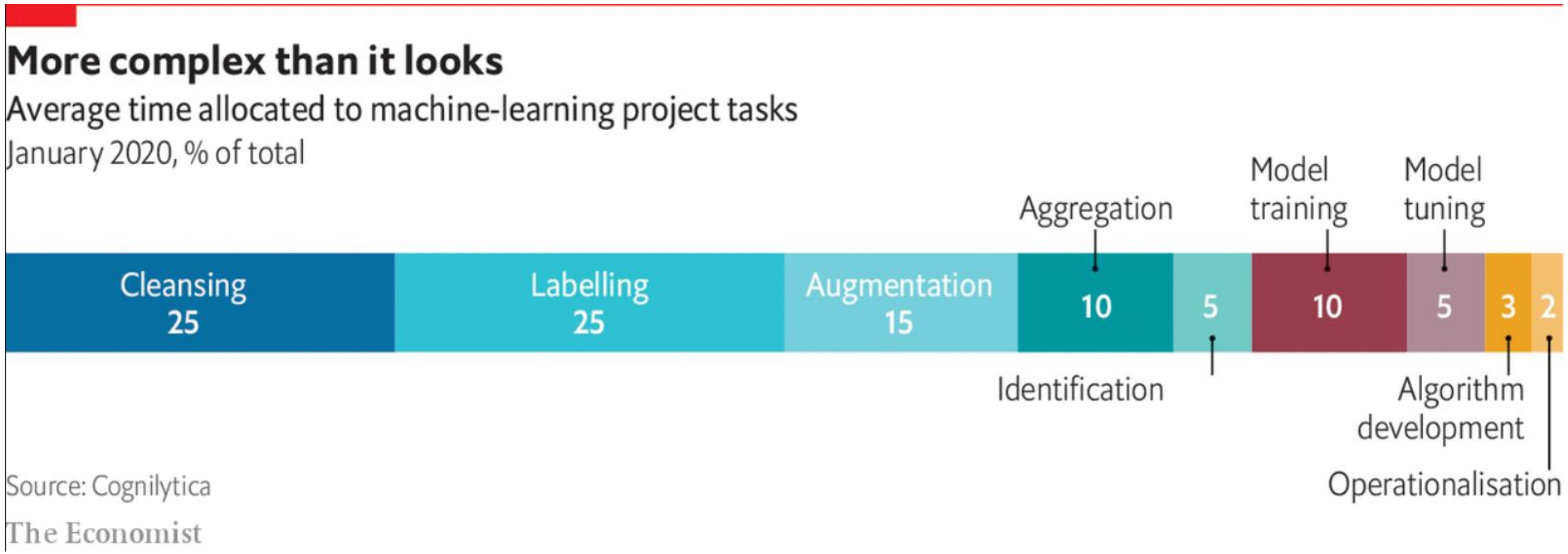


Metadata: It describes the types, versions, relationships and other characteristics of digital materials.

https://stackoverflow.com/questions/23660839/need-help-on-an-er-diagram-for-an-automobile-company



https://www.informationisbeautifulawards.com/showcase/611-the-graphic-continuum?fbclid=IwAR0EEemaI9z53qe4uMH-x5eLRc7KpTJkAgd88-NvirUDwjPB7nu5RKLYphs



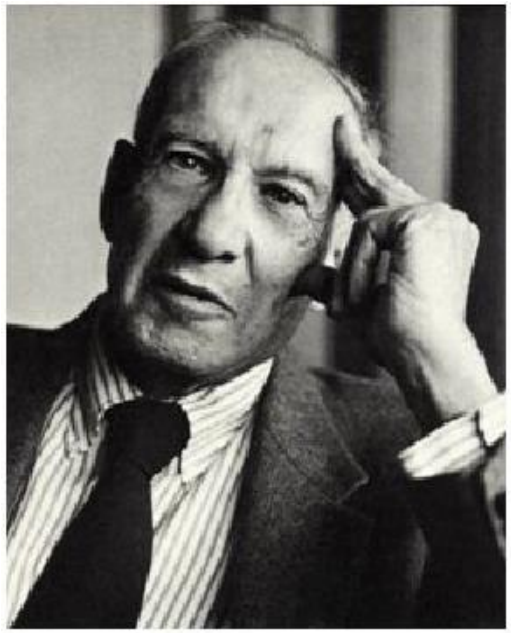
The Economist, 2020. For AI, data are harder to come by than you think.
https://www.economist.com/technology-quarterly/2020/06/11/for-ai-data-are-harder-to-come-by-than-you-think

“In God we trust, all others must bring data”

- Edward Deming (1900-1993)

“What gets measured, gets managed”

- Peter Drucker (1909-2005)???



https://medium.com/centre-for-public-impact/what-gets-measured-gets-managed-its-wrong-and-drucker-never-said-it-fe95886d3df6

實證個案分析
Empirical Case Studies

案例一

Process Diagnosis
(製程診斷)

Feature Engineering and Quality Prediction
(特徵工程與品質預測)

案例二

案例三

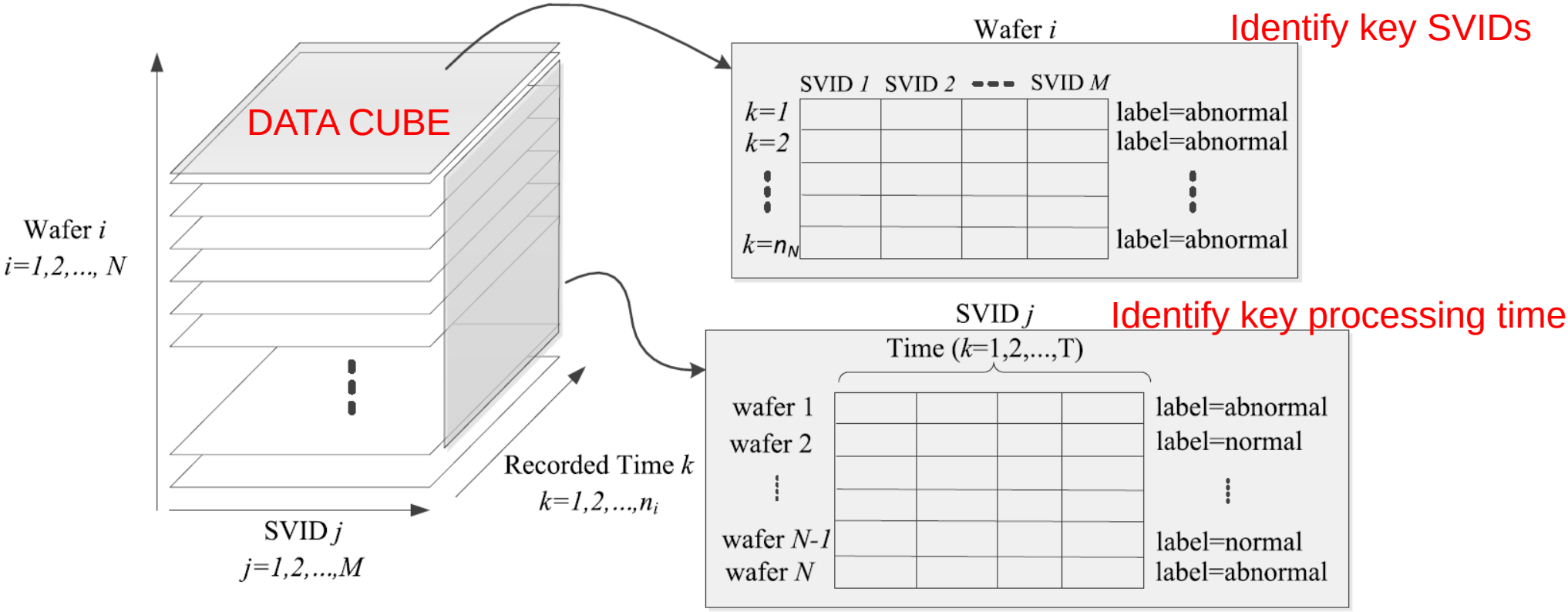
PHM & PdM
(故障預測與健康管理)

Material Price & Procurement Decision
(原料價格預測與採購決策)

案例四

一個典型製程診斷專案：FDC案例

- Data-Driven Methods for Fault Detection and Diagnosis
  - Fault detection: screen the key SVIDs capable of distinguishing normal and abnormal wafers.
  - Fault diagnostic: the processing time points of the identified key SVIDs are used as the features in classification to identify high-impact time steps.



Fan, S.-K., Hsu, C.-Y., Tsai, D.-M., He, F., and Cheng, C.-C. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE Transactions on Automation Science and Engineering, 17(4), 1925-1936.

一個典型製程診斷專案：FDC案例

Data Source

- The fabrication facility is a global semiconductor foundry.
- The FDC data from an equipment with two chambers using chemical vapor deposition (CVD) were collected.
- 66 SVIDs with recorded values, among which 7 SVIDs were removed because they were constants or purely wafer-count variables.
- Data Collection
  - Chamber A: 1153 wafers, including 1130 normal wafers and 23 abnormal wafers.
  - Chamber B: 965 wafers, including 919 normal wafers and 46 abnormal wafers.
- Inconsistent time length of sensor readings
  - Wafers processed in chamber A are approximately sampled 315 s
  - in chamber B are approximately sampled 309 s

Fan et al. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING.

一個典型製程診斷專案：FDC案例

- Processing time and steps in Chamber A and B
  - the process steps defined by the domain engineers, the total process time was separated into 15 process steps.

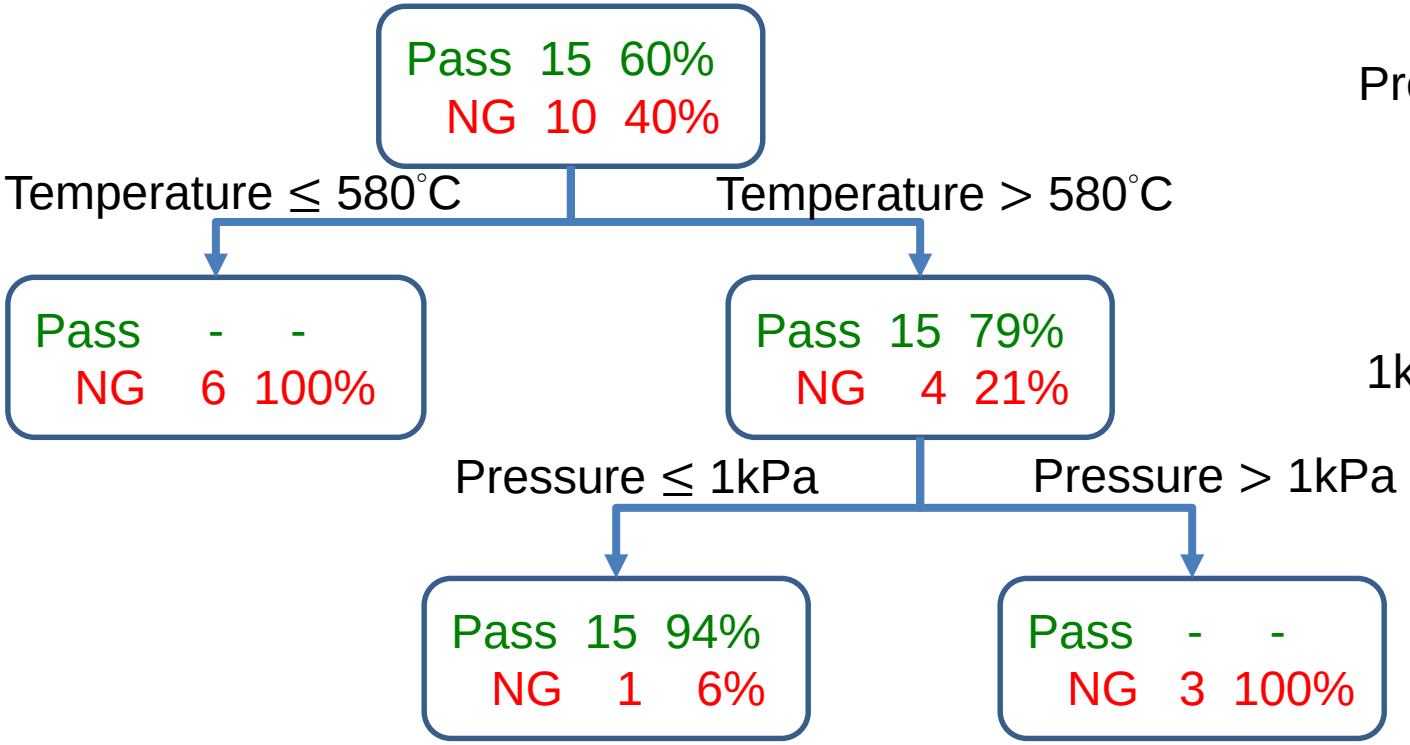
Processing step in chamber A				
#1	#2	#3	#4	#5
01-16	17-91	92-100	101-106	107-166
#6	#7	#8	#9	#10
167-176	177-206	207-210	211-224	225-229
#11	#12	#13	#14	#15
230-259	260-261	262-265	266-280	281-315
Processing step in chamber B				
#1	#2	#3	#4	#5
01-12	13-87	88-94	95-100	101-160
#6	#7	#8	#9	#10
161-170	171-200	201-204	205-217	218-222
#11	#12	#13	#14	#15
223-252	253-2255	256-258	259-273	274-309

Fan et al. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING.

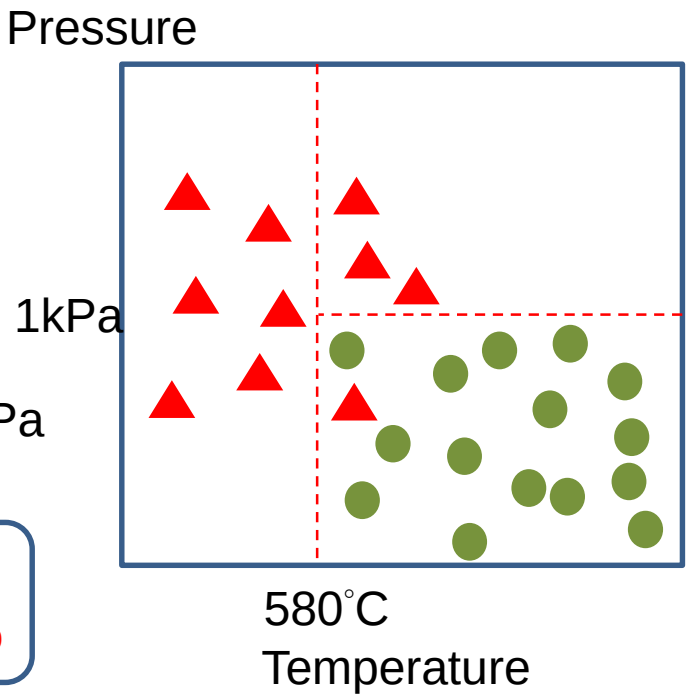
Decision Tree

- 分類 (Classification) (eg.分類與迴歸樹, CART, Breiman et al., 1984)
  - 決策樹 Decision Tree

1. 愈往上層因子愈重要!
2. 考慮因子間交互作用



Rectangle Partitions



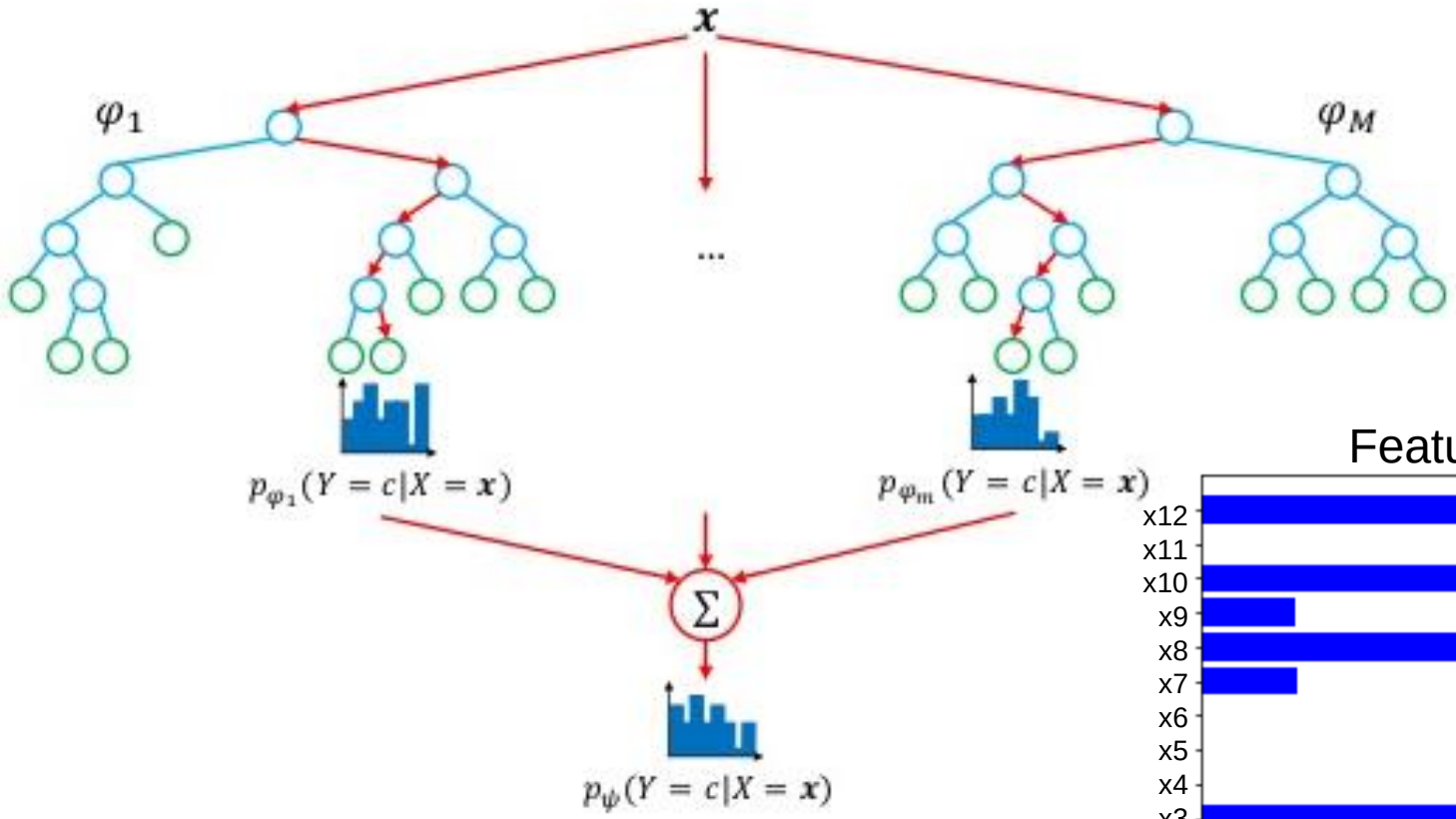
Rule Extraction

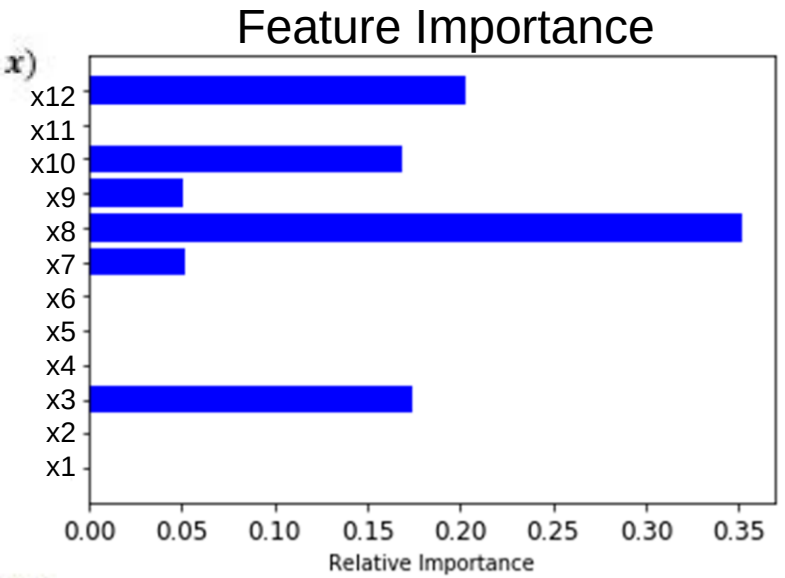
- If Temperature ≤ 580˚C, then NG. (Accuracy: 100%)
- If Temperature > 580˚C and Pressure > 1kPa, then NG. (Accuracy: 100%)
- If Temperature > 580˚C and Pressure ≤ 1kPa, then Pass. (Accuracy: 94%)

Lee, C.-Y., Hung, Y.-H., and Chen, Y.-W., 2020. "Hybrid Data Science and Reinforcement Learning in Data Envelopment Analysis", book chapter edited in: Zhu, J. and Charles V. (Editor), Data-Enabled Analytics: DEA for Big Data, Springer (Springer International Series in Operations Research and Management Science).

Random Forest

Random forests





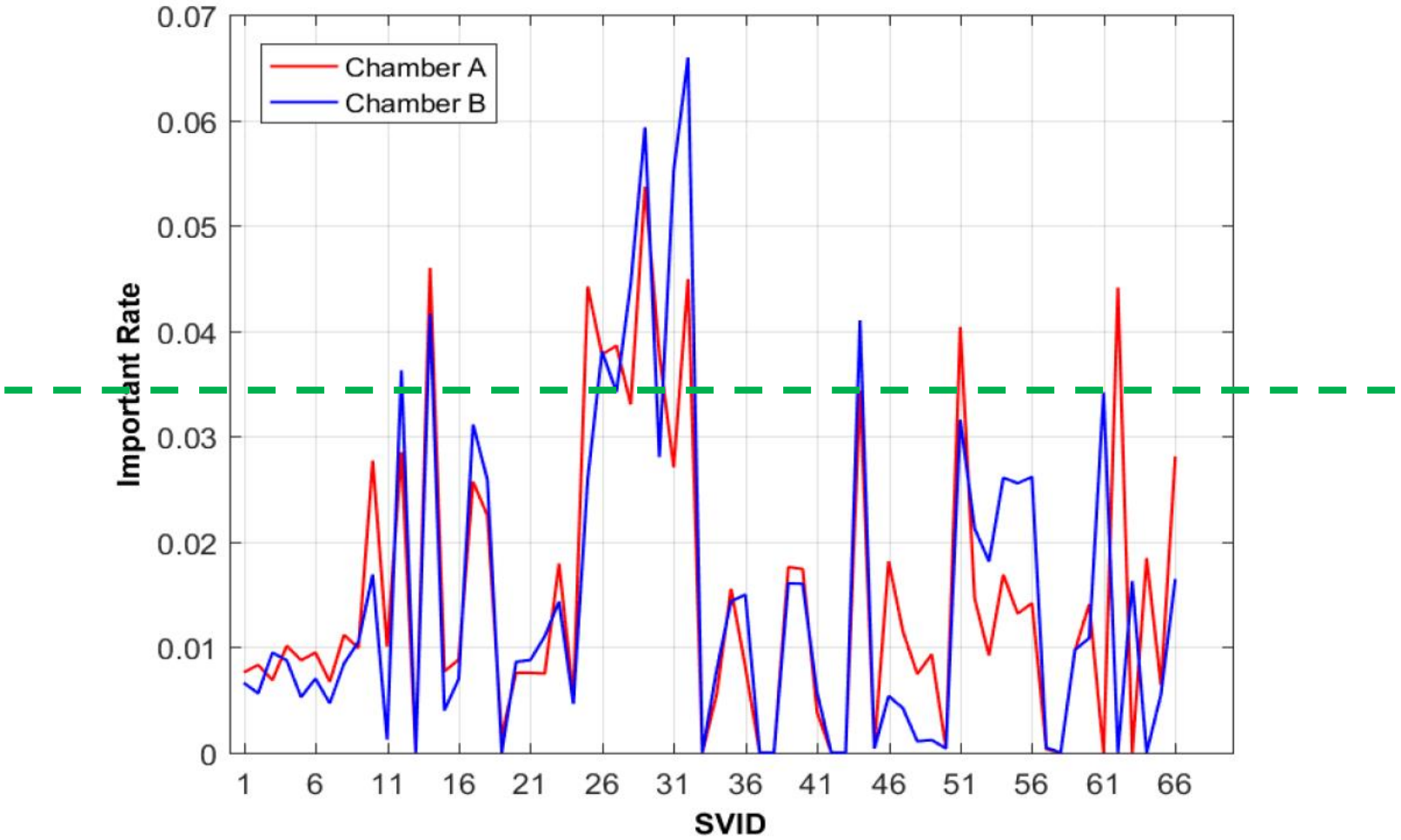
Randomization

- Bootstrap samples
- Random selection of $K \leqslant p$ split variables } Random Forests
- Random selection of the threshold } Extra-Trees

https://www.kdnuggets.com/2017/10/random-forests-explained.html

一個典型製程診斷專案：FDC案例

- Feature importance of two chambers by Random Forest
  - How to identify the importance SVID?

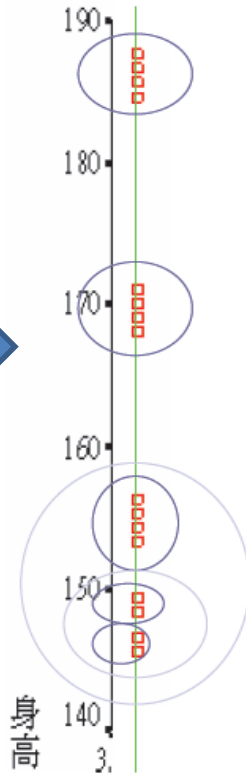


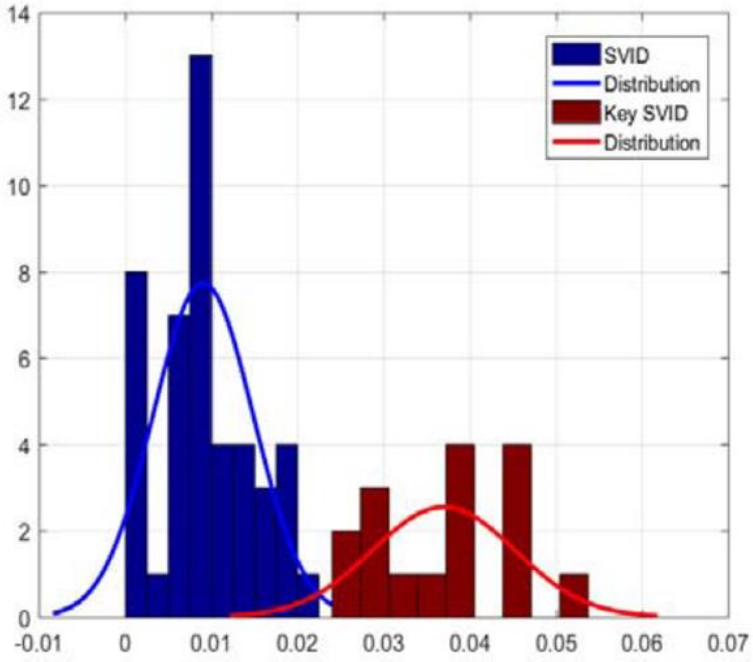
Fan et al. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING.

一個典型製程診斷專案：FDC案例

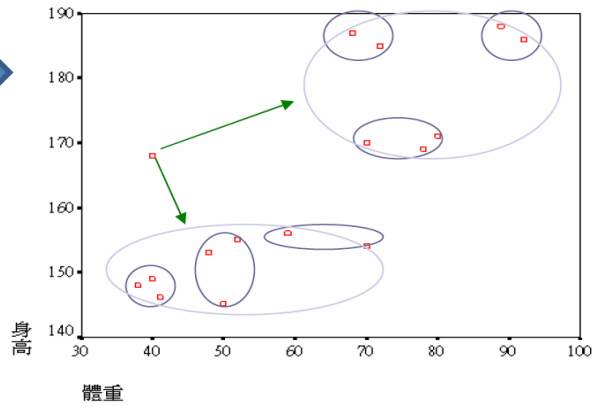
- How to identify the importance feature?
  - Intuition: Threshold…determined by experience?
  - Method: automatically generates the threshold
    - 1. box plot or take quartile/percentile
    - 2. pareto (scree) plot and linear segmentation
    - 3. clustering for 2 clusters
    - 4. statistical (distribution) test

身高
145
146
148
149
155
156
154
153
168
169
170
171
185
187
188
186





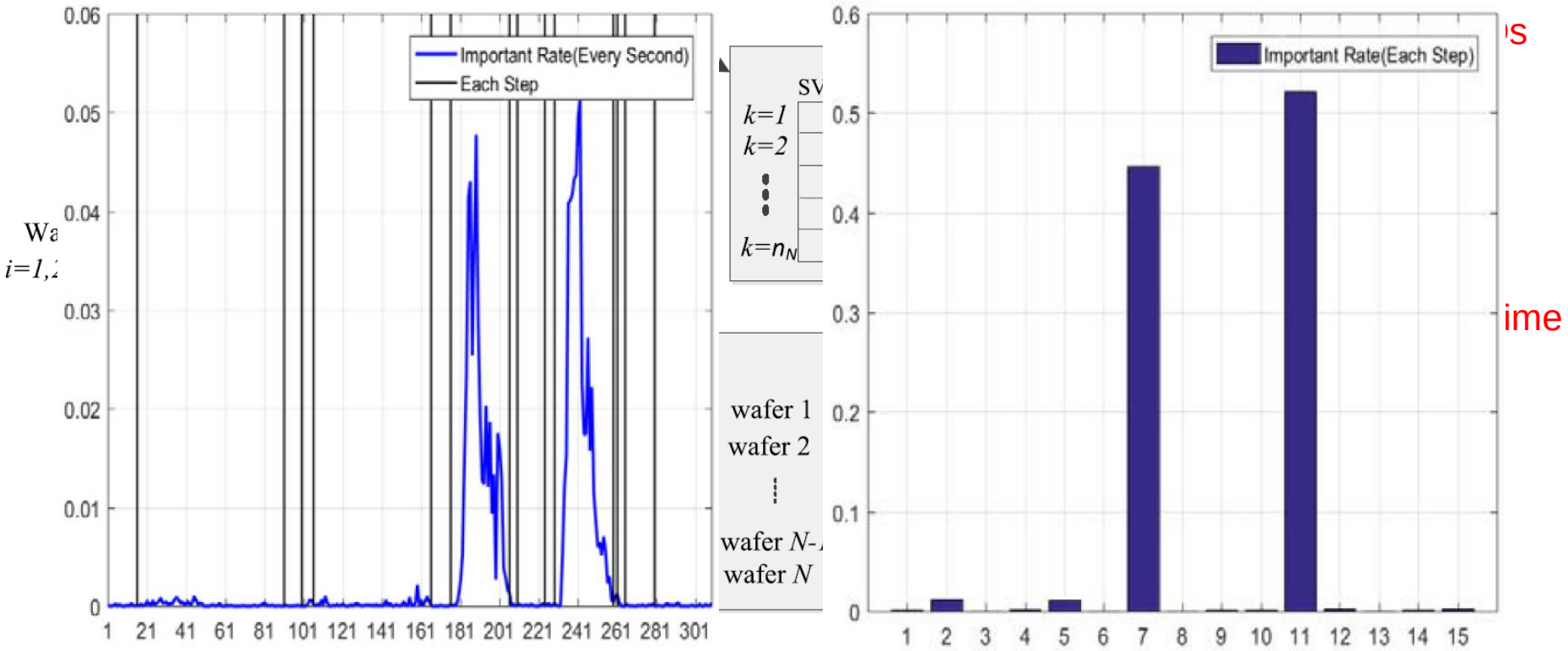
身高	體重
145	50
146	41
148	38
149	40
155	52
156	59
154	70
153	48
168	40
169	78
170	70
171	80
185	72
187	68
188	89
186	92



一個典型製程診斷專案：FDC案例

Fault Diagnostic via Key Processing Time Identification

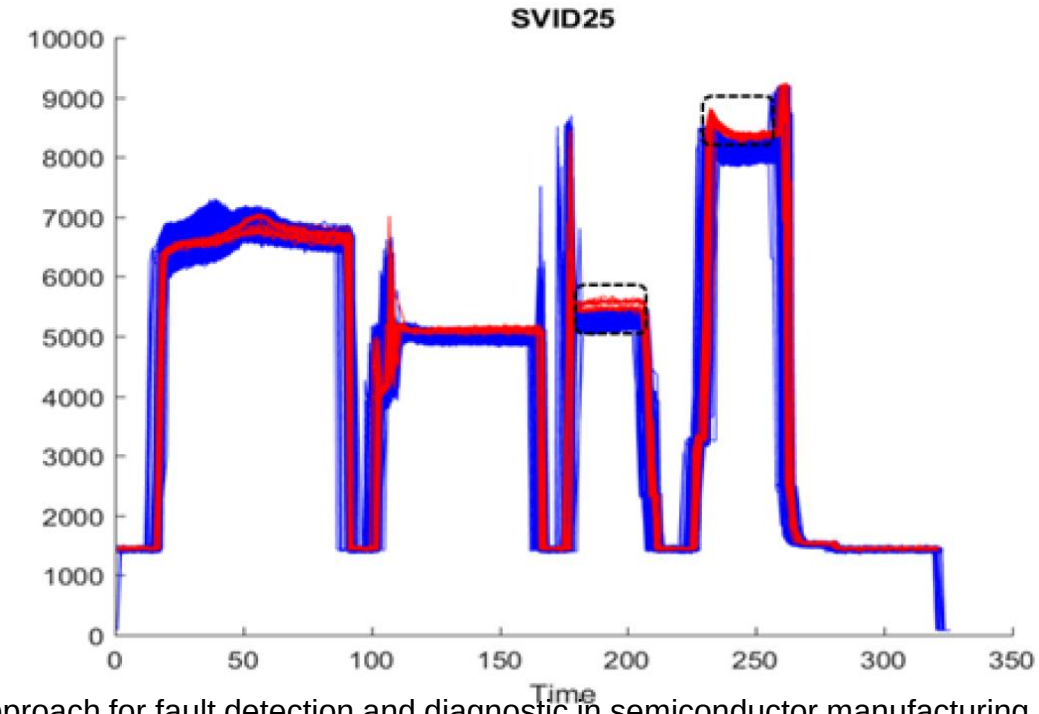
- Importance of processing time and steps in SVID #25 in Chamber A.
  - Processing steps #7 (177–206 s) and #11 (230–259 s) for chamber A.



Fan et al. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING.

一個典型製程診斷專案：FDC案例

- Fault Diagnostic via Key Processing Time Identification
  - The sensor reading values (y-axis) of SVID #25 in chamber A.
  - The blue lines denote the values of SVID for all the normal wafers
  - The red lines denote the values of SVID for all the abnormal wafers.
  - There are discrepancies between normal and abnormal wafers exactly in processing steps #7 (177–206 s) and #11 (230–259 s) in chamber A.

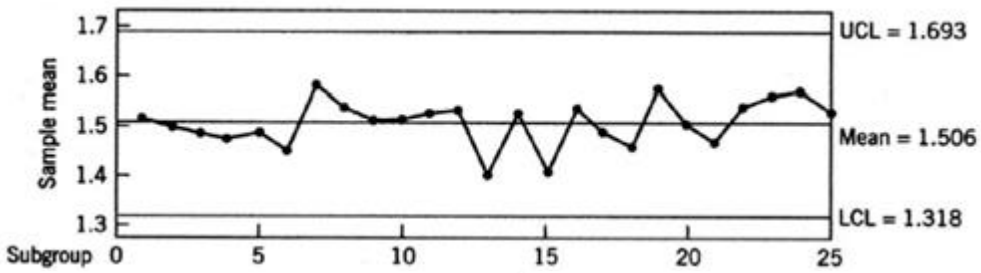


Fan et al. (2020). Data-driven approach for fault detection and diagnostic in semiconductor manufacturing. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING.

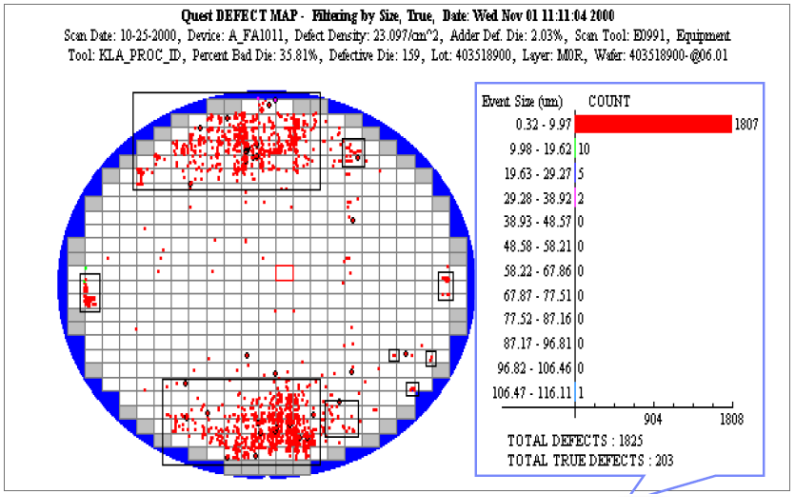
案例1: Process Diagnosis/ Troubleshooting (製程診斷)

- 良率提升方法論

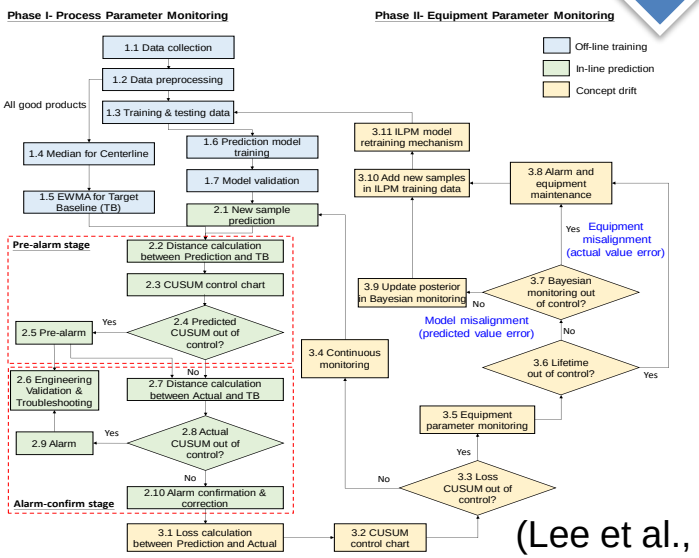
SPC製程監控

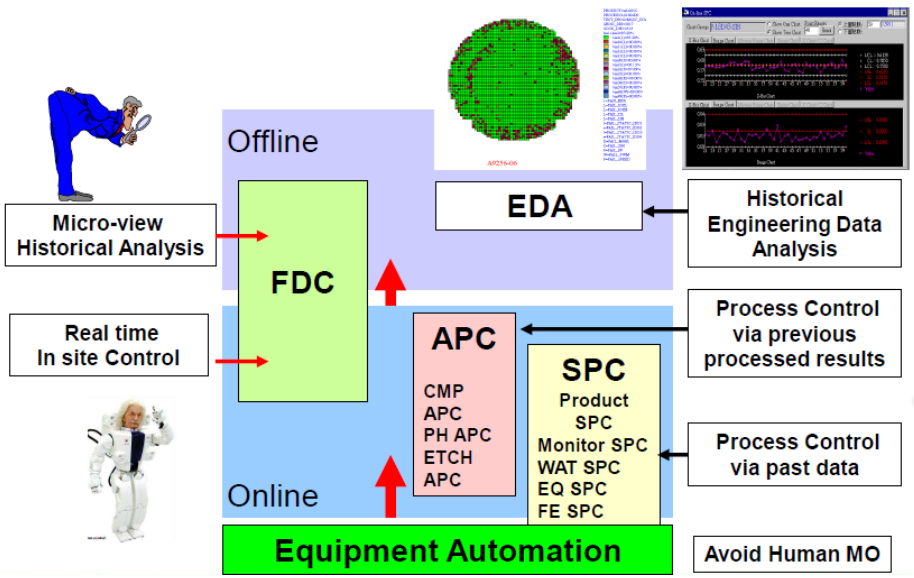


Defect Wafer



故障診斷與模式建構





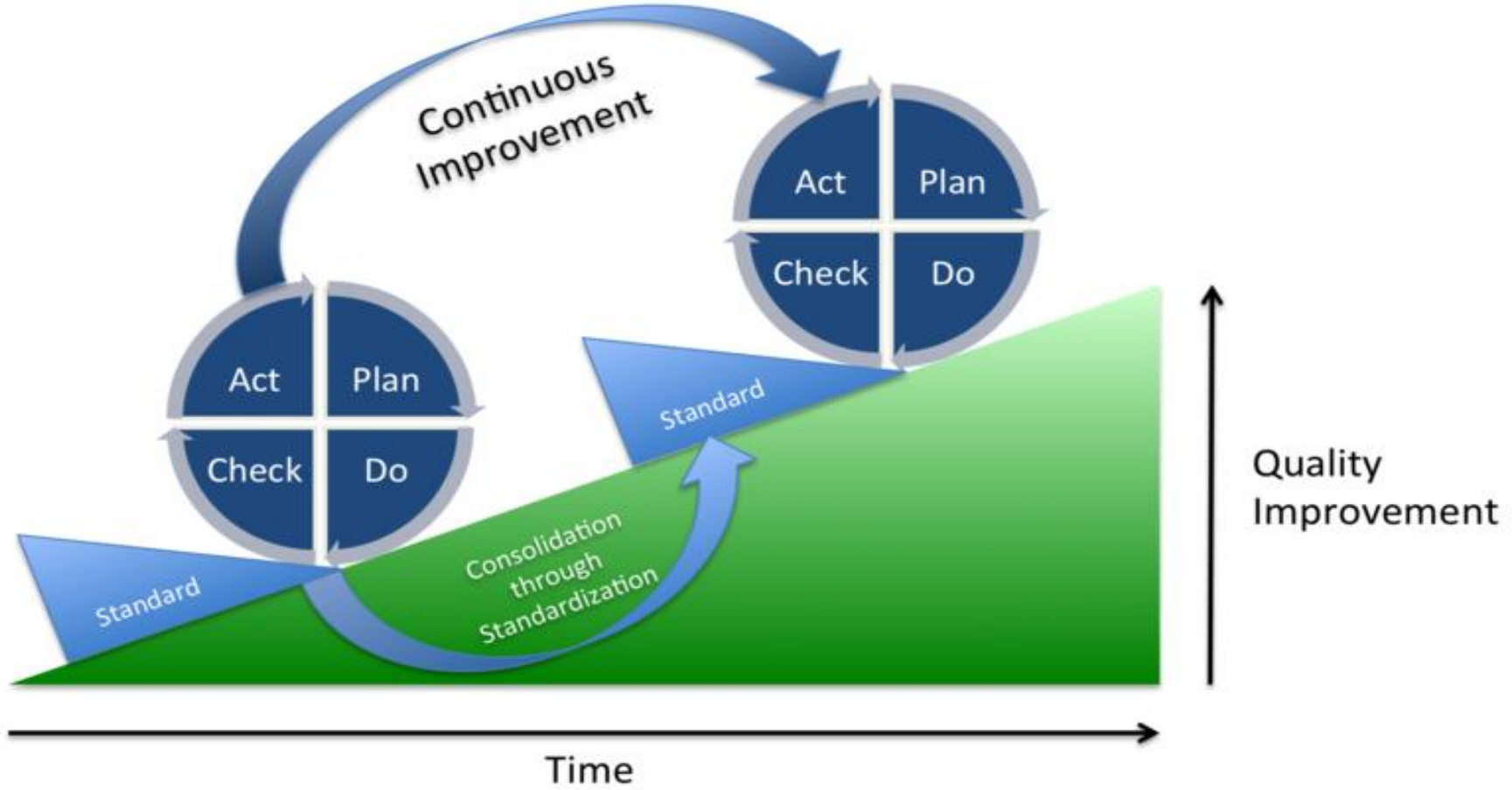
(Wang，2012）

自動化工程系統

（Lee et al., 2020）

案例1: Process Diagnosis/ Troubleshooting (製程診斷)

Continuous Improvement by PDCA



標準化(standardization) → 制度化(institutionalization)

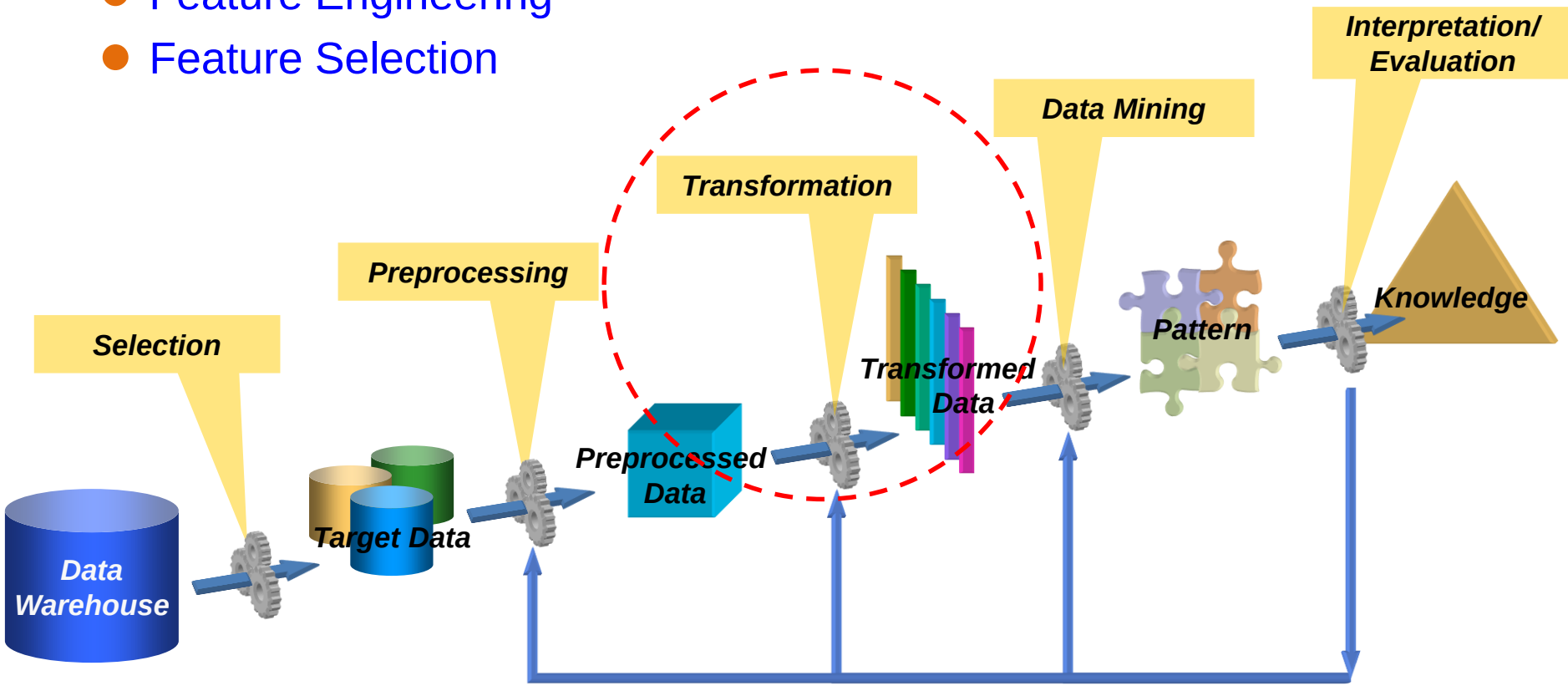
降低浪費、標準化、與制度化→ 成本降低cost down

Wikiwand (2016). http://www.wikiwand.com/en/PDCA

案例二：特徵工程與品質預測

Knowledge Discovery in Databases (KDD)

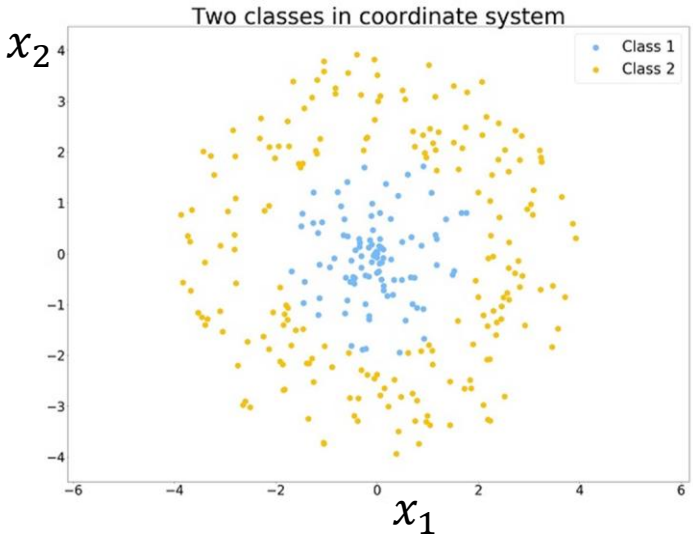
- Data Analytics Framework
  - Feature Engineering
  - Feature Selection



Feature Engineering (特徵工程)

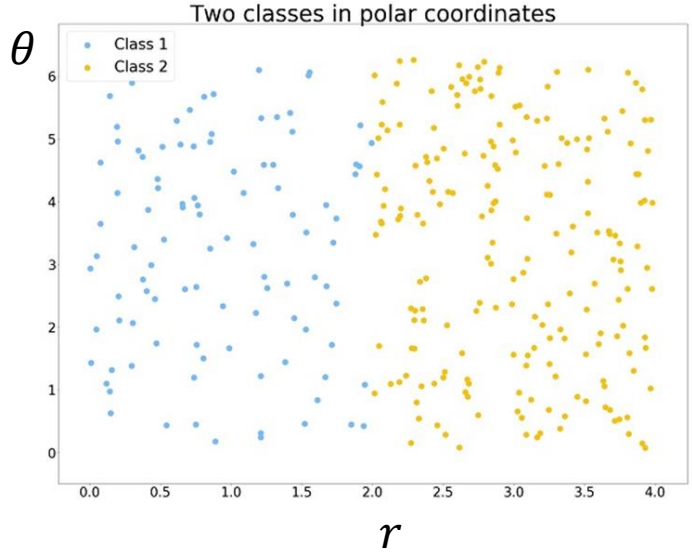
Feature Engineering

- is to manipulate the new feature manually from the original features.



$$r = \sqrt{x_1^2 + x_2^2}$$

$$\theta = \arctan\frac{x_2}{x_1}$$



- Temporal Features 時間特徵
  - For date / time, we can transform to timestamp and extract “day”, “month”, and “year” as new columns.
    - “hour” can be binning as “morning/afternoon/night”, or different shifts(早/晚班)
    - “day” can be binning as “weekday”, “weekend”
    - For weather, holiday, or event, we can build “is_national_holiday”, “has_xxxx_events” (eg. related to company, fab, machine, labor, …)

https://www.kdnuggets.com/2018/12/feature-engineering-explained.html

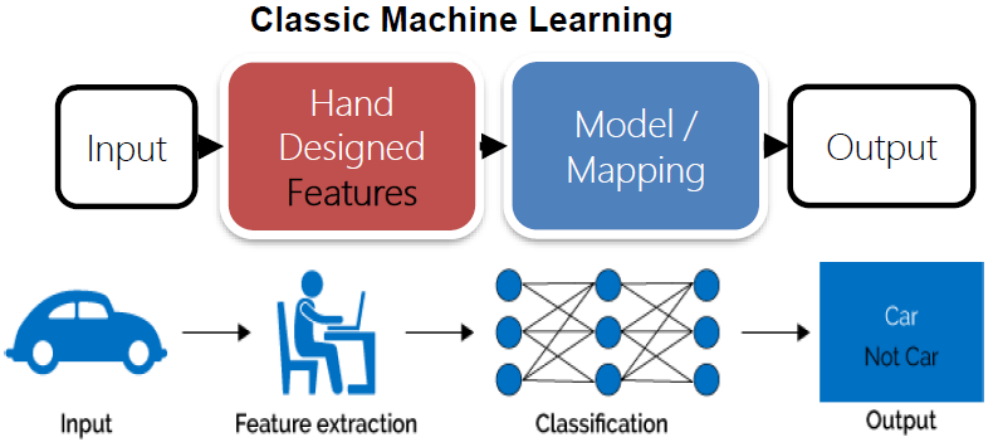
If-Then → Feature

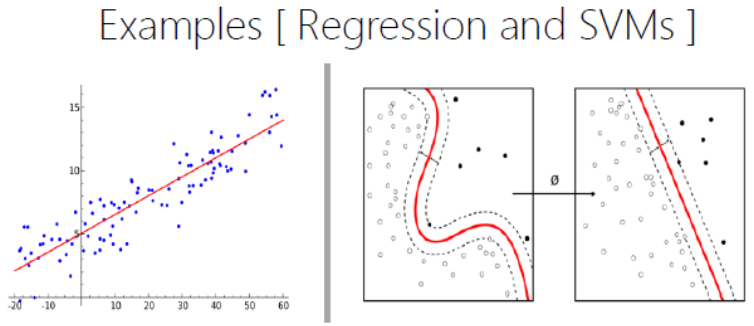
Feature Engineering

- 特徵工程可否協助轉出更多有意義的欄位？
  - 尤其是已知的交互作用
  - Rule-based features (Binarization 二值化)
    - Eg. If x1(材料) is equal to a category and x2(溫度) is larger than a threshold, then add a new variable z equal to 1; otherwise 0.
    - 用樹狀圖divide-and-conquer
  - 工程師的domain knowledge對於「改善」有重要的影響
  - 把Domain Knowledge轉為Feature!

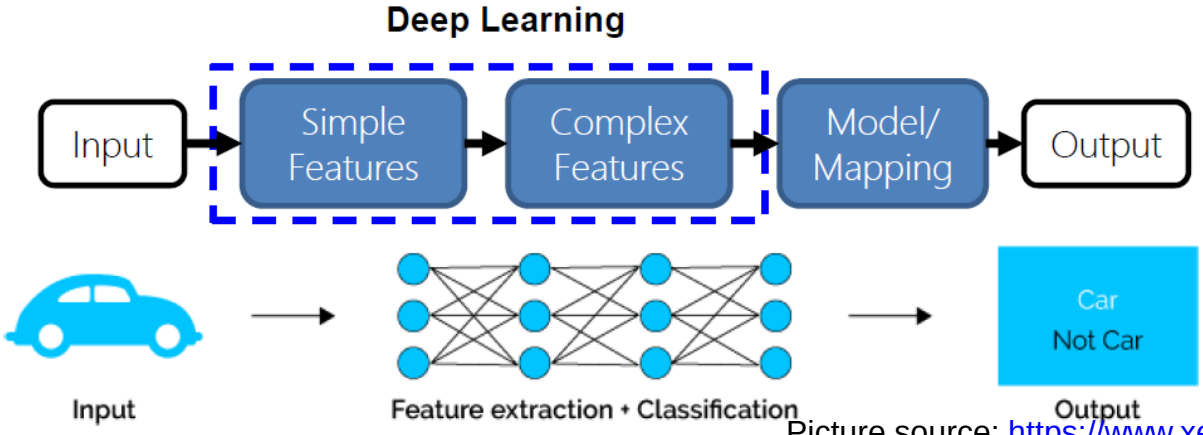
Deep Learning vs Classic Machine Learning

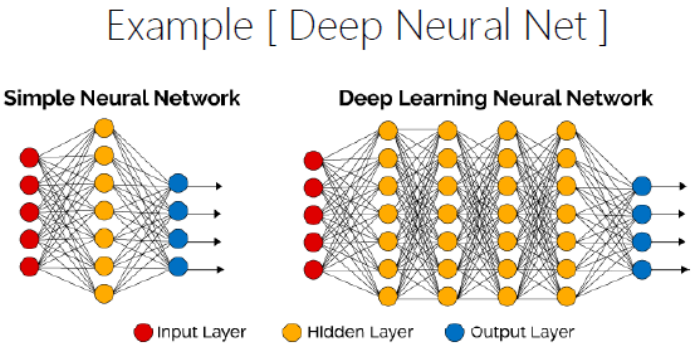
- 深度學習 (Deep Learning, DL)是一種機器學習 (Machine Learning, ML)方法
- 適合採用深度學習的問題主要特性有
  - 重要特徵不易定義(eg. 數學公式、規則等)
  - 需要更多、多元/異質的數據，但也造成需要更多的運算資源(computing)
- ML與DL有何差異：透過權重調整 ，來提取特徵





Picture source: https://en.wikipedia.org/wiki/Machine_learning





Picture source: https://www.xenonstack.com/blog/log analytics deep machine learning/

案例2: 特徵工程與品質預測

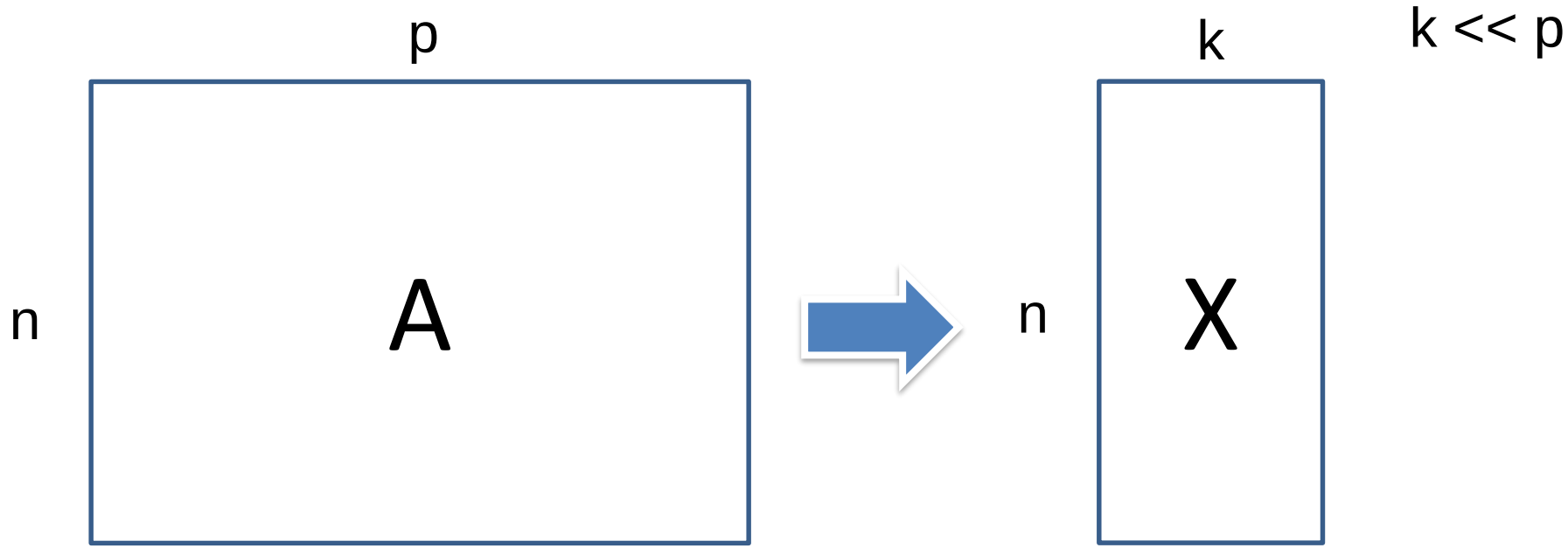
- 為什麼要選重要參數/因子?
  - 易於決策判斷
    - 看"____"就知道要不要決定出去旅遊
    - 看"____"就知道這衣服適不適合
    - 量"____"就知道身體健康狀況

- 製造現場篩選重要因子的目的
  - Troubleshooting
    - 掌握影響機台品質變異的主要因子、上下游因子的交互作用
    - Engineering Process Control (EPC)
  - 建立管理機制、簡單法則
    - 看Bottleneck就可推估現場WIP level
  - 精度預測?
    - 提升預測準確度
    - On-line real-time prediction
  - 監控Monitoring → 用較低成本/較少管制圖
    - 環境因子監控、機台參數監控

案例2: 特徵工程與品質預測

Feature Selection

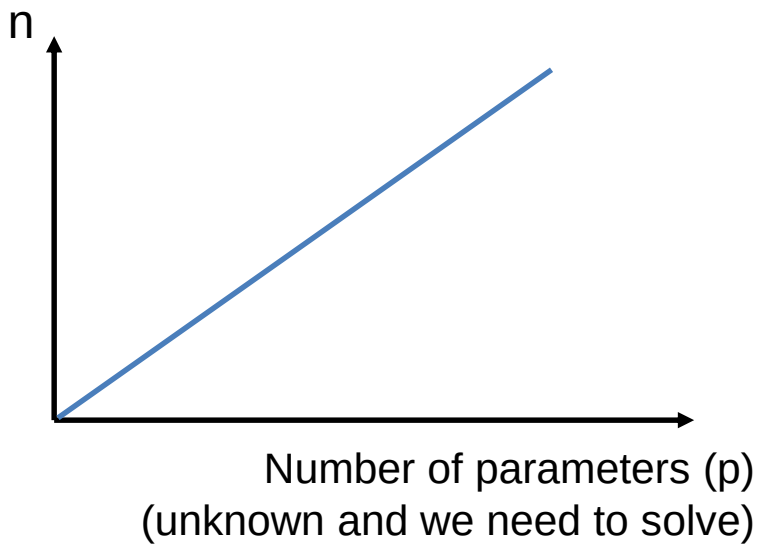
- In a large-scale dataset, select a few important variables (i.e. columns)
- In particular, # of variables (p) much larger than # of observations (n), i.e. p >> n issue
- Address “Curse of Dimensionality”
  - The number of observations required exponentially grows to estimate the function or model parameters.



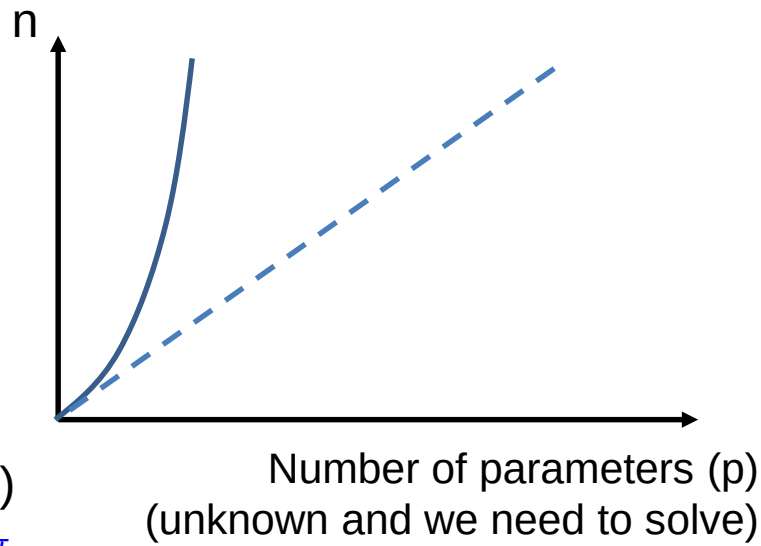
Curse of Dimensionality

Curse of Dimensionality

- system of equations
- $\begin{cases} 2x + y = 12 \\ x + 3y = 11 \end{cases}$
- 2 parameters (p) need 2 equations (n)



- ML/DS
  - # of obs. (n) required exponentially grows…
- Reason: (為什麼ML需要比較多的樣本？)
  - Nonlinear (eg. quadratic shows + and - roots)
  - Combination (eg. x, y, xy)
  - NN/DL system (eg. fully-connected arc/weights)
  - 樣本之間或欄位之間相關性高，可能不線性獨立

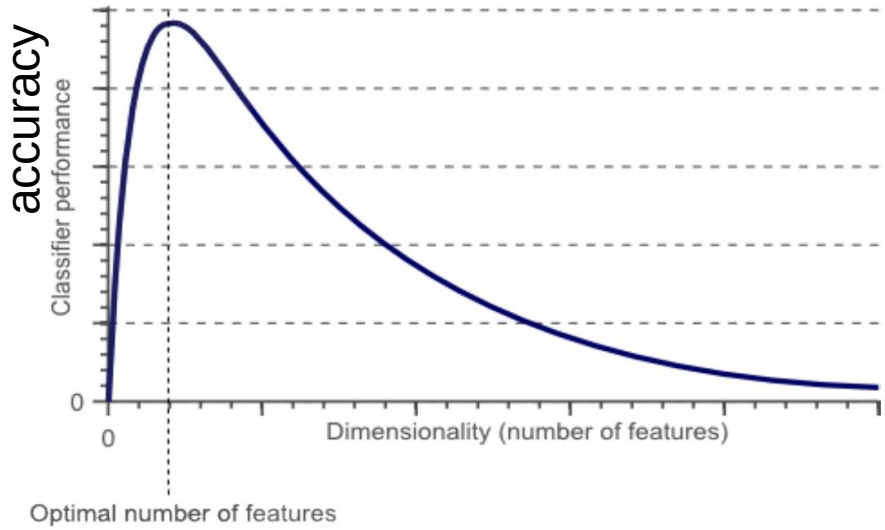


Curse of Dimensionality

Problem

- In practice, the curve of learning performance w.r.t. the feature dimension looks like this

For a fixed sample size n, there is an optimal number of features to use…



Treatment

- Volume of Dataset (nodes N, weights W, # of samples I)
  - Widrow's rule of thumb (Widrow, 1987): $I \geq 10W$
  - Vapnik-Chervonenkis (VC) Dimension: $I \geq O(\frac{W}{\varepsilon} log \frac{N}{\varepsilon})$
- Feature Selection
  - Variable selection (supervised learning) with "Y" as label
  - Dimension reduction (unsupervised learning) without label

案例2: 特徵工程與品質預測

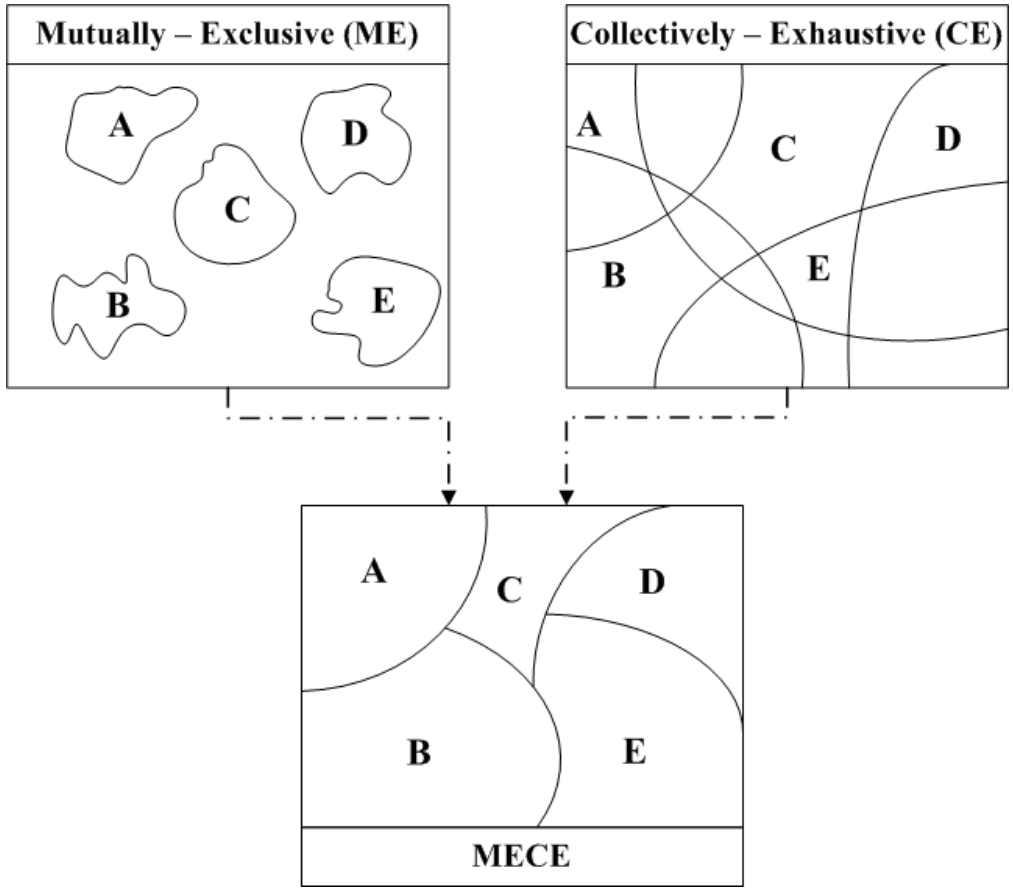
- Objective (Guyon and Elisseeff, 2003)
  - improving the prediction performance of the predictors
  - providing faster and more cost-effective predictors
  - providing a better understanding of the underlying process that generated the data. (eg. for process monitoring)

- Types
  - Feature/Variable selection: select the "best" subset of the existing variables/features without a transformation.
    - Supervised Learning (監督式學習) with "Y" as label
    - Eg. stepwise regression, LASSO, random forest, etc.
  - Dimension Reduction (feature extraction/ variable transformation): transforming the existing variables into a lower dimensional space
    - Unsupervised Learning (非監督式學習) with only "X"
    - Eg. independent component analysis (ICA), principal component analysis (PCA), etc.

案例2: 特徵工程與品質預測

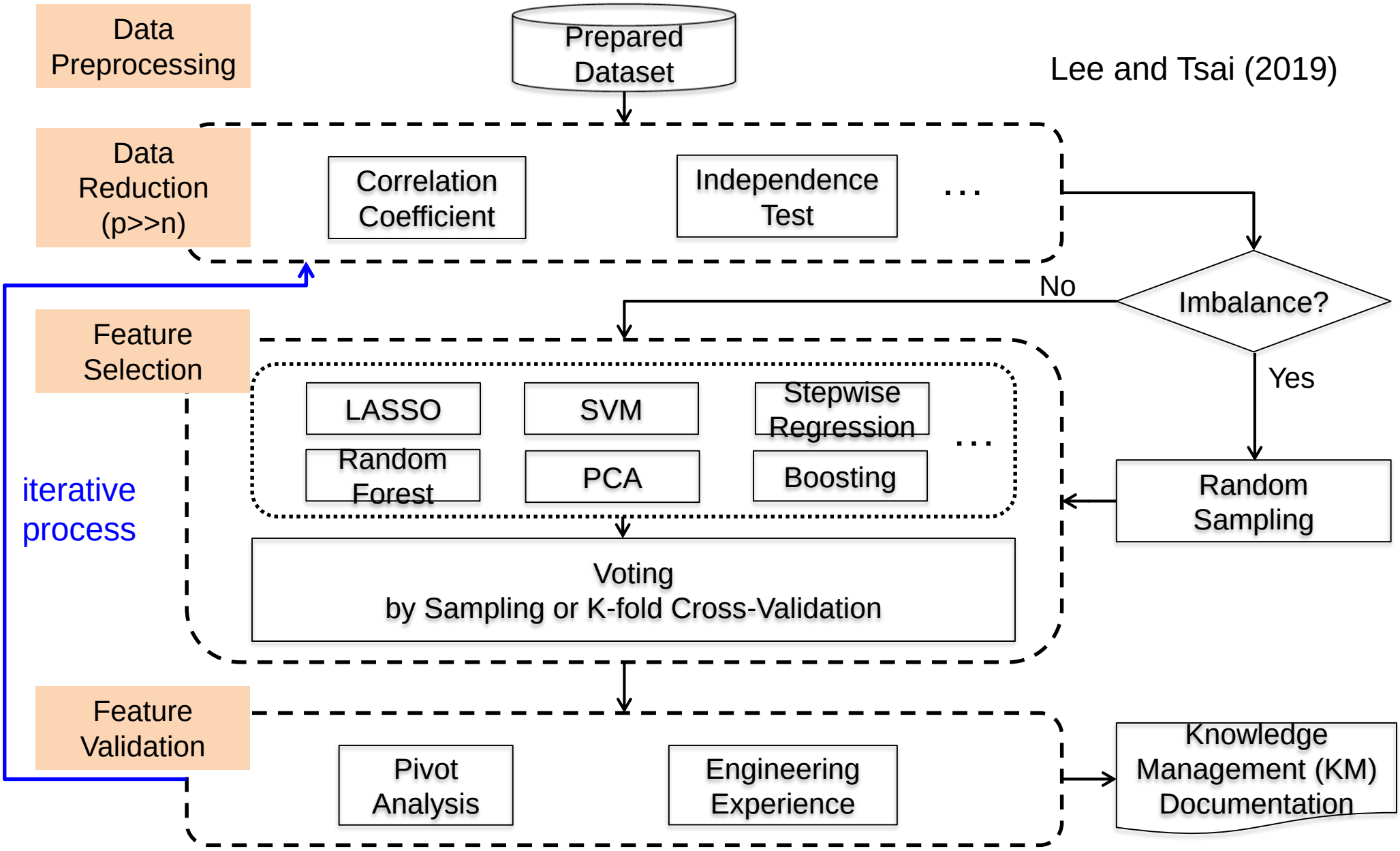
篩選原則(Selection Principle)

- Mutually-Exclusive Collectively-Exhaustive (MECE) Feature Selection
- claims that the important variables should not contain overlapping information and should provide sufficient information.



Lee and Chen (2018)

案例2: 特徵工程與品質預測



案例2: 特徵工程與品質預測

- 變數挑選的邏輯
  - 天下雨 → 地濕 (若A則B：A稱為B的充分條件，B稱為A的必要條件)
  - 地濕 → 不一定天下雨 (B不一定則A)
  - 地沒濕 → 天一定沒下雨 (非B則非A)
- 同理...
  - 因果 → 相關
  - 相關 → 不一定因果
  - 沒相關 → 絕對沒因果
- 結論
  - 當變數欄位太多時，可試著透過X跟Y的相關係數，來刪除低相關的變數欄位 (強假設：因子之間無交互作用)
  - 接著應該做 實驗設計(DOE)、Fused Lasso、Tree-based Method, etc. 確認交互作用影響

Lee, C.-Y., and Chien, C.-F., 2022. Pitfalls and protocols of data science in manufacturing practice. Journal of Intelligent Manufacturing, 33, 1189–1207.

- Stepwise Regression (i.e. 逐步迴歸) (Hocking, 1976)
  - Starting with no variables in the model, then adding the variable (if any) that improves the model the most (with smallest p-value).
  - Forward selection (y, x_1, x_2, x_3, x_4)

$$y = \alpha + \beta x_1 + \varepsilon$$
$$y = \alpha + \beta x_2 + \varepsilon$$
$$y = \alpha + \beta x_3 + \varepsilon$$
$$y = \alpha + \beta x_4 + \varepsilon$$

⇨

$$y = \alpha + \beta_2 x_2 + \beta x_1 + \varepsilon$$
$$y = \alpha + \beta_2 x_2 + \beta x_3 + \varepsilon$$
$$y = \alpha + \beta_2 x_2 + \beta x_4 + \varepsilon$$

⇩

$$y = \alpha + \beta_2 x_2 + \beta_4 x_4 + \beta x_1 + \varepsilon$$
$$y = \alpha + \beta_2 x_2 + \beta_4 x_4 + \beta x_3 + \varepsilon$$

⇨ 統計顯著的變數 x_2 and x_4

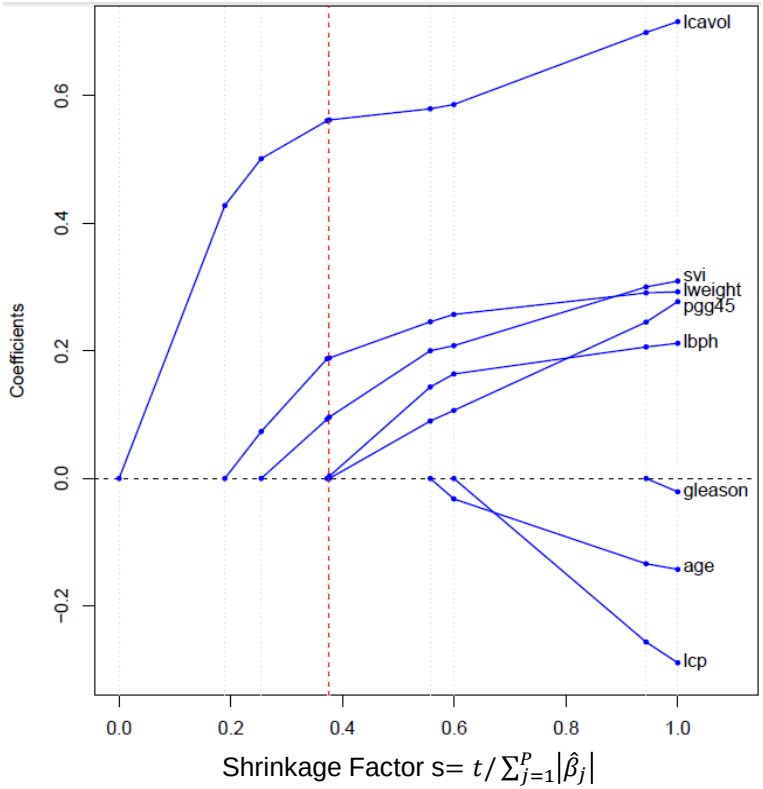
案例2: 特徵工程與品質預測

LASSO Regression (Tibshirani, 1996)

- $\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{P} x_{ij}\beta_j)^2$

  Subject to $\sum_{j=1}^{P}|\beta_j| \le t$

- *Lagrangian form* $\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{\frac{1}{2}\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{P} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{P}|\beta_j|\right\}$



Penalty(λ)	x1	x2	x3	x4	x5	x6	x7
λ = 0	*	*	*	*	*	*	*
λ = 40	*	*	*	*	*	*	*
λ = 41.8		*	*	*	*	*	*
λ = 41.9		*	*	*	*		*
λ = 42			*	*	*		*
λ = 50			*	*			*

Lee and Cai (2019)

Hastie et al. (2008). *The Elements of Statistical Learning*. https://hastie.su.domains/ElemStatLearn/

Voting (投票法)

- When using several selection methods, calculate the selecting frequency for "**robust**" variable selection.

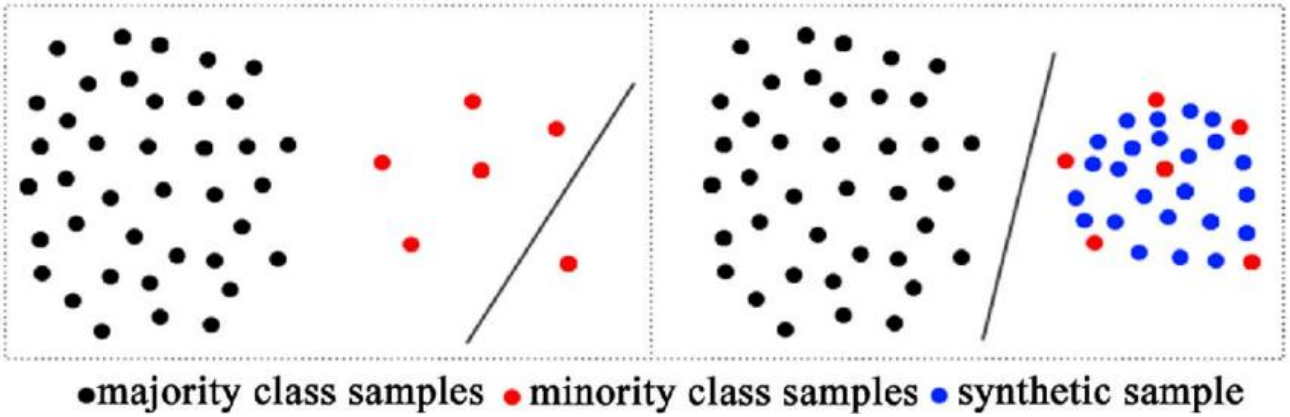
SVID	Stepwise	LASSO	Random Forest	Boosting	Voting
SVID_003	○	○	○	○	4
SVID_101		○	○	○	3
SVID_021		○	○	○	3
SVID_040	○		○	○	3
SVID_002	○	○		○	3
SVID_128	○		○		2
SVID_062	○	○			2
SVID_077		○		○	2
⋮	⋮				⋮

Class Imbalance Solutions

- Undersampling
  - samples a subset of the majority class. Due to ignoring many majority class examples, we generally sample several times (resampling).
  - Example
    - For Y label, 良品 vs. 不良品 = 1000 : 50
    - Samples 50 良品 at a time for model training
    - # of replications: 20 times
    - Rank the variables by the “voting”
    - Hint: 1:1 can be properly extended to 5:1

SVID	Voting by Undersampling
SVID_003	19
SVID_101	18
SVID_021	18
SVID_040	18
SVID_002	17
SVID_128	17
SVID_062	17
SVID_077	17
⋮	⋮

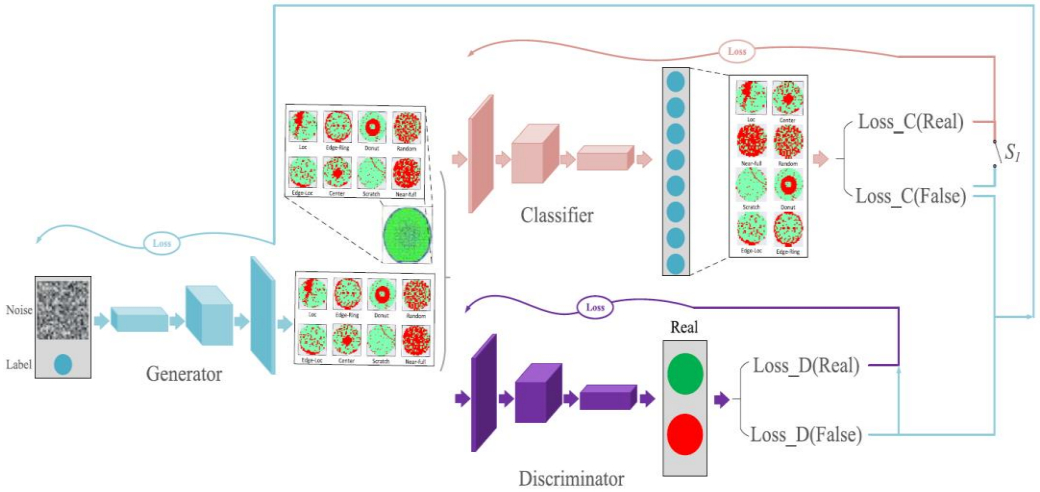
- Oversampling (eg. SMOTE)



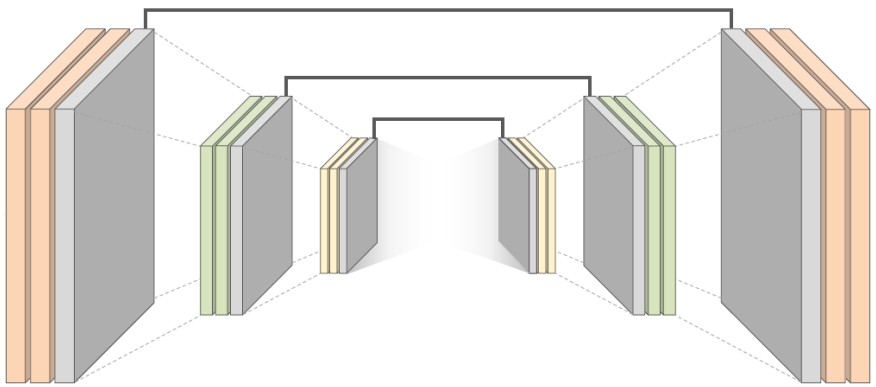
- Others: cost-sensitive, ensemble-based, autoencoder, GAN,…

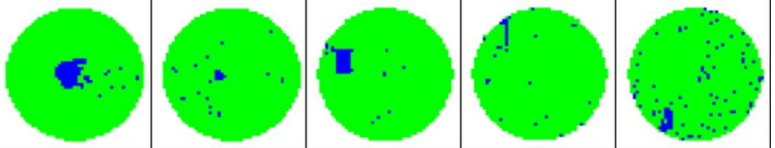
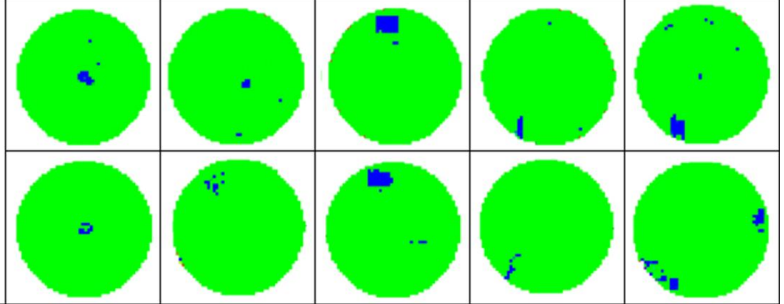
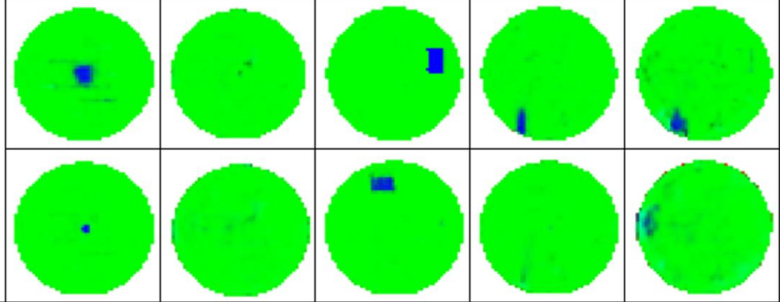
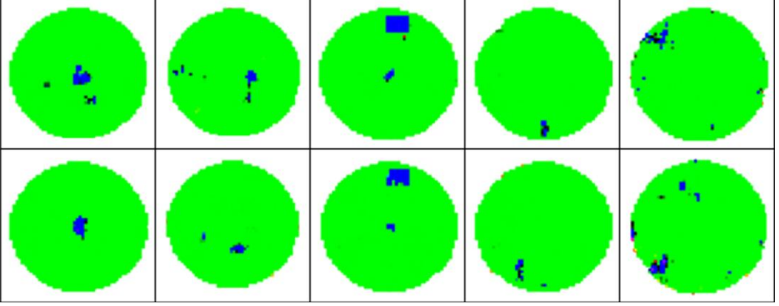
特徵工程、數據增強與數據平衡

Generative Adversarial Network (GAN)



Autoencoder



Original data and Generated data	Defect Type				
	Center	Loc	Peeling	Scratch	Oxidation
Original					
CAE					
CVAE					
ACGAN					

Shen, P.-C., and Lee, C.-Y. (2022). Wafer bin map recognition with autoencoder-based data augmentation in semiconductor assembly process. IEEE Transactions on Semiconductor Manufacturing, 35(2), 198 - 209.

Wang, J., Yang, Z., Zhang, J., Zhang, Q., and Chien, W.-T. K. (2019). AdaBalGAN: An Improved Generative Adversarial Network With Imbalanced Learning for Wafer Defective Pattern Recognition. IEEE Transactions on Semiconductor Manufacturing, 32(3), 310-319.

案例2: 特徵工程與品質預測

製程預測

- 透過製程的處方設定 (recipe)來進行反應變數(Y)的推論，eg. 長寬預測、厚度預測、精度預測、虛擬量測…

預測?

- 良品/ 不良品
- 膜厚(thickness)、線寬(Critical Dimension, CD)、覆蓋(Overlay)、缺陷數(defects)、缺陷面積大小(area)、缺陷位置層(layer), 良率(yield)等…

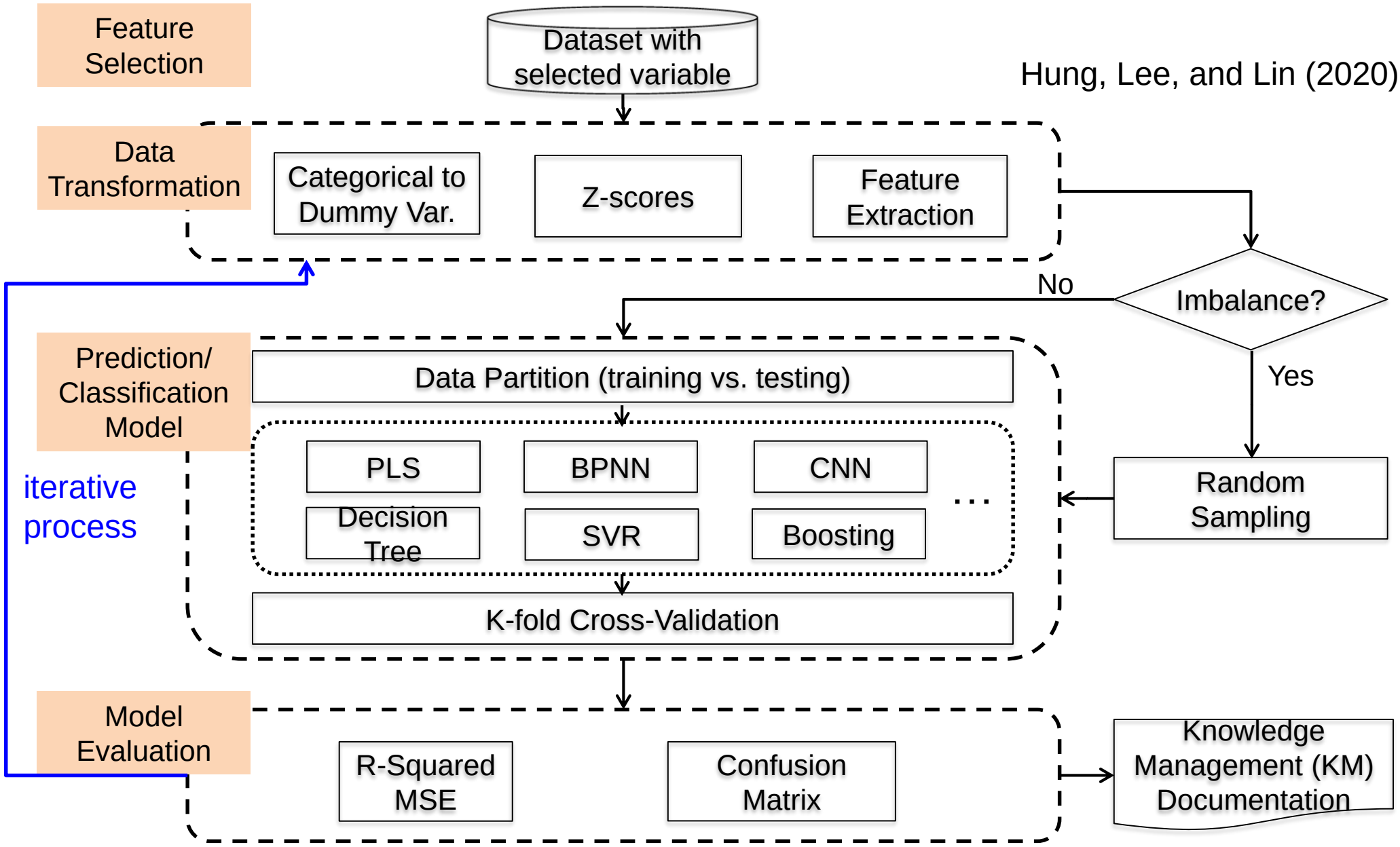
方法

- 推論 → 就是進行「因果關係」的建構
- 解釋 → 就是進行「物理特性」的說明

Benefits

- 協助機台校正或產品開發
- 降低抽樣頻率 (協同製程能力Cp, Cpk)
- 發展預測保養 (predictive maintenance)

案例2: 特徵工程與品質預測



Model Construction

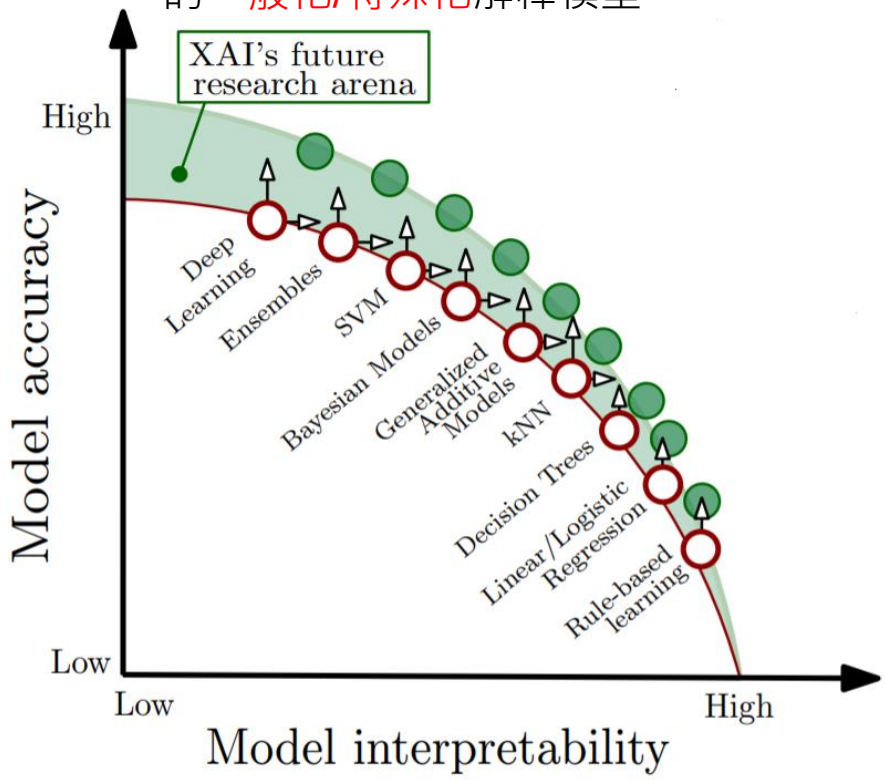
Supervised Learning Models

- Regression, Logistic regression, Partial Least Squares (PLS), Multivariate Adaptive Regression Splines (MARS), SVM/SVR, Decision Tree, Random Forest, LightGBM, Deep learning (DNN, CNN, RNN, graphCNN), GAN…
- Time Series: ARIMA, SARIMAX, LSTM, convolutional LSTM, GRU, …
- Accuracy Enhancement: Ensemble, Stacking, Attention, Transformer…

Unsupervised Learning Models

- Clustering: Hierarchical(Ward's Method), non-hierarchical(k-means, k-medoids), density-based (DBSCAN), Spectral Clustering, SOM, ART, EM-GMM…
- Dimension Reduction: PCA, ICA, t-SNE…

數學建模用以產生適合各種不同情境的一般化/特殊化解釋模型



Arrieta et al. (2019)

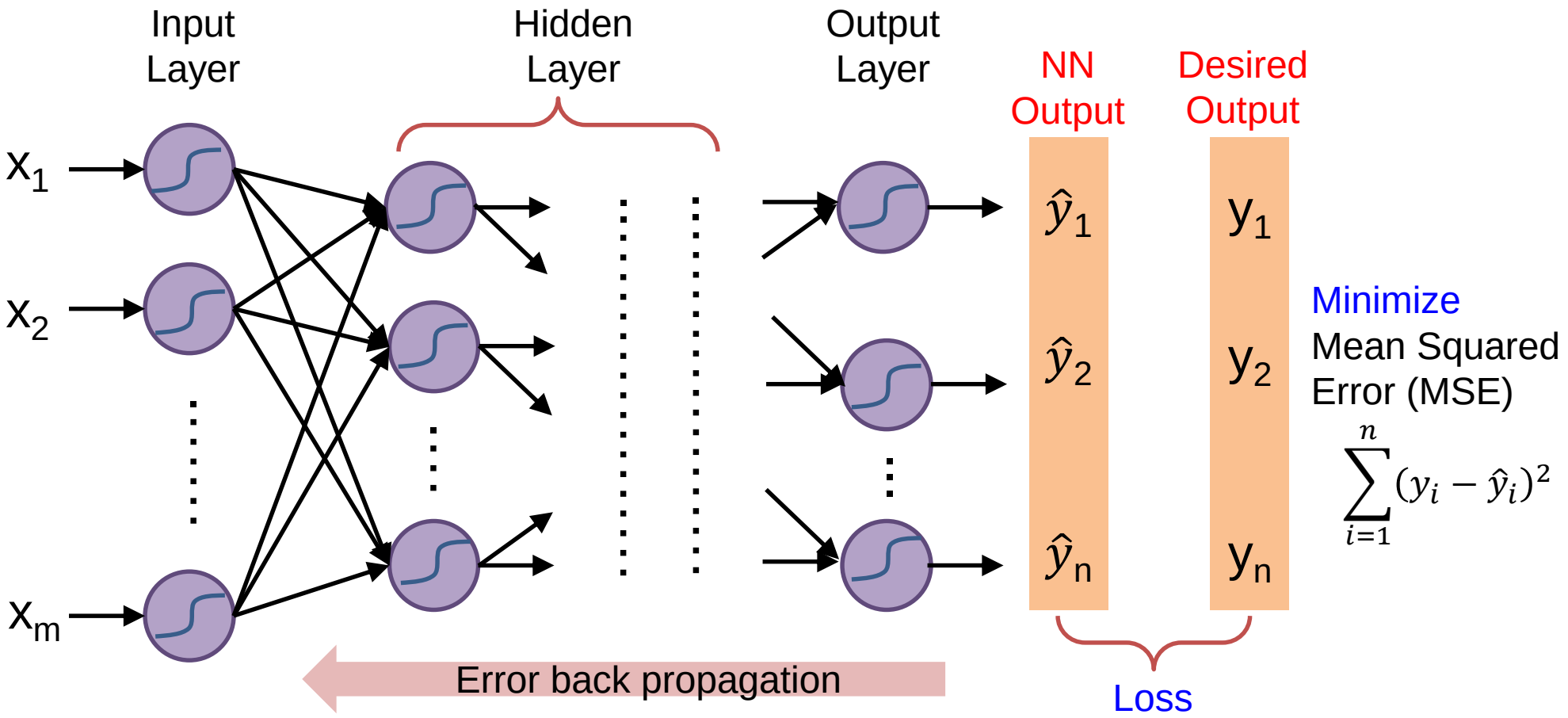
Issues

- Curse of Dimensionality, Overfitting vs. Underfitting, Accuracy vs. Interpretation, Data Imbalance

Arrieta et al. (2020), "Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI," Information Fusion, 58, 82-115.

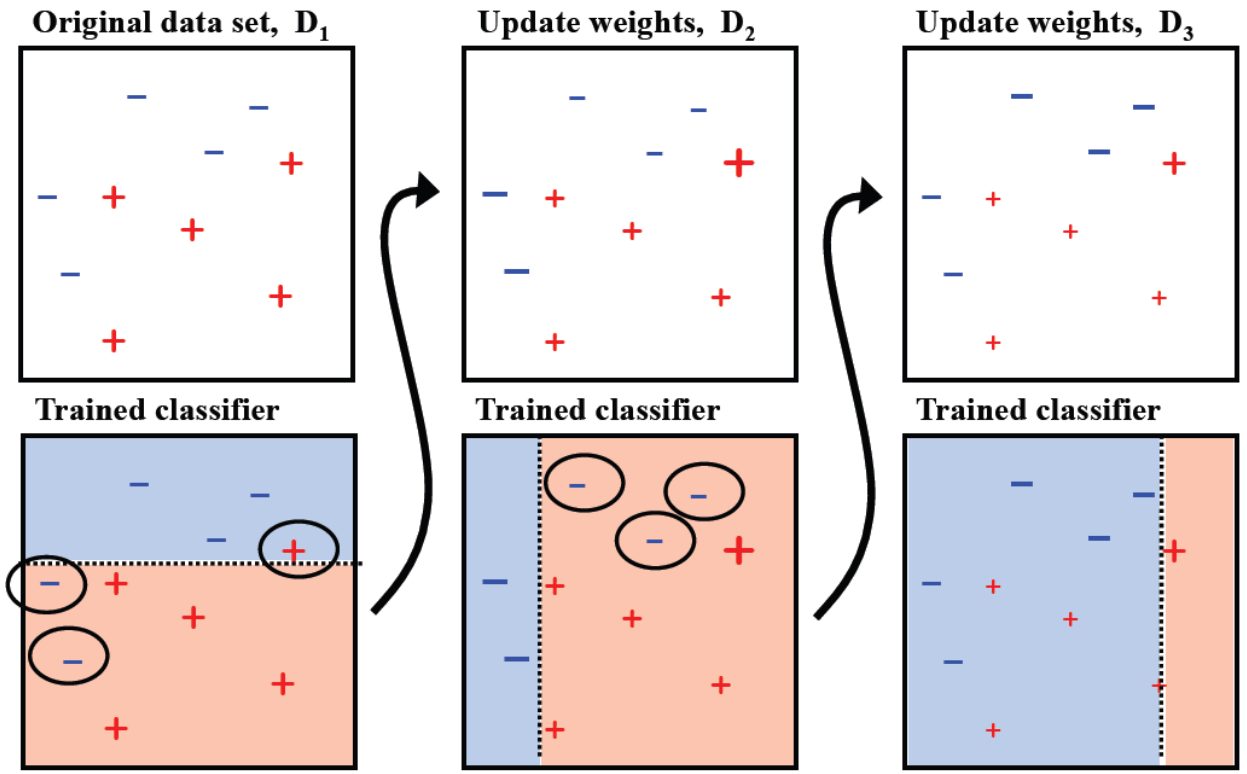
案例2: 特徵工程與品質預測

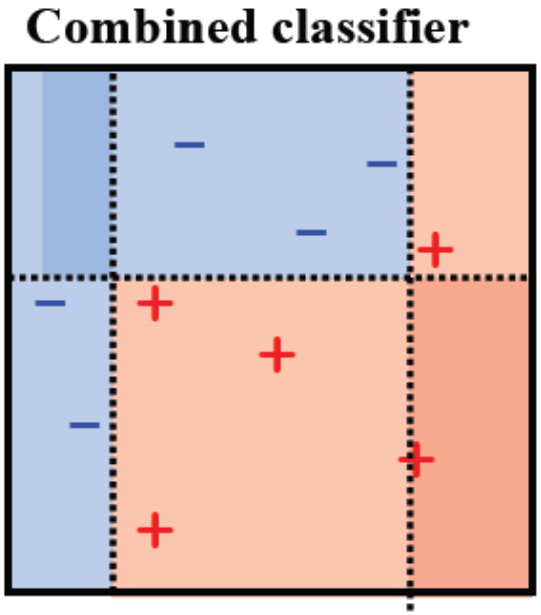
- Backpropagation Network (BPNN) (Werbos, 1974; Rumelhart & McClelland, 1985)
  - Multi-Layer Feedforward Network + Error Back Propagation (EBP)
  - Minimize the error between NN output and desired output by "(stochastic) gradient descent". (a large number of hidden layers → Deep Learning)



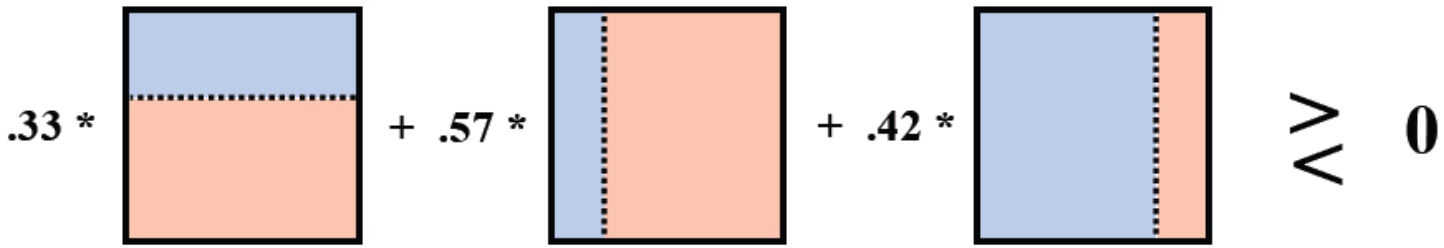
案例2: 特徵工程與品質預測

- Boosting (eg. Gradient Boosting Machine, GBM)





Weight each classifier and combine them:



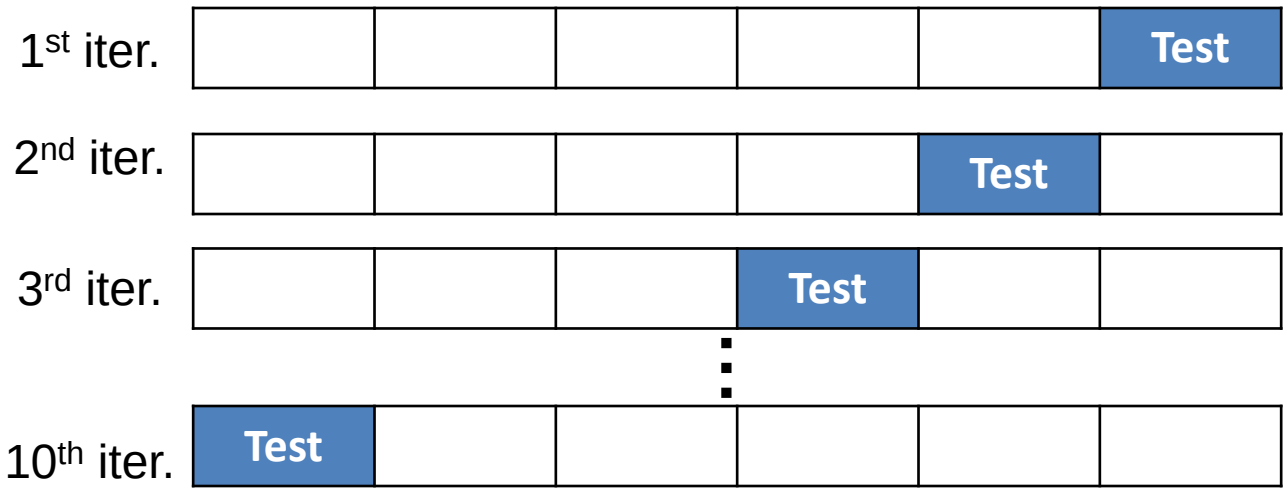
1-node decision trees
"decision stumps"
very simple classifiers

Alexander Ihler (2012). http://sli.ics.uci.edu/Classes/2012F-273a? action=download&upname=10-ensembles.pdf

數據分割

K-Fold Cross Validation

training fold



$$\text{Minimize Error} = \frac{1}{10}\sum_{i=1}^{10} \text{Error}_i$$

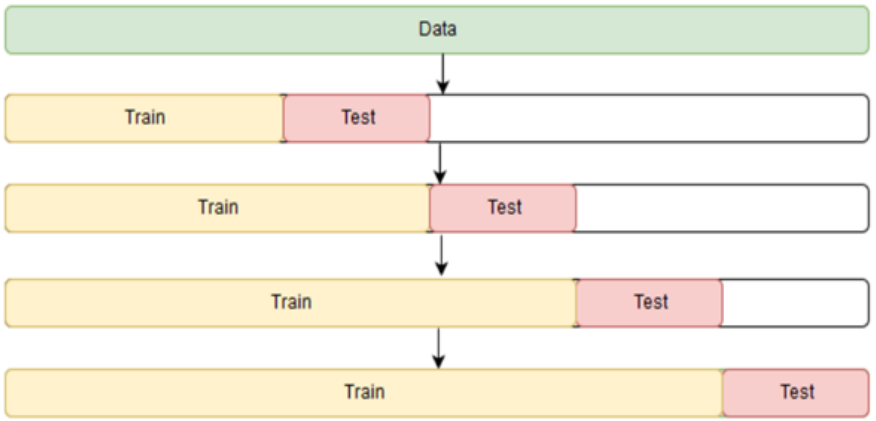
Error_1

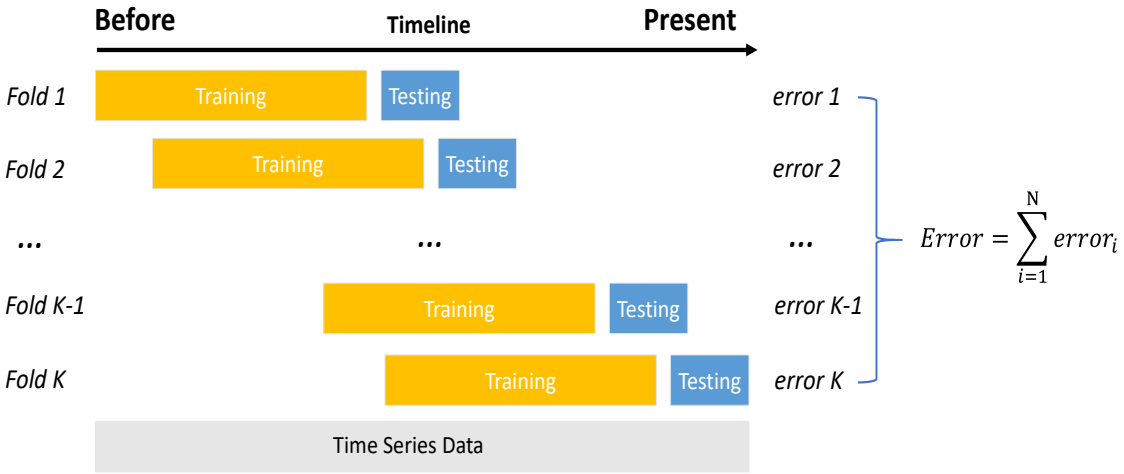
Error_2

Error_3

Error_{10}

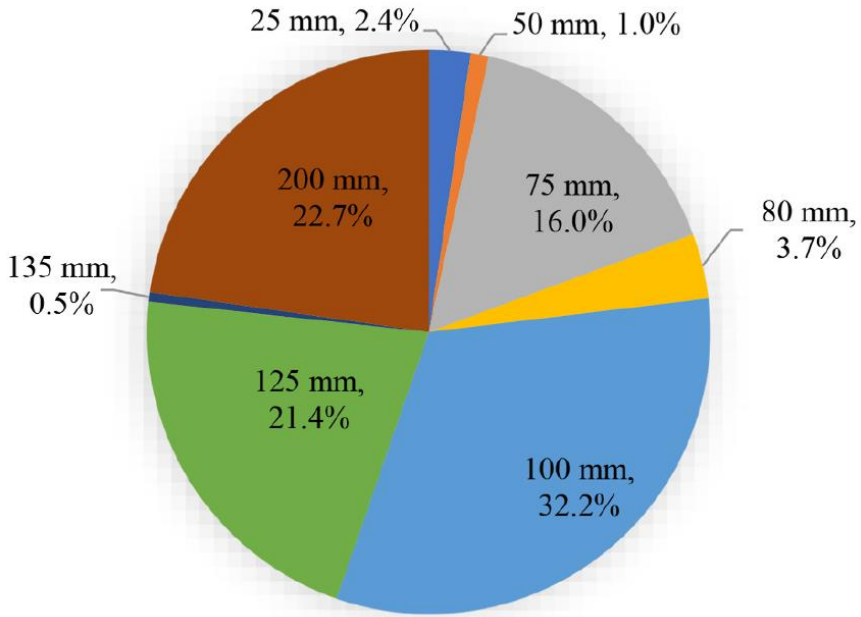
Time-Series Nested CV/ Rolling Time Window

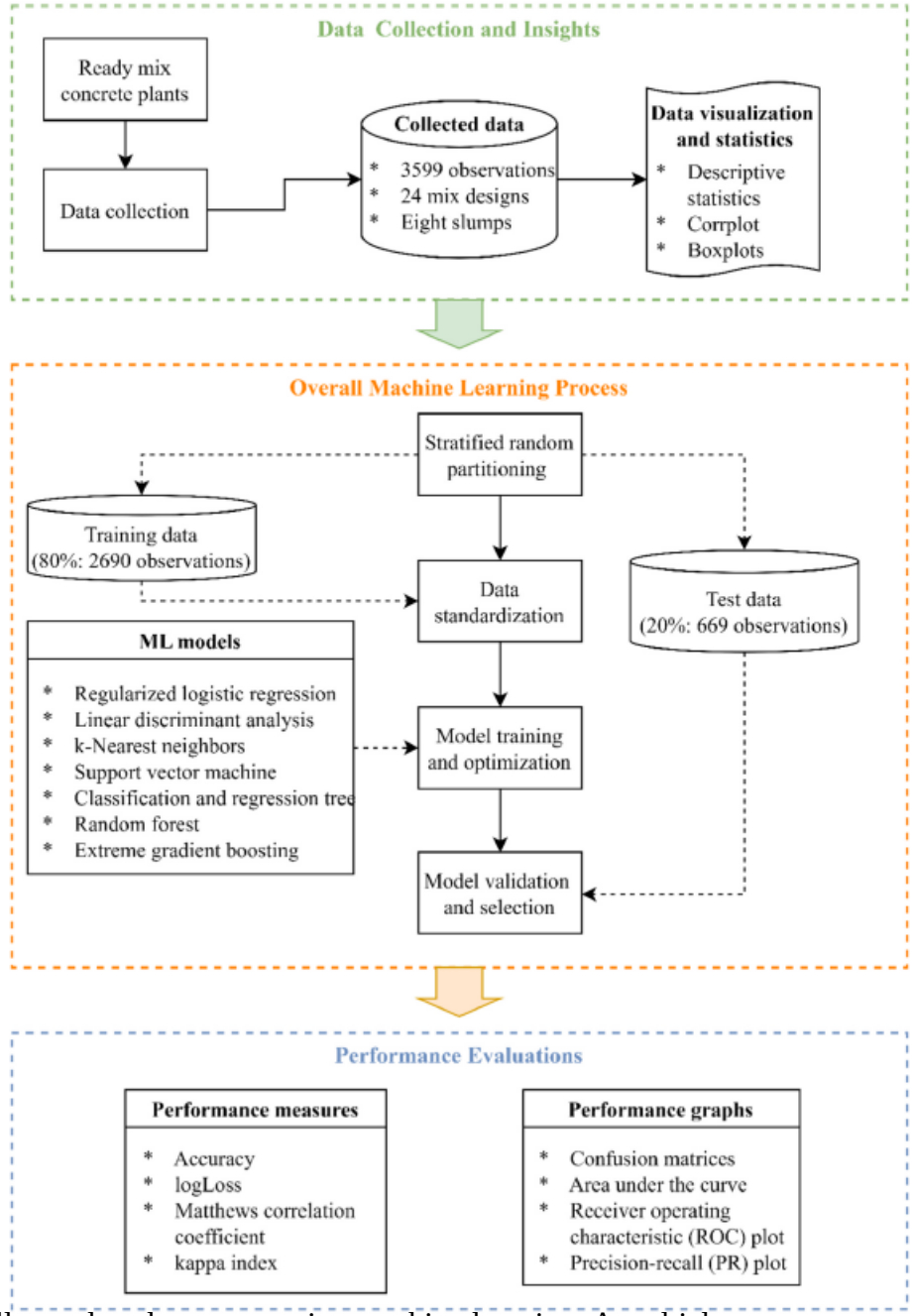




數據分割隨機抽樣？分層抽樣？

- 預拌混泥土坍度預測
  - This study attempts to develop a machine learning model to predict the concrete slump as a function of mix proportions, taking advantage of the 3599 observations of industrially produced ready-mix concrete applied in various construction projects.



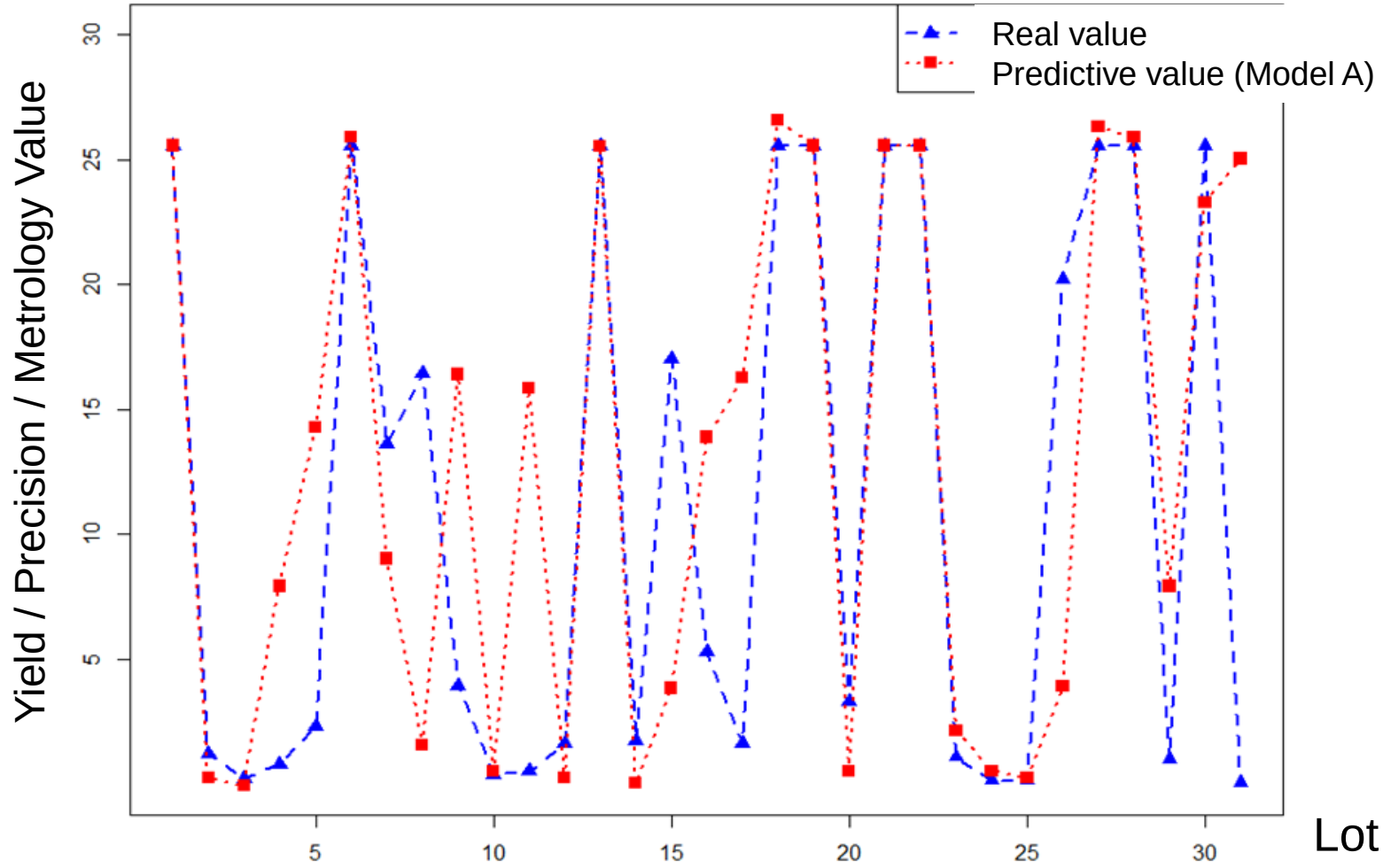


Zhang, X., Zkber, M. Z., and Zheng, W. (2022). Predicting the slump of industrially produced concrete using machine learning: A multiclass classification approach. Journal of Building Engineering, 58, 104997.

案例2: 特徵工程與品質預測

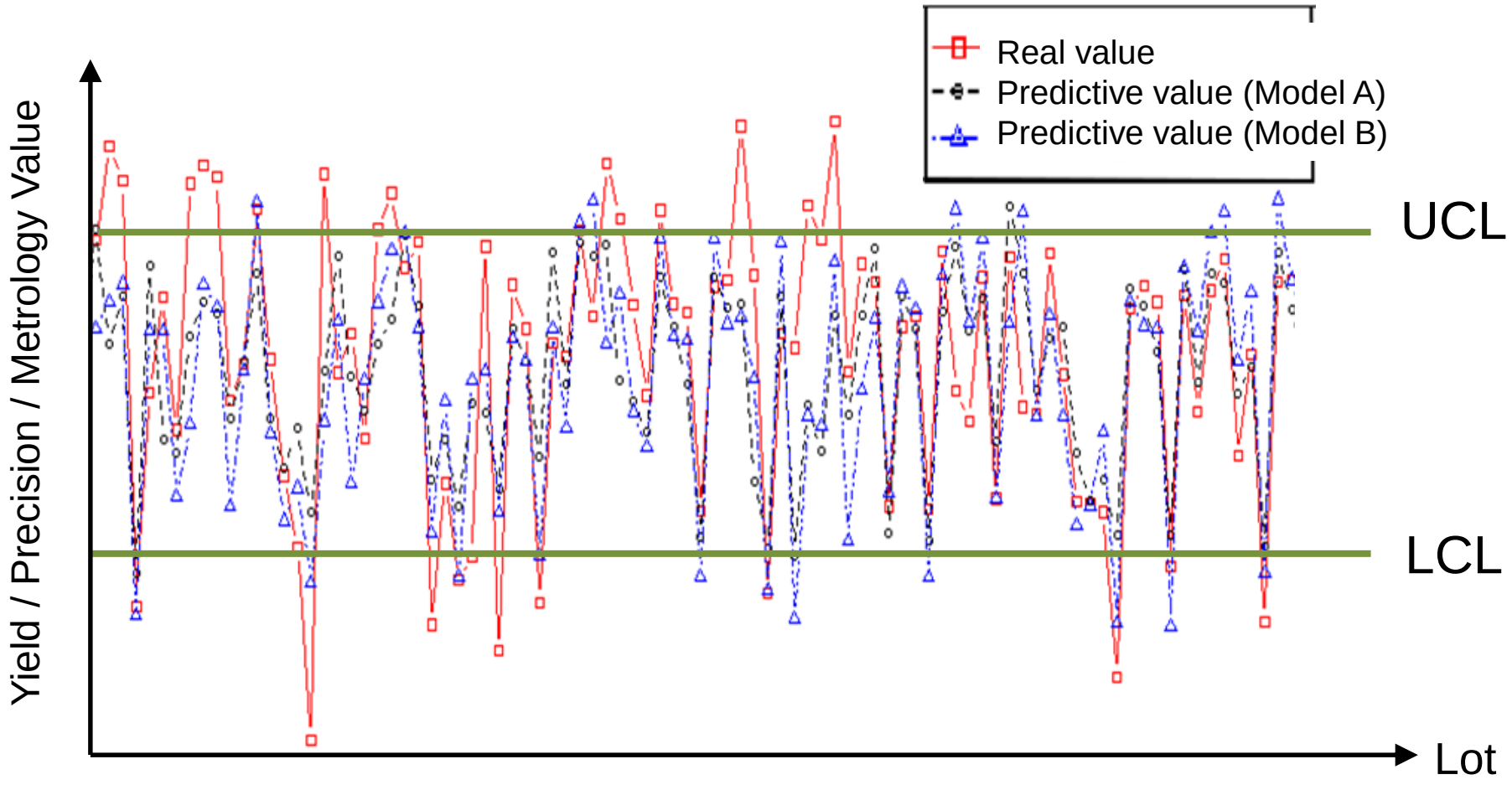
預測的結果

- Testing Dataset with R^2, Adjusted R^2, Mean Squared Error(MSE), etc.



案例2: 特徵工程與品質預測

Statistical Control Chart for Classification (分類)



- 預測一個"值"，本身沒有對錯的問題。
- 預測一個"類別"，就有對錯的問題。

案例2: 特徵工程與品質預測

分類結果- Confusion Matrix

- 以測試組資料的結果來客觀評估較佳的分類模型
- 假設是二元分類模型，也就是只有兩種類別的模型，例如：
  - （良品 / 不良品）（陽性 / 陰性）（有病 / 沒病）（發生 / 不發生）等。

		預測類別	
		類別1 (不良品)	類別2 (良品)
實際類別	類別1 (不良品)	TP (true positive)	FN (false negative) (Type II error) (miss)
	類別2 (良品)	FP (false positive) (Type I error) (false alarm)	TN (true negative)

根據分類結果，可計算出正確率 $Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$

案例2: 特徵工程與品質預測

- 靈敏度 (Sensitivity, Recall)
  - 為實際類別1(不良品)當中，被正確預測的比率

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

  - Miss (漏報) Rate = 1 － Sensitivity
- 特異度 (Specificity)
  - 為實際類別2(良品)當中，被正確預測的比率

$$\text{Specificity} = \frac{TN}{TN+FP}$$

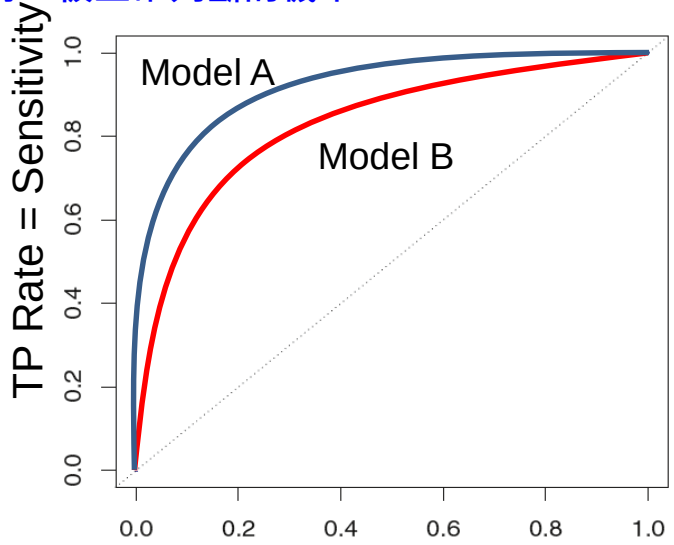
  - False Alarm (假警報) Rate = 1 － Specificity
- 精確度 (Precision)
  - 為預測類別1(不良品)當中，被正確預測的比率

$$\text{Precision} = \frac{TP}{TP+FP}$$

		預測	
		類別1	類別2
實際	類別1	TP	FN
	類別2	FP	TN

- ROC曲線(Receiver Operating Characteristic curve)

描述當資料屬於類別1(不良品)時，被正確判斷的機率



當資料不屬於類別1(不良品)時，被誤判的機率 (Type I error)

一般來說，右下方的面積愈大，該模型的分類效果愈佳!

案例2: 特徵工程與品質預測

精度/良率預測

- Model performance (128個觀測值)

Model A		預測	
		Bad	Good
實際	Bad	61	7
	Good	29	31

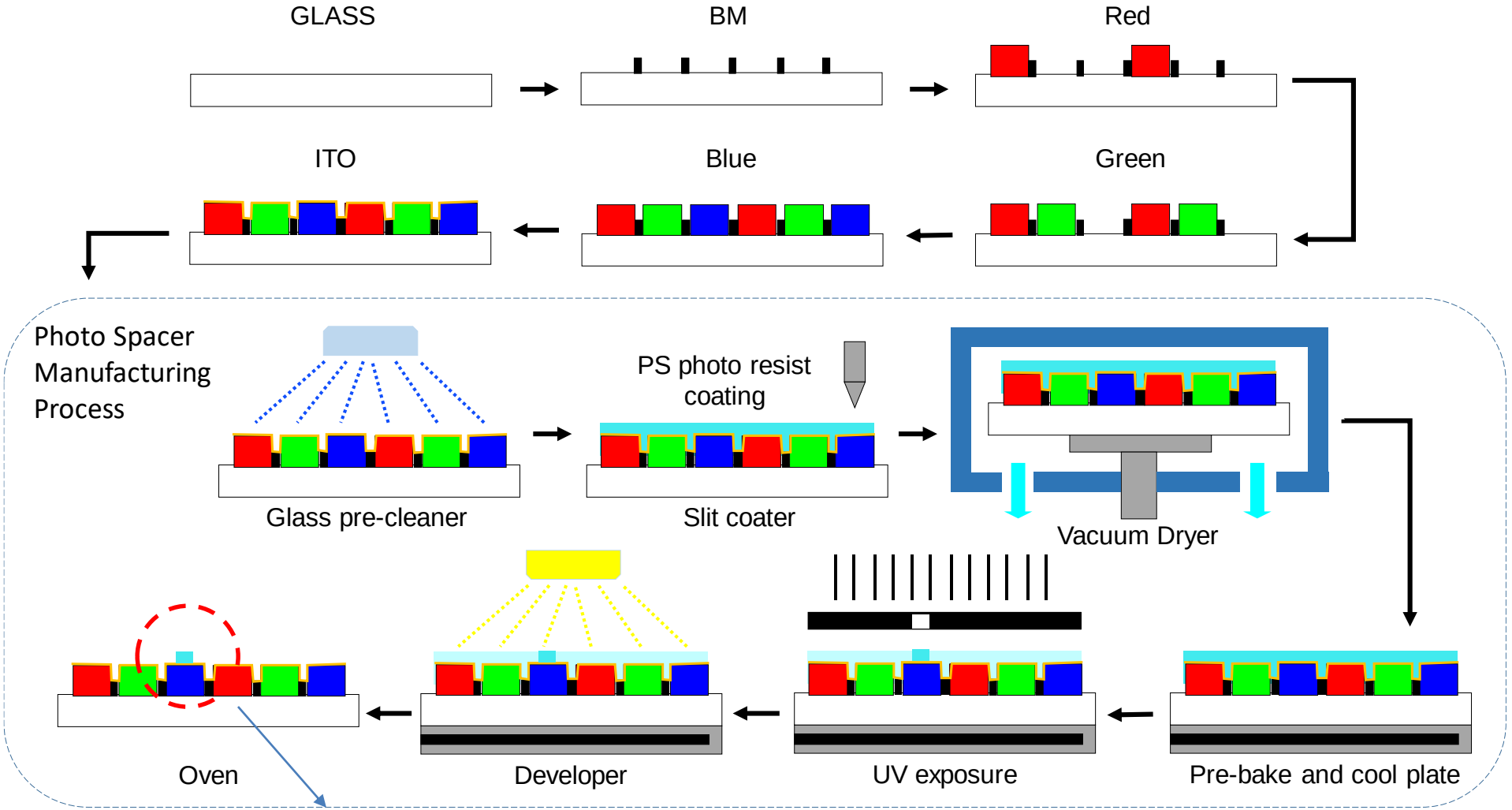
Model B		預測	
		Bad	Good
實際	Bad	47	21
	Good	7	53

	Testing			
	Accuracy	TP Rate	TN Rate	AUC
Model A	71.9%	89.7%	51.7%	70.2%
Model B	78.1%	69.1%	88.3%	78.9%

AUC: Area under the Curve of ROC

案例2:彩色濾光片工程參數篩選與膜厚預測

Color Filter



Thickness of PS prediction

Lee and Tsai (2019)

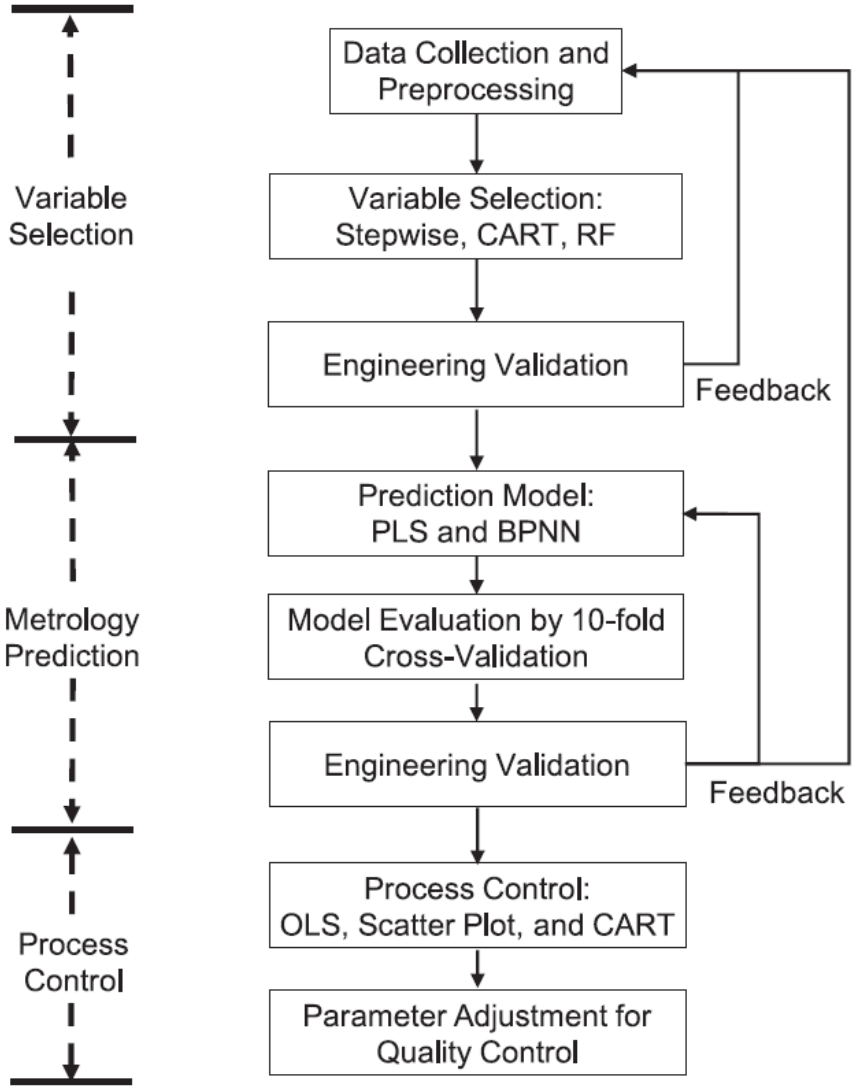
案例2:彩色濾光片工程參數篩選與膜厚預測

Data Source

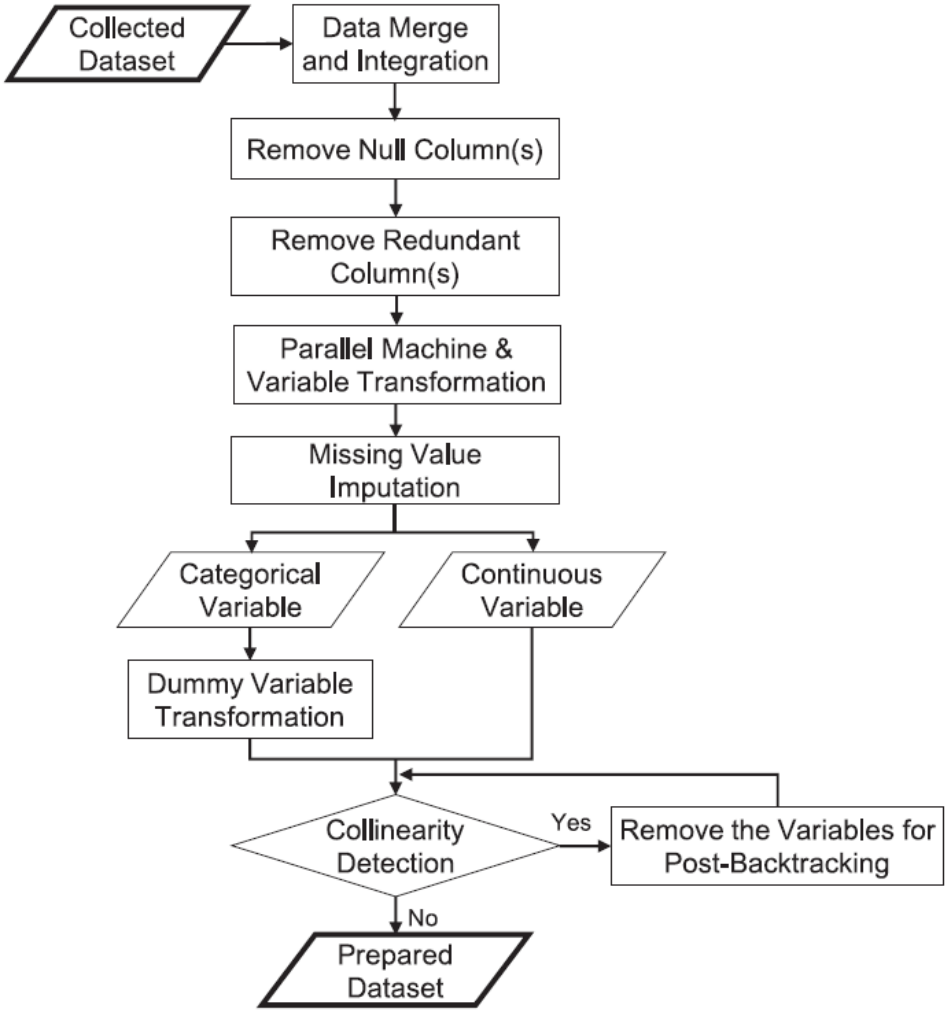
廠商 (Vendor)	Fab A	備註
收集對象 (Target)	Color filter process BM →R →G →B →UV Asher →ITO→MVA →PS	
資料來源 (Data Source)	MES and engineering data center (EDC) database	
資料收集時間(Time)	2020/10	
樣本數 (Sample size)	1000	Training:Testing = 8:2 (randomly sampling)
獨立變數(Independent Variable)	20000 factors Continuous: Categorical:	Null column: Identical column: Category w/ 1 sample: Missing value:
依變數 (Dependent Variable)	Category: Pass (-1) or Fail (1)	Pass:Fail: 700:300

案例2:彩色濾光片工程參數篩選與膜厚預測

Analytics Framework



Data Preprocessing



案例2:彩色濾光片工程參數篩選與膜厚預測

Feature Selection

- 10 out of 20,000 variables

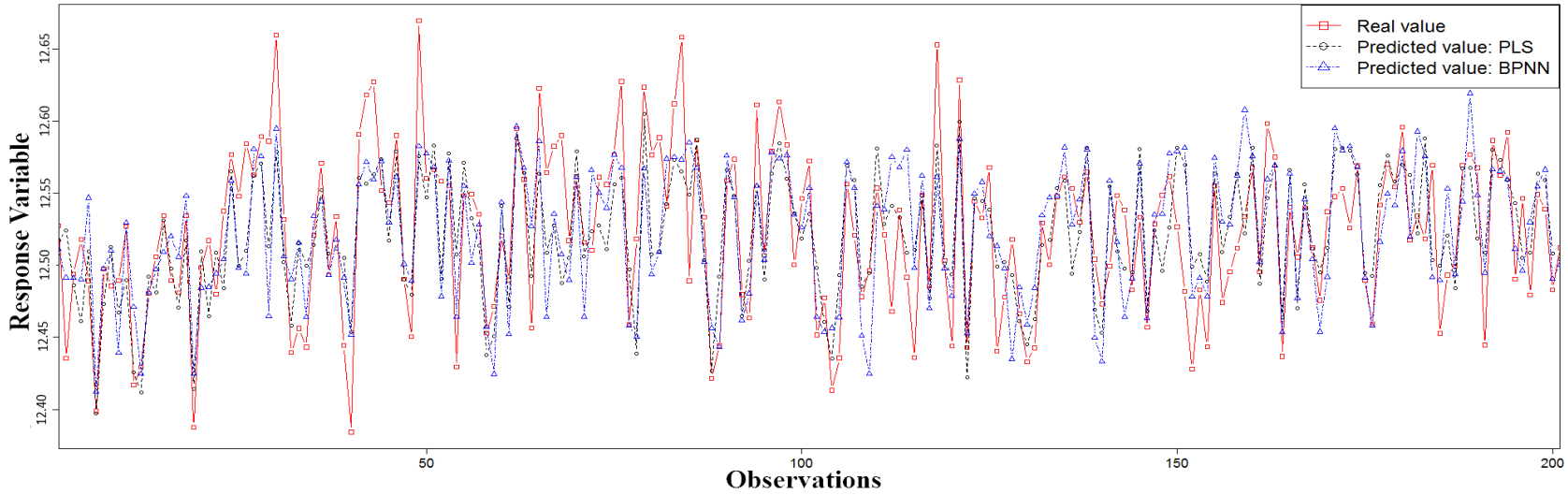
Variables	SR	CART	RF	Votes
X_097	◯	◯	◯	3
X_034	◯		◯	2
X_126		◯	◯	2
X_019		◯	◯	2
X_005			◯	1
…	…	…	…	…

Prediction Performance

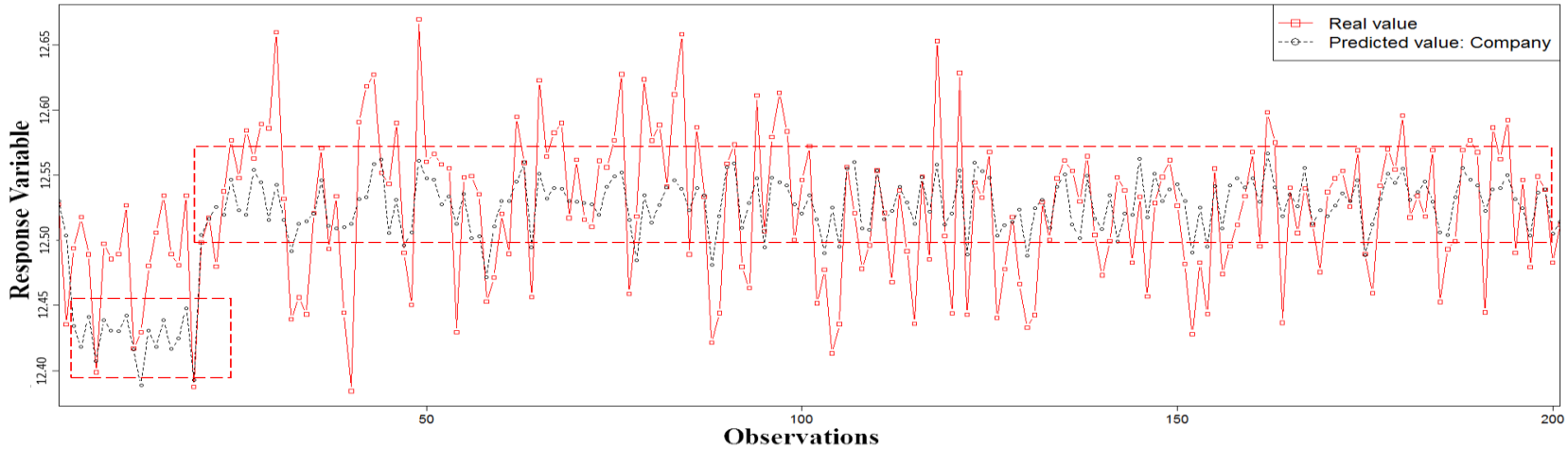
	R-squared	MSE	# of selected var.
As-Is (PLS)	0.392	8.15E-05	373
PLS	0.561	5.57E-05	10
BPNN	0.760	7.02E-05	10

案例2:彩色濾光片工程參數篩選與膜厚預測

- Proposed BPNN & PLS

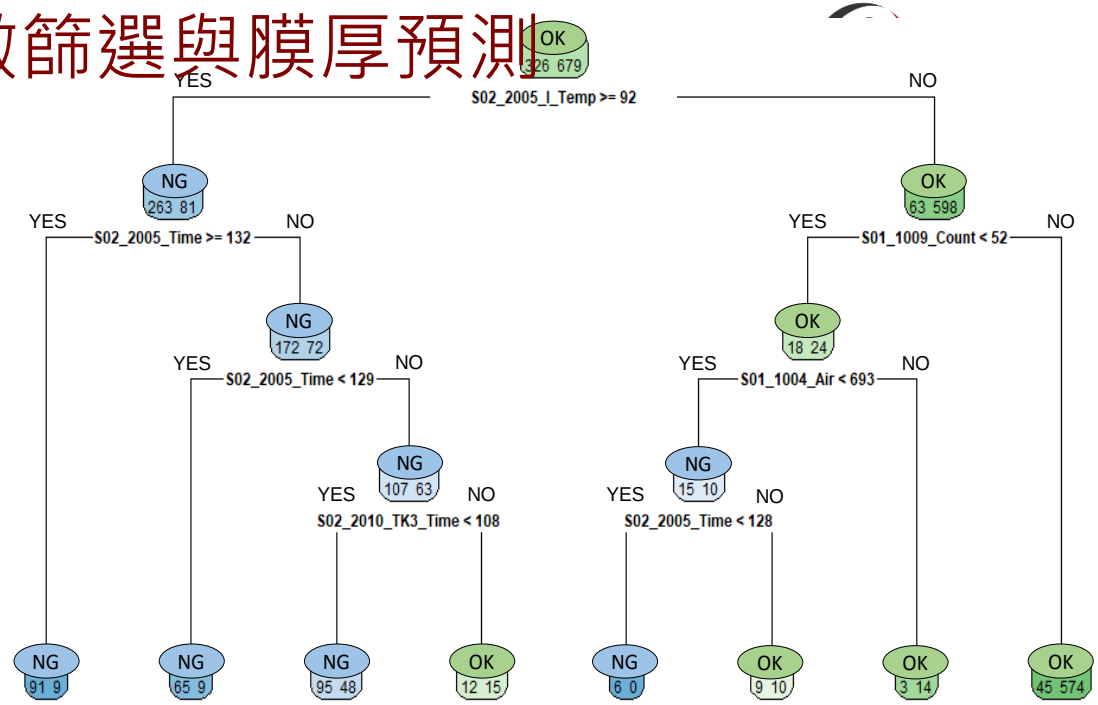


- As-Is method

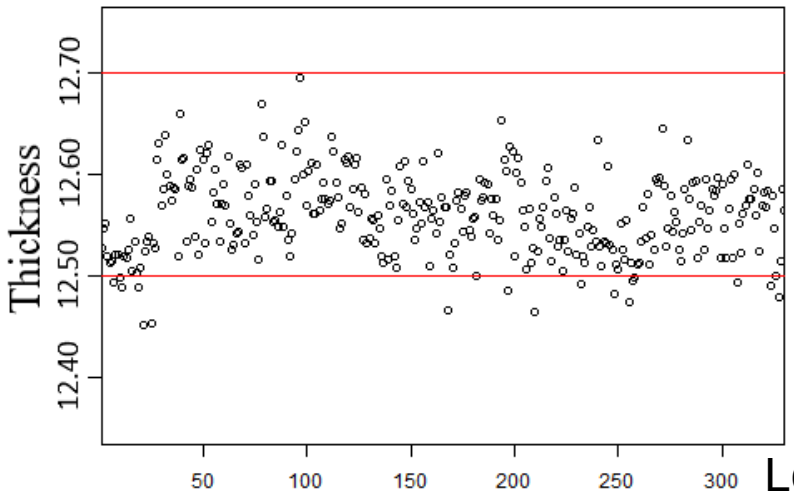


案例2:彩色濾光片工程參數篩選與膜厚預測

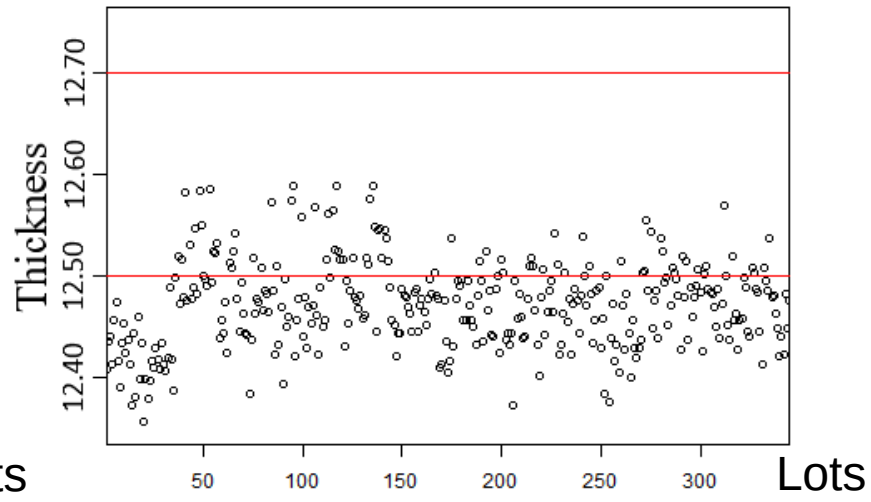
- Process Control



(a) X_034 between 89.1 and 89.4

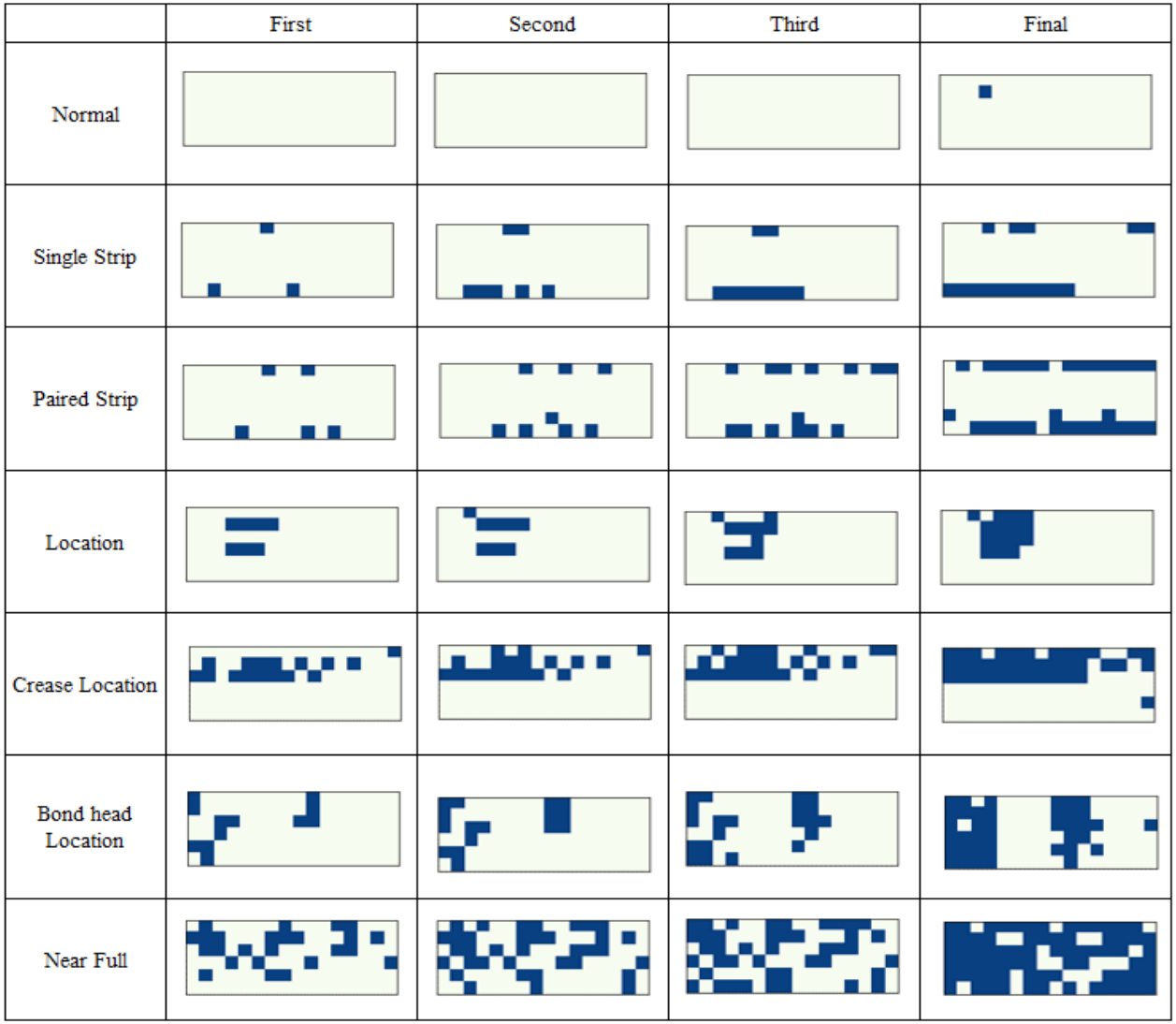


(b) X_034 higher than 92



Spatio-Temporal Anomaly Detection

Spatio-Temporal Visualization



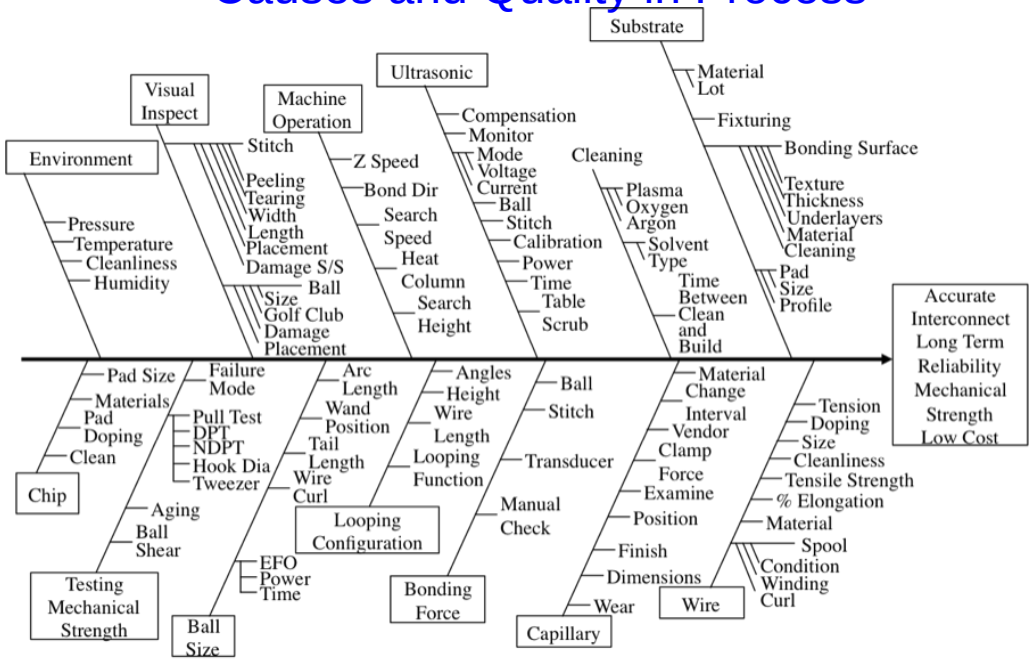
Shen, P.-C., Lu, M.-X., and Lee, C.-Y., 2022. Spatio-temporal anomaly detection for substrate strip bin map in semiconductor assembly process. IEEE Robotics and Automation Letters, 7(4), 9493-9500.

案例三： PHM & PdM

Prognostic and Health Management (PHM)

- How to manage thousands of equipment?

Causes and Quality in Process



- Unsupervised Learning and Supervised Learning
  - Unsupervised → anomaly detection (from control chart)
    - Direct measure: mechanical parameters identification
    - Indirect measure: signal processing
  - Supervised → feature engineering & selection (from signals)

https://www.semitracks.com/newsletters/june/2016-june-newsletter.php

Lee, C.-Y., Z.-H. Dong. 2019. Hierarchical Equipment Health Index Framework. IEEE Transactions on Semiconductor Manufacturing, 32 (3), 267-276.

案例三：PHM & PdM

Data Collection

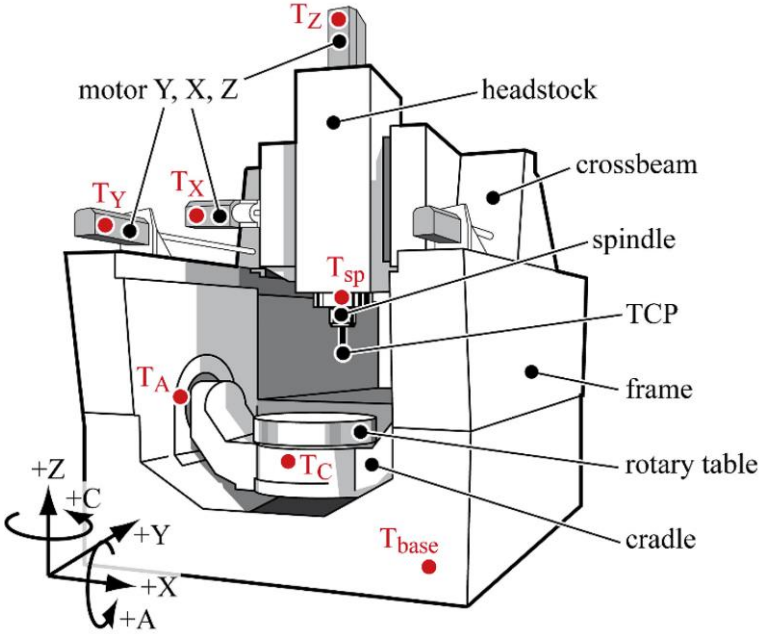
- **直接**(direct)且**離線**(off-line)
  - 多為**基於模型**(model-based)的方法
  - 是對設備、機構本身物理特性直接地量測，例如與材料特性有關的**剛性**(stiffness)、**阻尼**(damping)、**慣量**(mass)、**摩擦力**(friction)、**齒隙**(backlash)等，須藉由相關的物理模型與離線的量測才能估計出這些物理特性的參數
- **間接**且**線上**(on-line)
  - 多為**基於數據**(data-based or model-free)的方法
  - 是以感測器或內建的驅動器存取數據，例如**電流**(current)、**震動**(vibration)、**聲發射**(acoustic emission)、**油屑**(oil debris)、**影像**(image)、**溫度**(temperature)、**壓力**(pressure)等與設備間接相關的特性，須由特徵工程進一步對特徵進行萃取與轉換才能得出與設備有關的健康狀態。

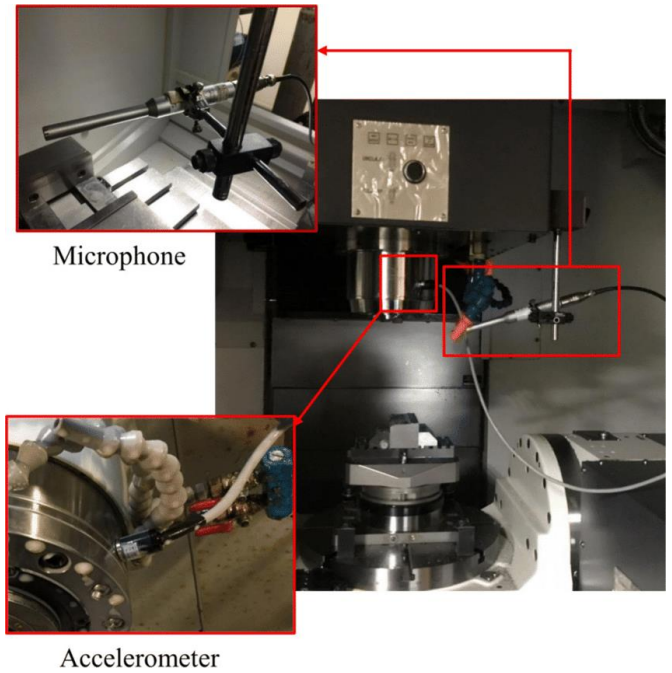
	Model-based	Model-free
Supervised Learning	System identification	RUL
Unsupervised Learning	軸承元件損壞的對應頻率	Feature extraction

案例三：PHM & PdM

Data Collection

- computer numerically controlled (CNC) components
  - mechanical system (shaft), bearing, gear, pump, alternator, and cutting tool
- Sensor/Accelerometer Installation
  - 安裝位置(定子、轉子、內壁、外壁)、安裝環境(有其他機構影響)、安裝工況(等速、加速、作動一致與否)、安裝鬆緊(鬆脫、損毀)等





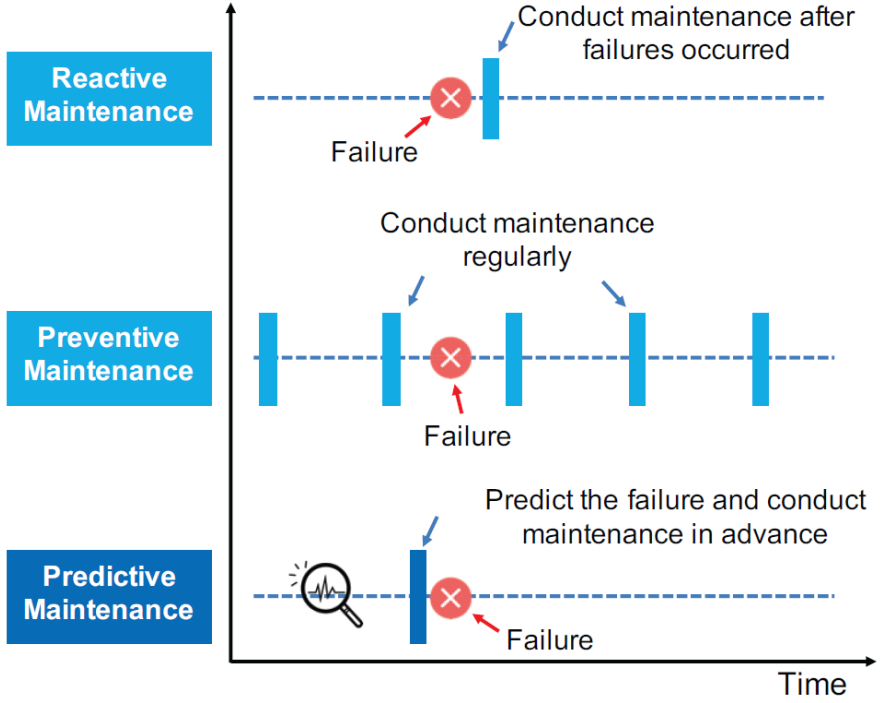
https://doi.org/10.1016/j.precisioneng.2020.06.010

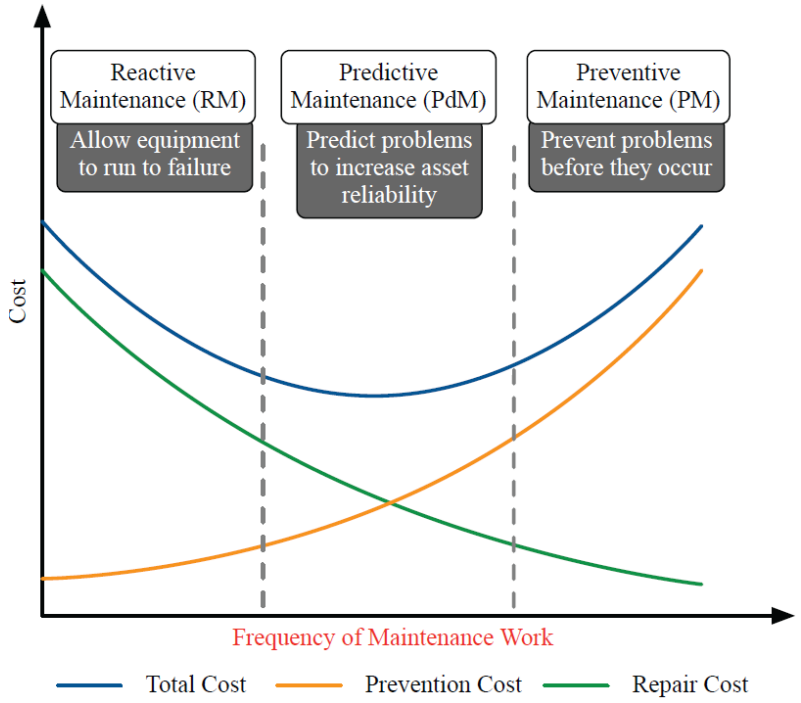
Tran, MQ., Liu, MK. & Tran, QV. Milling chatter detection using scalogram and deep convolutional neural network. Int J Adv Manuf Technol 107, 1505–1516 (2020).

案例三：PHM & PdM

維修保養

- Reactive (RM or CM): Service or replace equipment after it fails
- Preventive: Service/replace machine according to the manufacturer's suggested schedule, the amount of time it has been in service, or operational observations
- Condition-based (CBM): Service or replace equipment based on monitoring performed to assess its current condition
- Predictive maintenance (PdM): Maintaining components according to fact-based expectations for when they will fail or require service, i.e., remaining useful life.





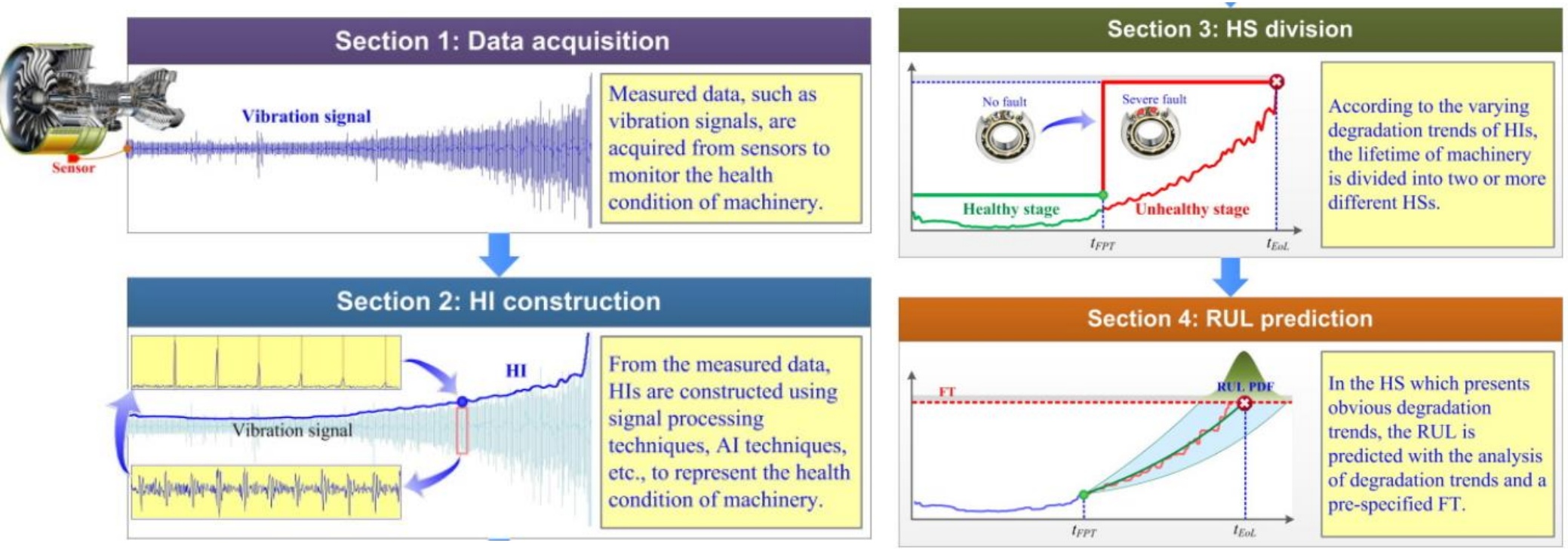
Ran, et al. (2019). A survey of predictive maintenance: systems, pruposes and approaches. IEEE Communications Surveys & Tutorials.

案例三：PHM & PdM

- *HI: Health Indicator*
- *HS: Health Stage*
- *RUL: Remaining Useful Life*

PdM- Supervised Learning

- predict the condition of equipment to estimate when the equipment is likely to fail and decide which maintenance activity should be performed such that a good trade-off between maintenance frequency and cost can be achieved.
  - Purpose: eliminate unexpected downtime, improve overall availability/reliability of systems and reduce operating costs.
- PdM issues are different/customized across industries, plants and machines.



Lei, et al. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. Mechanical Systems and Signal Processing, 104, 799-834.

Ran, et al. (2019). A survey of predictive maintenance: systems, purposes and approaches. IEEE Communications Surveys & Tutorials.

案例三：PHM & PdM

- Feature Engineering (Time Domain, Frequency Domain, Time-frequency Domain)
  - Root Mean Square (RMS), Mean, Variance, Skewness, Kurtosis, and Crest Factor/Max/Min, …
  - Time synchronous averaged (TSA) signal, sliding window, residual signal (RES), difference signal (DIF), …
  - Time series decomposition, Hilbert vibration decomposition, empirical mode decomposition, intrinsic mode functions (IMF), …
  - Regression (intercept, slope), exponential degradation $\theta\exp(\beta t)$ (amplitude θ, slope β), autoregression, …

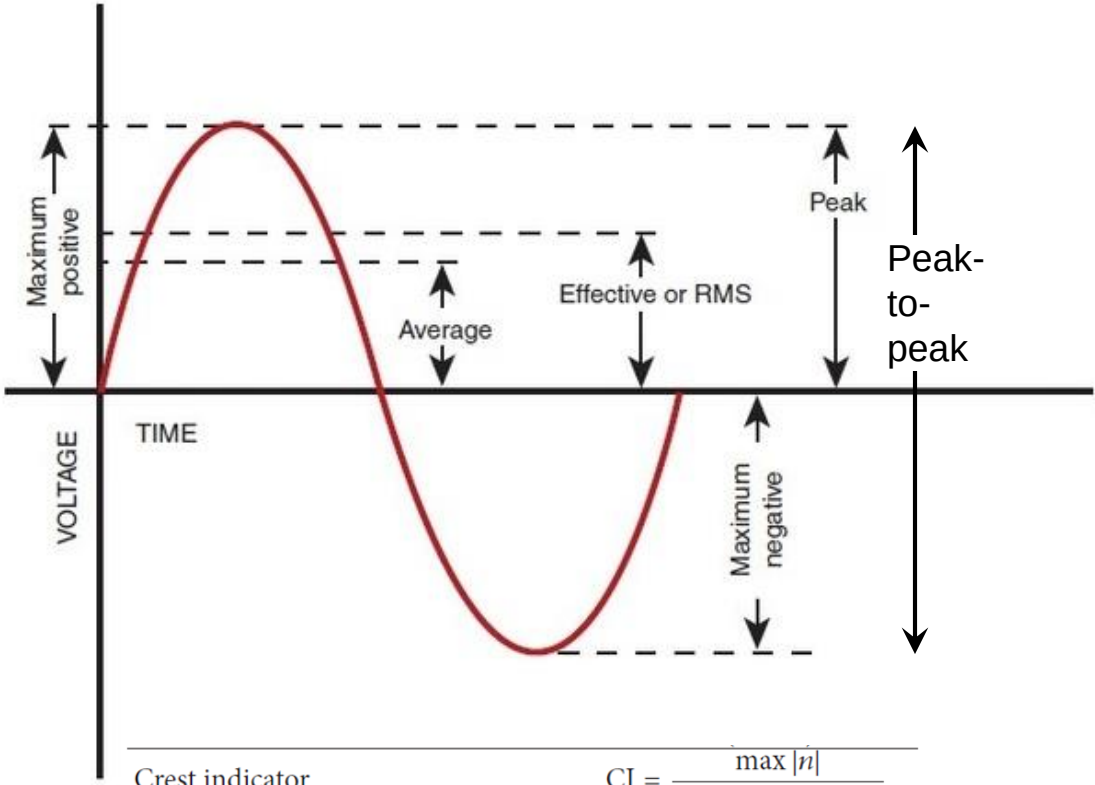
Component	Issue & failure	Characteristic	Common measures	Common features	Common algorithms used
Bearing	Outer-race, inner-race, roller, and cage failures	Raw data does not contain insightful information; low amplitude; high noise	Vibration, oil debris, acoustic emission	Vibration characteristic frequency, time domain statistical characteristics, metallic debris shape, size, quantity, sharp pulses and rate of development of stress-waves propagation	Fourier Transform (FT) [18,19], Short Time Frequency Transform (STFT) [20], Wavelet Transform (WT) [21], Empirical Mode Decomposition (EMD) [22], Bispectrum [23], Autoregression (AR) Frequency Spectra [24], Hilbert Spectrum [25], Instantaneous Power Spectrum [26], Hilbert–Huang Transform (HHT) [27], Neural

Lee, et al. (2014). Prognostics and health management design for rotary machinery systems- Reviews, methodology and applications. Mechanical Sysetms and Signal Processing, 42, 314-334.

案例三：PHM & PdM

Feature Engineering

Feature	Equation
Maximum Value	$f_{1i} = max(X(i))$
Mean Value	$f_{2i} = \frac{1}{N}\sum_{i=1}^{N} X(i)$
Minimum Value	$f_{3i} = min(X(i))$
Standard Value	$f_{4i} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X(i) - f_{1i})^2}$
Peak to Peak Value	$f_{5i} = f_{1i} - f_{3i}$
Mean Amplitude	$f_{6i} = \frac{1}{N}\sum_{i=1}^{N} \lvert X(i)\rvert$
Root Mean Square Value	$f_{7i} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X(i)^2}$
Skewness Value	$f_{8i} = \frac{1}{N}\sum_{i=1}^{N} X(i)^3$
Kurtosis Value	$f_{9i} = \frac{1}{N}\sum_{i=1}^{N} X(i)^4$
Waveform Indicator	$f_{10i} = \frac{f_{7i}}{f_{6i}}$
Pulse Indicator	$f_{11i} = \frac{f_{1i}}{f_{6i}}$
Kurtosis Index	$f_{12i} = \frac{f_{9i}}{f_{7i}}$
Peak Index	$f_{13i} = \frac{f_{1i}}{f_{7i}}$
Square Root Amplitude	$f_{14i} = (\frac{1}{N}\sum_{i=1}^{N} \sqrt{\lvert X(i)\rvert})^2$
Margin Indicato	$f_{15i} = \frac{f_{1i}}{f_{14i}}$
Skewness Indicator	$f_{16i} = \frac{f_{8i}}{f_{7i}^4}$

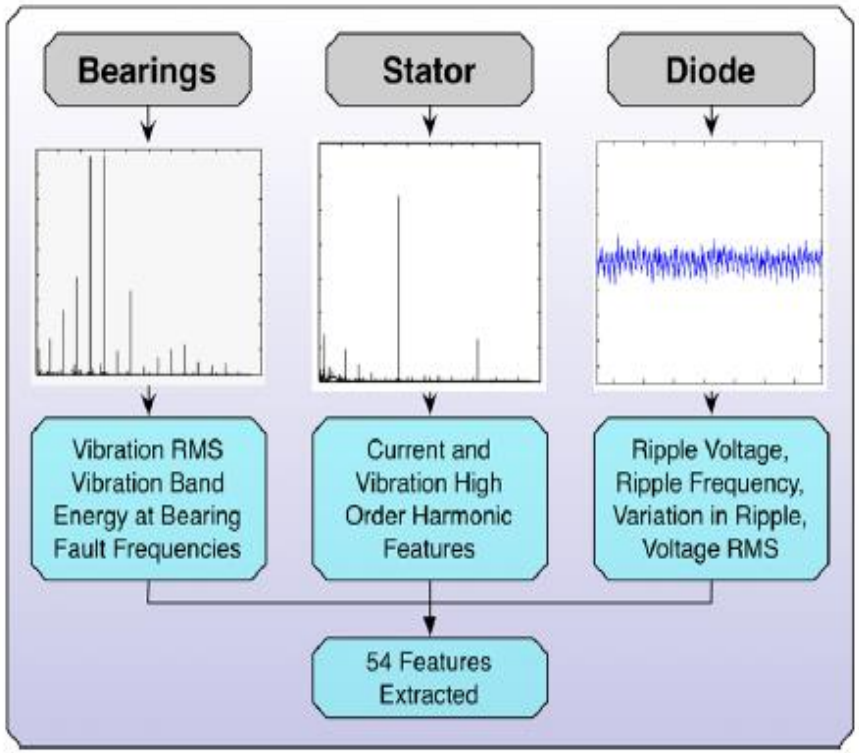


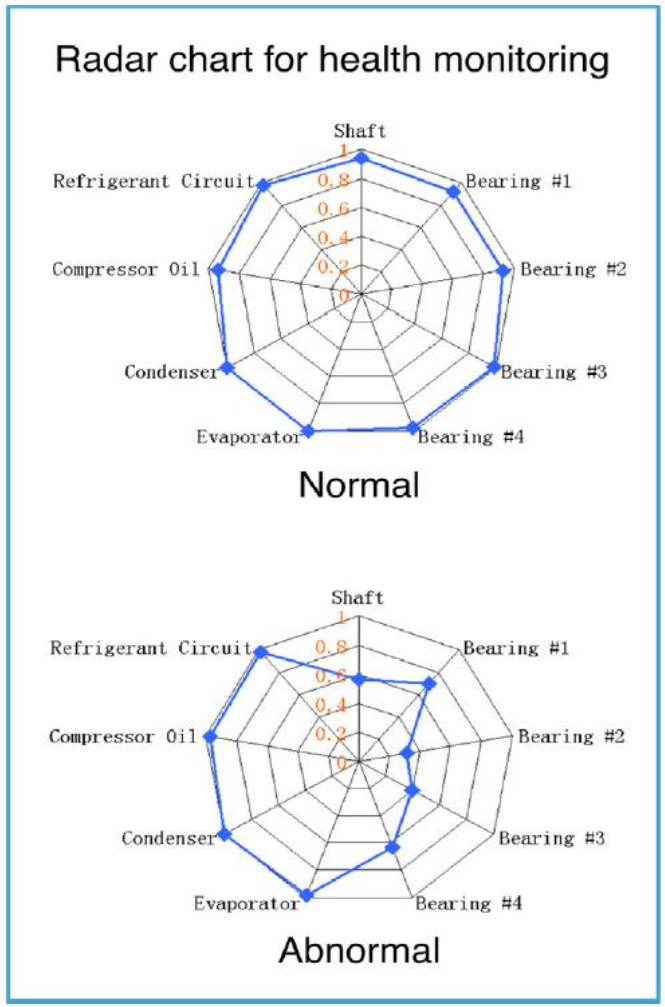
Crest indicator	$\mathrm{CI} = \frac{\max\lvert n\rvert}{\sqrt{(1/N)\sum_{j=1}^{N}(n_j)^2}}$
Clearance indicator	$\mathrm{CLI} = \frac{\max\lvert n\rvert}{\left((1/N)\sum_{j=1}^{N}\sqrt{\lvert n_j\rvert}\right)^2}$
Shape indicator	$\mathrm{SI} = \frac{\sqrt{(1/N)\sum_{j=1}^{N}(n_j)^2}}{(1/N)\sum_{j=1}^{N}\lvert n_j\rvert}$
Impulse indicator	$\mathrm{MI} = \frac{\max\lvert n\rvert}{(1/N)\sum_{j=1}^{N}\lvert n_j\rvert}$

W. Jiang, Y. Hong, B. Zhou, X. He, and C. Cheng, "A gan-based anomaly detection approach for imbalanced industrial time series," IEEE Access, vol. 7, pp. 143 608–143 619, 2019.
https://www.quora.com/Is-the-DC-voltage-the-same-in-the-RMS-voltage

案例三：PHM & PdM

Equipment → Sensor Data Collection → Modelling → Visualization





(Lee et al., 2014)

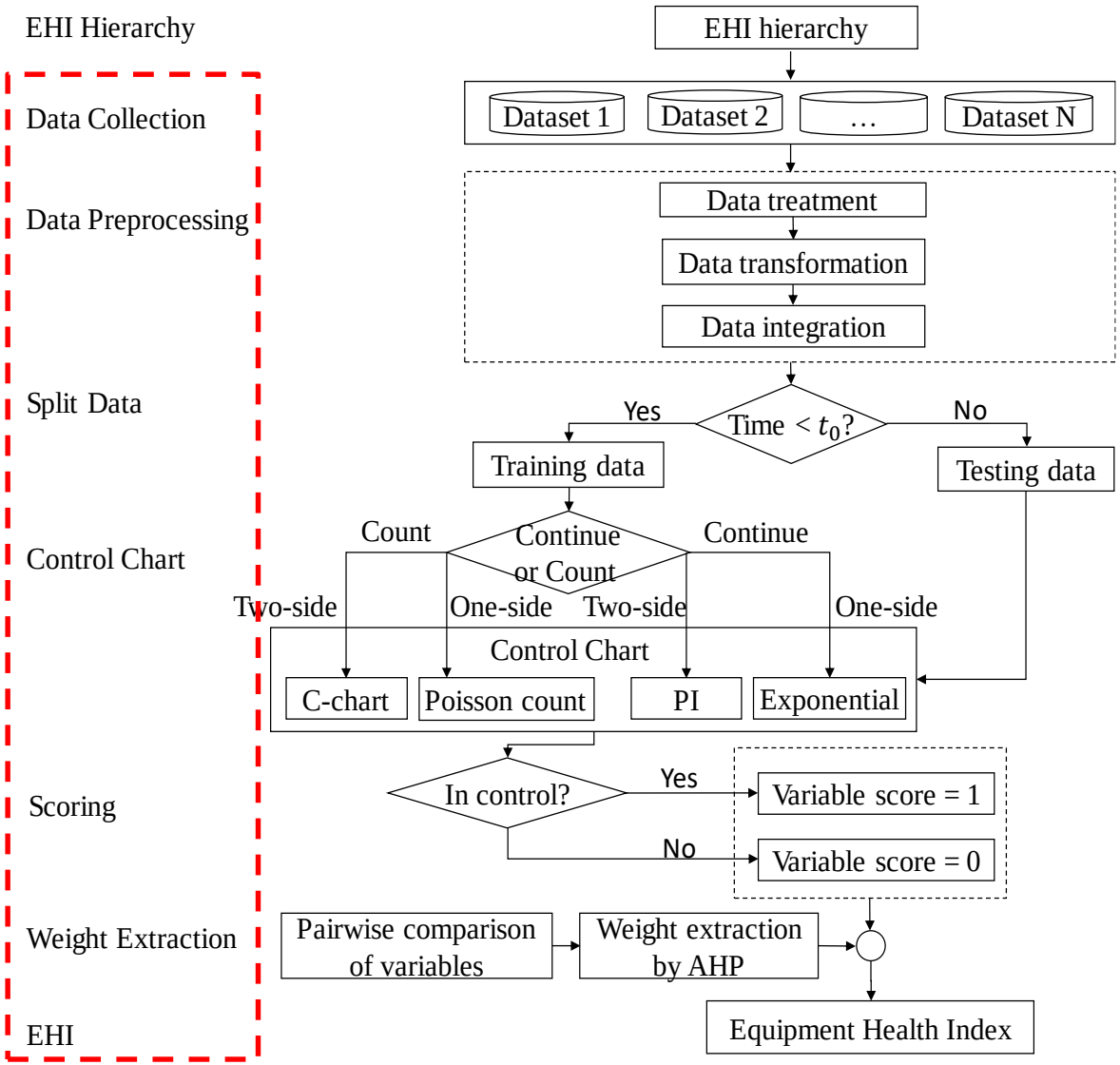
Lee, et al. (2014). Prognostics and health management design for rotary machinery systems- Reviews, methodology and applications. Mechanical Sysetms and Signal Processing, 42, 314-334.

Equipment Health Index (EHI)

Health Index

- Feature Engineering
  - **Correlation(相關性)**
  - **Monotonicity(單調性)**
  - **Robustness(穩健性)**
- EHI
  - Independent
  - Subjective weights
- HTI (Hotelling's T^2)
  - Correlation
  - Objective weights

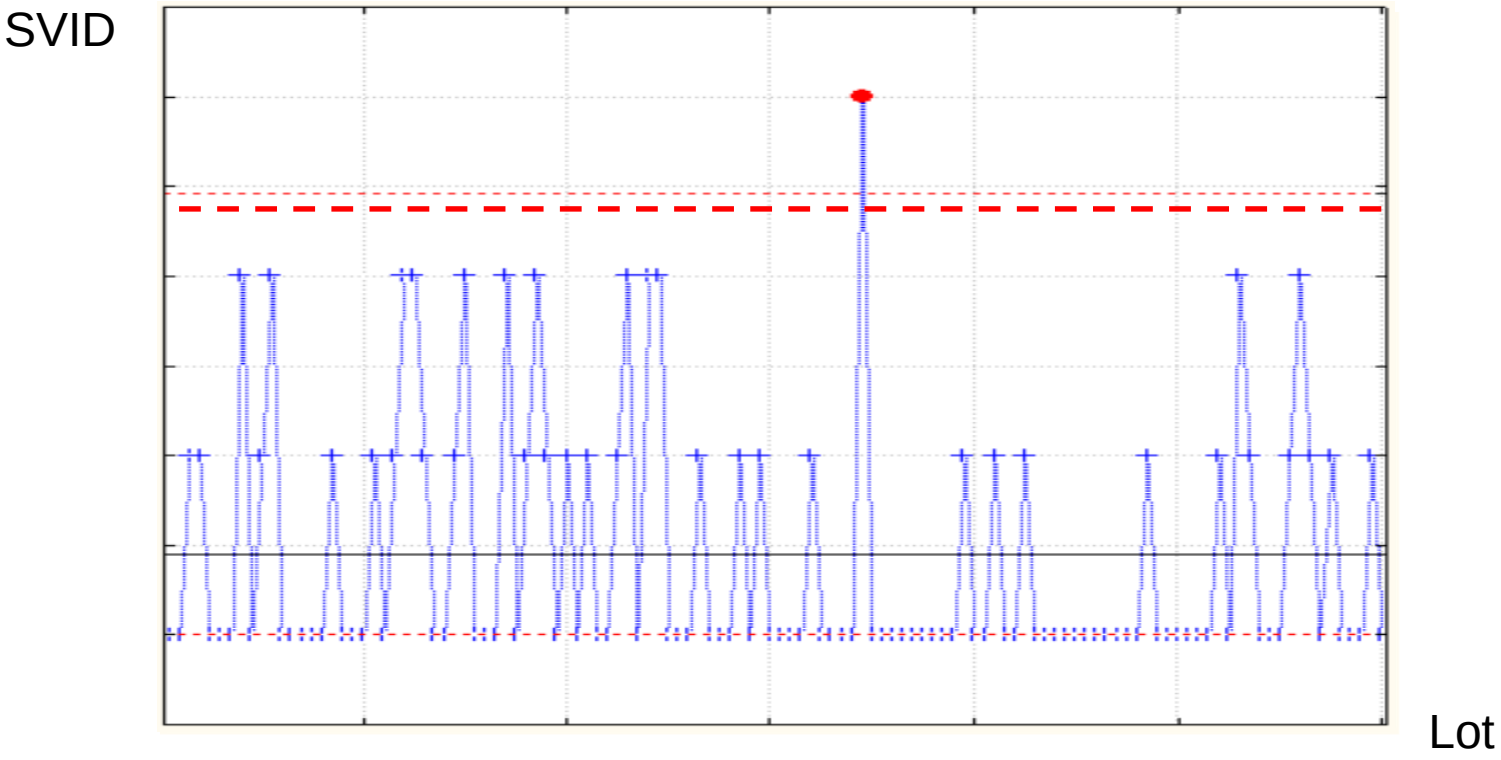
EHI Framework



Lee, C.-Y., Z.-H. Dong. 2019. Hierarchical Equipment Health Index Framework. IEEE Transactions on Semiconductor Manufacturing, 32 (3), 267-276.

Equipment Health Index (EHI)

- Control Charts
  - One-side Variable vs. Two-side Variable
  - Continuous vs. Discrete
- Why do we apply so many different kinds of control charts?
  - Variable-specific control chart



Control Chart Performance

Average Run Length (ARL)

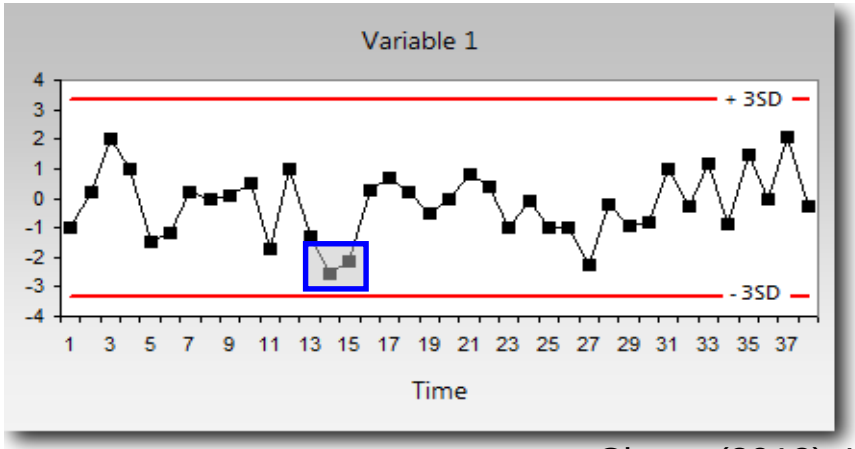
- Determine the appropriate sample size and sampling frequency.
- ARL is the avg. # of points plotted to signal an out-of-control condition.
- Let p = probability that any point exceeds the control limits. Then, $\text{ARL} = \frac{1}{p}$
  - $\bar{X}$ chart with 3-sigma limits, p=0.0027 is probability that a normally distributed point falls outside the limits when the process is in control, so ARL= $1/p$ = 370

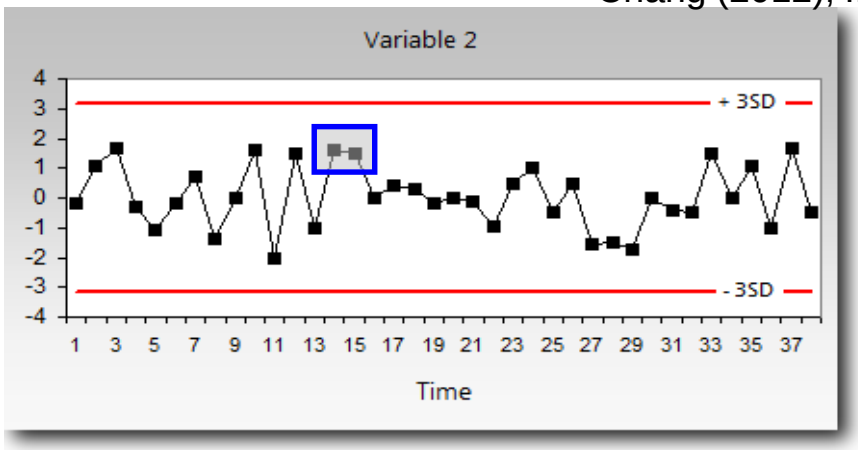
範圍	預期的樣本比例在範圍內	近似預期頻率超出範圍	近似頻率（假設每天實驗一次）
μ ± 0.5σ	0.382 924 922 548 026	3次中發生2次	每星期四至五次
μ ± σ	0.682 689 492 137 086	3次中發生1次	每星期兩次
μ ± 1.5σ	0.866 385 597 462 284	7次中發生1次	每星期
μ ± 2σ	0.954 499 736 103 642	22次中發生1次	每三個星期
μ ± 2.5σ	0.987 580 669 348 448	81次中發生1次	每三個月
μ ± 3σ	0.997 300 203 936 740	370次中發生1次	每年
μ ± 3.5σ	0.999 534 741 841 929	2 149次中發生1次	每六年
μ ± 4σ	0.999 936 657 516 334	15 787次中發生1次	每43 年（約一生兩次）
μ ± 4.5σ	0.999 993 204 653 751	147 160次中發生1次	每403 年（近代以來僅1次）
μ ± 5σ	0.999 999 426 696 856	1 744 278次中發生1次	每4776年（人類記錄歷史以來僅1次）
μ ± 5.5σ	0.999 999 962 020 875	26 330 254次中發生1次	每72 090年（智人出現以來僅4次）
μ ± 6σ	0.999 999 998 026 825	506 797 346次中發生1次	每138萬年（直立人出現以來僅1-2次）
μ ± 6.5σ	0.999 999 999 919 680	12 450 197 393次中發生1次	每3400萬年（恐龍滅絕以來僅2次）
μ ± 7σ	0.999 999 999 997 440	390 682 215 445次中發生1次	每10.7億年（地球誕生以來僅4次）

https://zh.wikipedia.org/zh-tw/68%E2%80%9395%E2%80%9399.7%E6%B3%95%E5%89%87

Equipment Health Index (EHI)

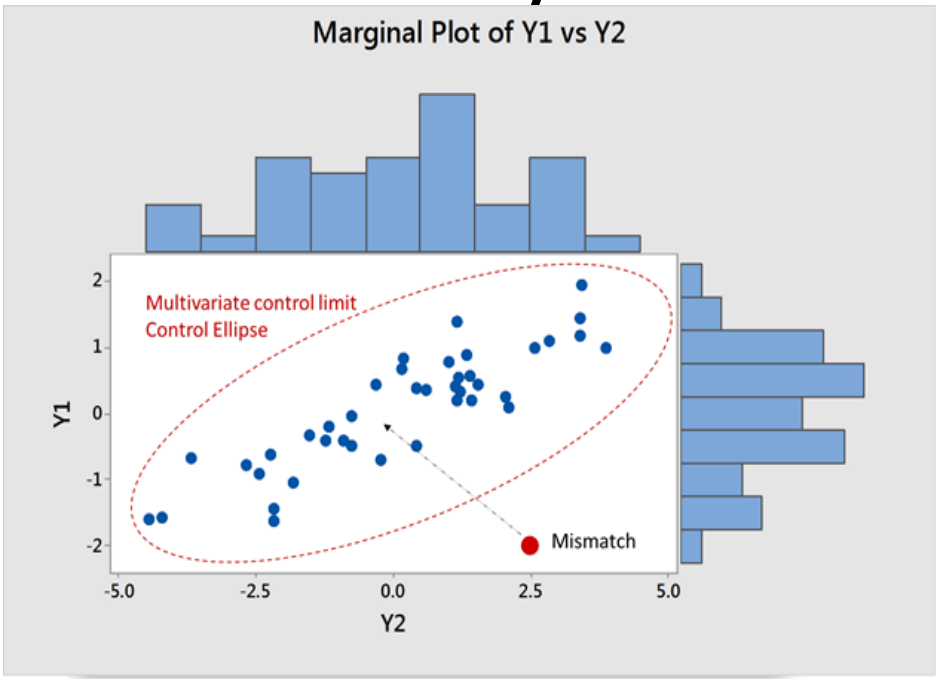
- How to consider the correlation among variables?
  - Multivariate Control Chart (statistical-based)





Chang (2012), IBM

Multivariate Control Limits



The information is found in the correlation pattern - not in the individual variables!

Scibilia, B., 2016. A simple guide to multivariate control charts. https://blog.minitab.com/blog/applying-statistics-in-quality-projects/a-simple-guide-to-multivariate-control-charts

Equipment Health Index (EHI)

Hotelling's T-squared distribution (HTI)

- Multivariate Control Chart (statistical-based)
- Mahalanobis distance (馬氏距離)

$$t^2 = (\bar{\mathbf{x}} - \boldsymbol{\mu})' \hat{\boldsymbol{\Sigma}}_{\bar{\mathbf{x}}}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu})$$

Also, from the distribution,

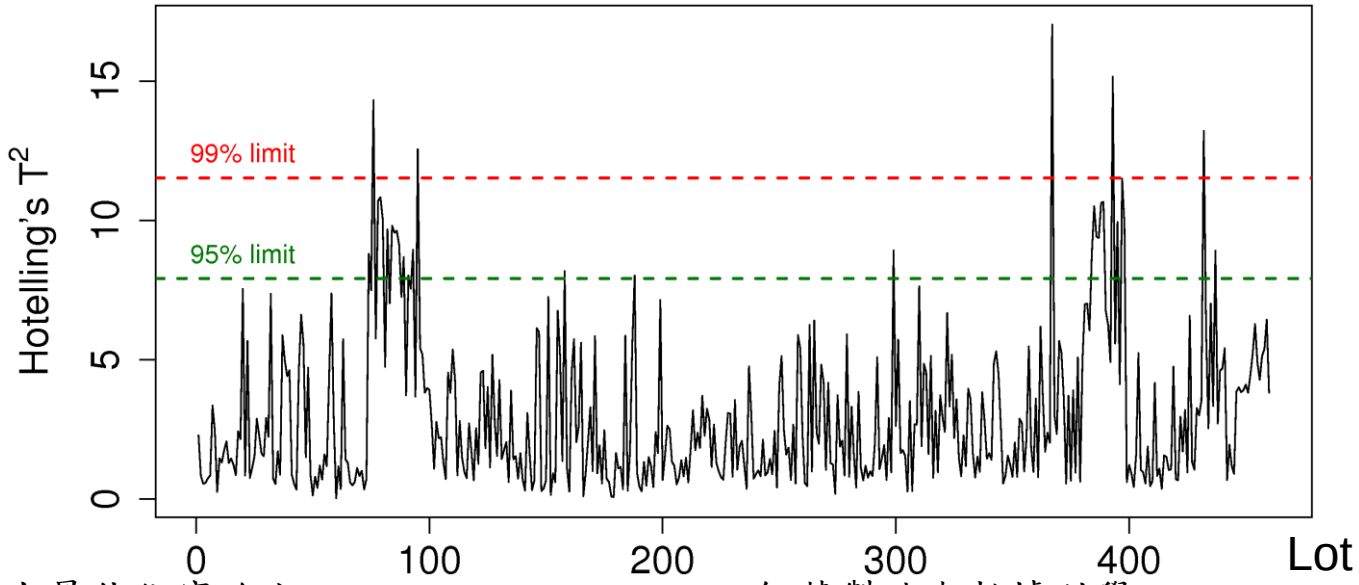
$$t^2 \sim T^2_{p,n-1} = \frac{p(n-1)}{n-p} F_{p,n-p},$$

where $F_{p,n-p}$ is the *F*-distribution with parameters *p* and *n* − *p*.

Sample covariance

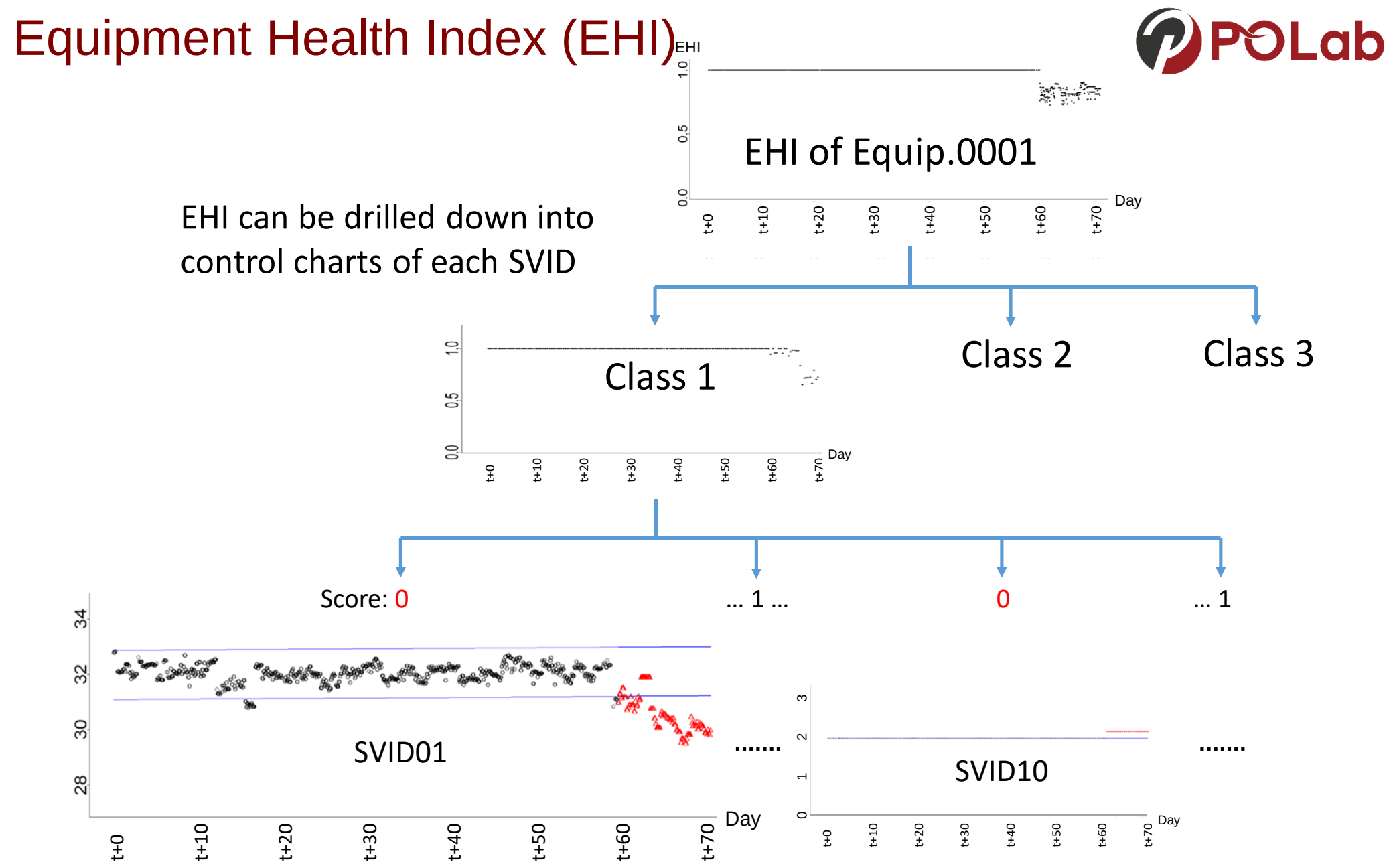
$$\hat{\boldsymbol{\Sigma}} = \frac{1}{n-1} \sum_{i=1}^{n} (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})'$$

The sample covariance matrix of the mean $\hat{\boldsymbol{\Sigma}}_{\bar{\mathbf{x}}} = \hat{\boldsymbol{\Sigma}}/n$



https://learnche.org/pid/latent-variable-modelling/principal-component-analysis/hotellings-t2-statistic

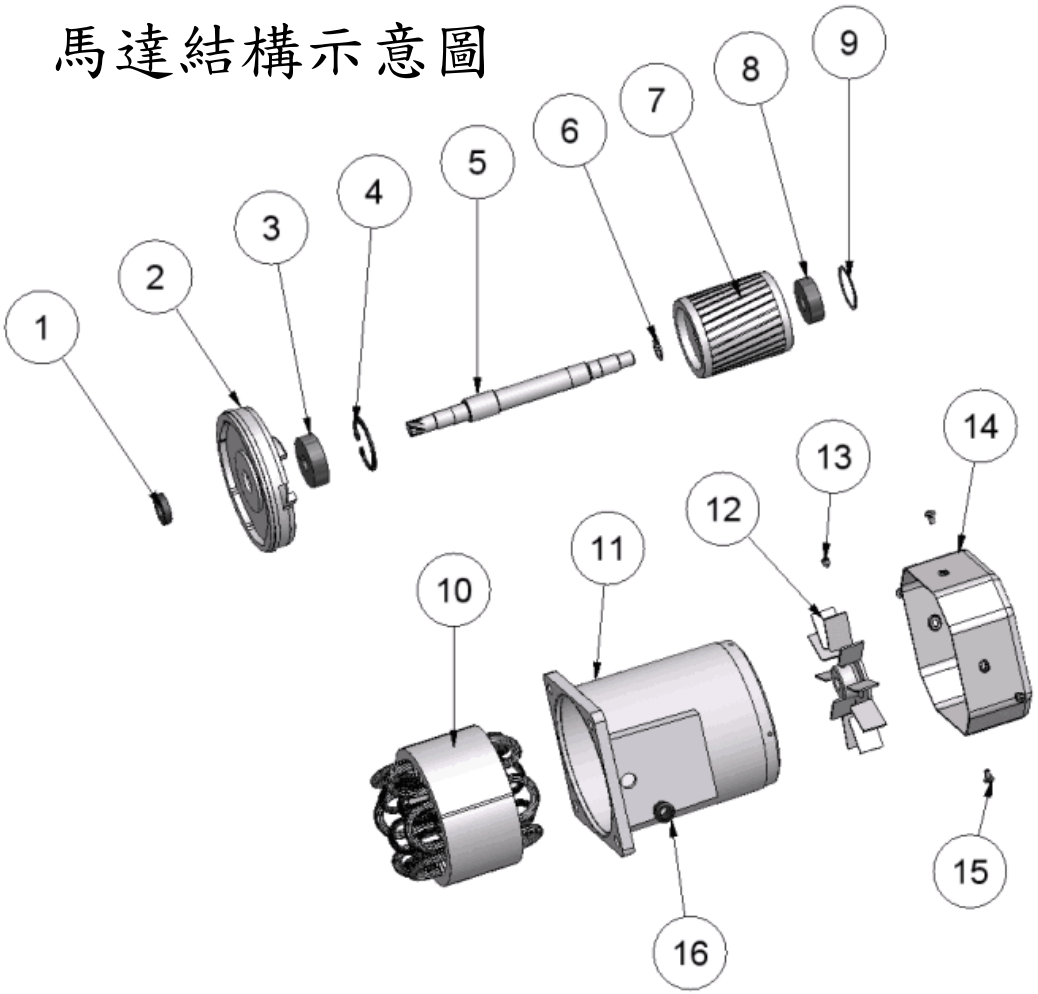
Equipment Health Index (EHI)



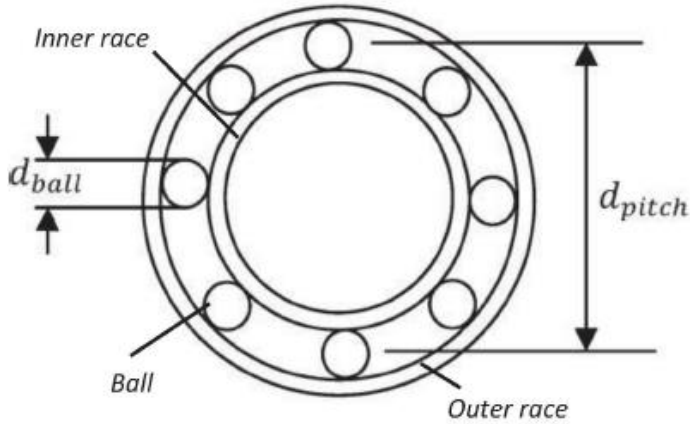
Lee, C.-Y., Z.-H. Dong. 2019. Hierarchical Equipment Health Index Framework. IEEE Transactions on Semiconductor Manufacturing, 32 (3), 267-276.

馬達軸承壽命預測 Remaining Useful Life (RUL) Prediction

馬達結構示意圖



No	名稱	No	名稱
1	油封	9	波型華司
2	馬達前蓋	10	定子線圈
3	滾珠軸承	11	馬達機殼
4	R扣環	12	風扇
5	馬達齒軸	13	固定螺絲
6	S扣環	14	風罩
7	轉子	15	十字頭螺絲
8	滾珠軸承	16	護線扣環

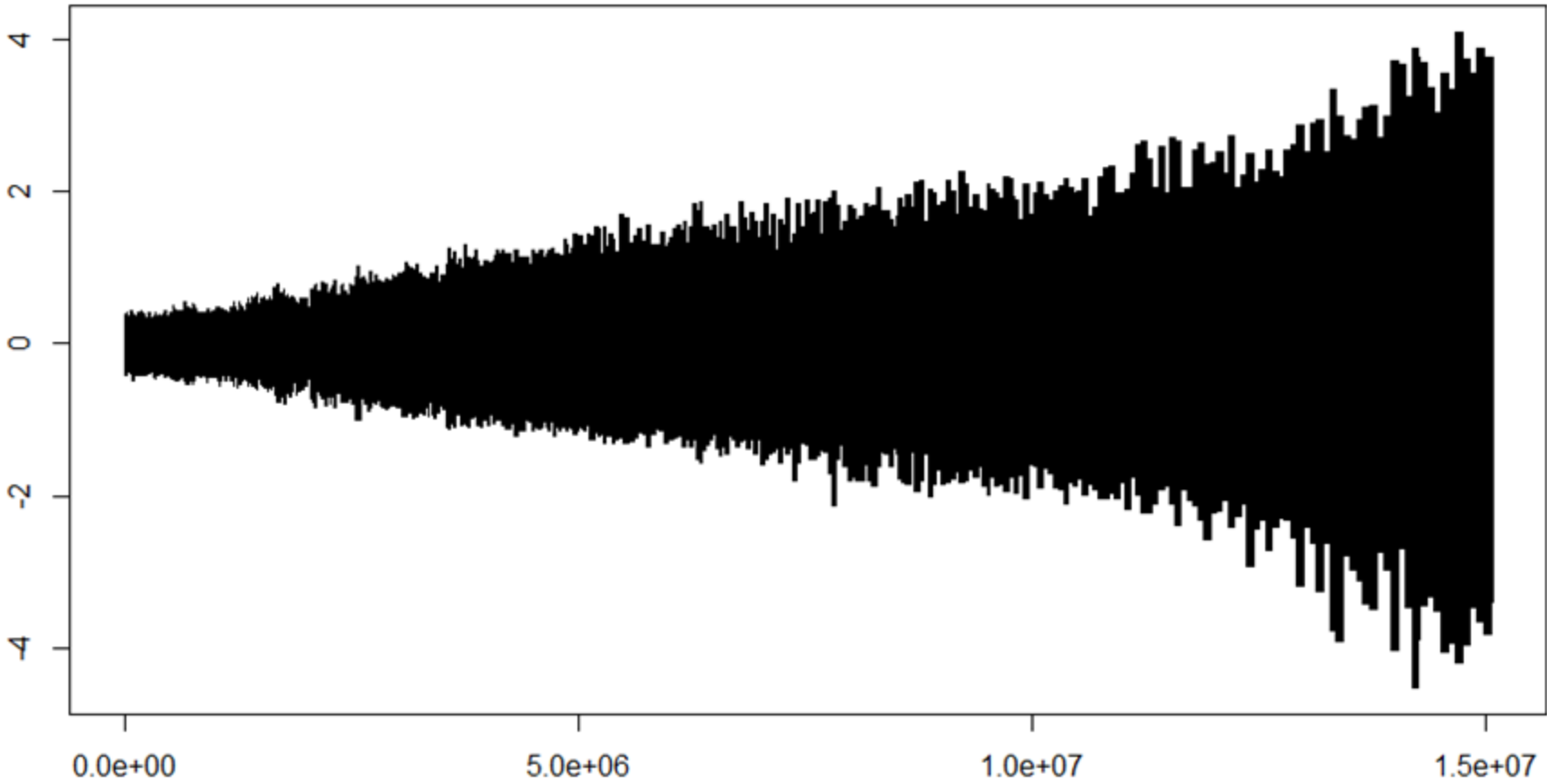


http://www.li-ming.com.tw/index.php?option=com_content&view=article&id=225&Itemid=351&lang=

案例三：PHM & PdM

Vibration Dataset

Amplitude



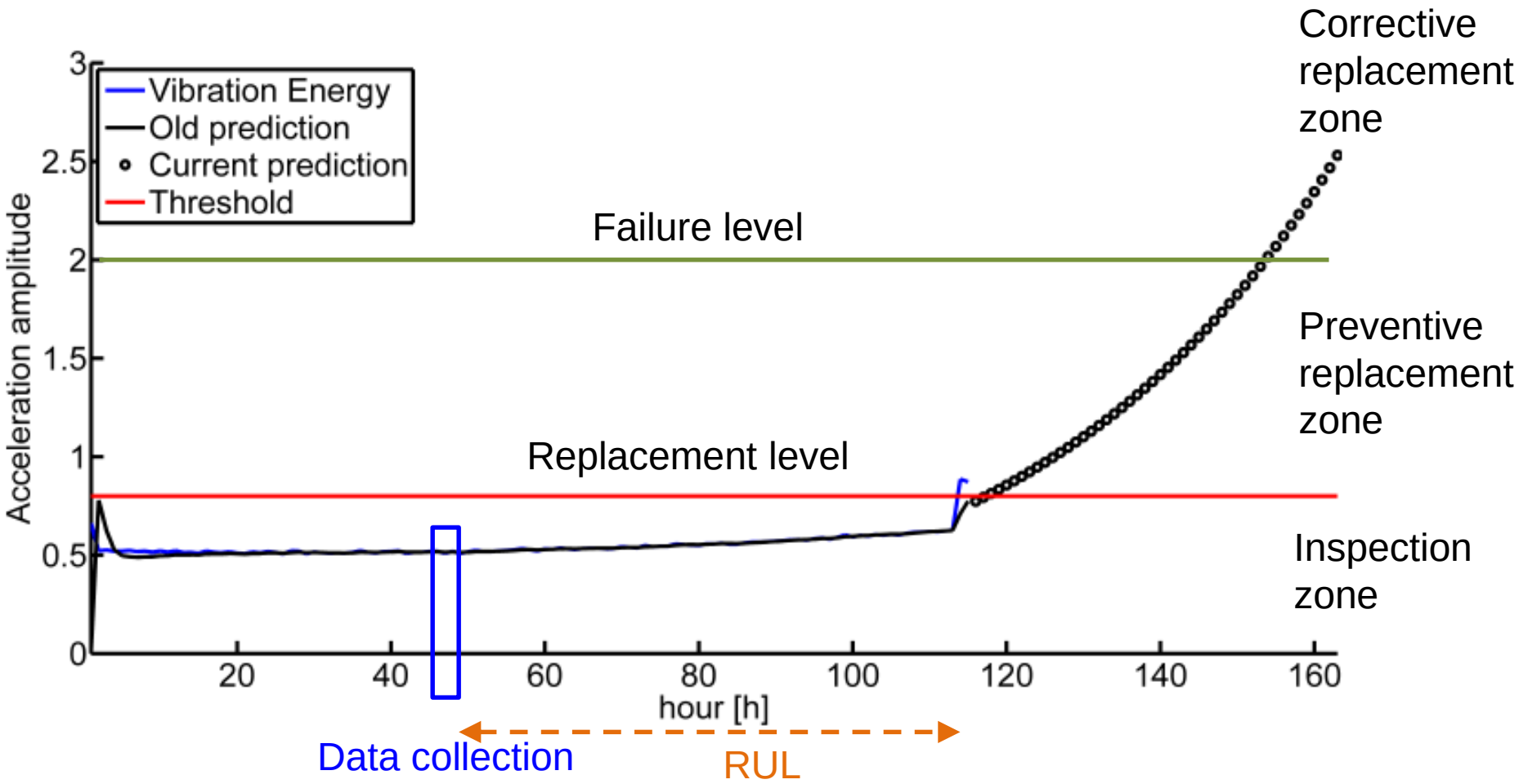
Lee et al. (2019)

Lee, C.-Y., T.-S. Huang, M.-K. Liu, and C.-Y. Lan. 2019. Data Science for Vibration Heteroscedasticity and Predictive Maintenance of Rotary Bearings. Energies., 12 (5), 801.

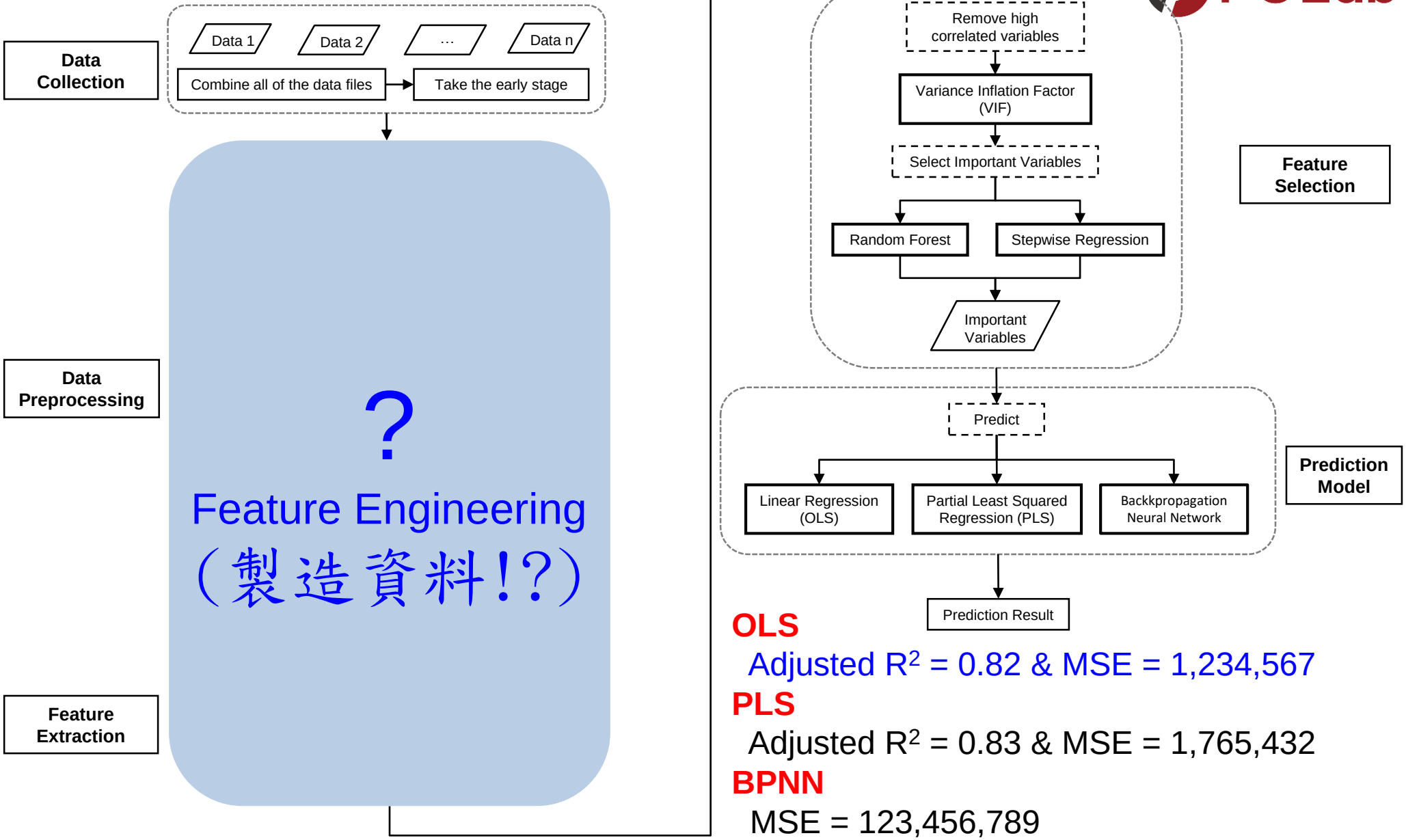
案例三：PHM & PdM

Prediction of the Deterioration

- Vibration acceleration signal



revised from Grall et al. (2002) and Rocchi et al. (2014)



OLS

Adjusted R^2 = 0.82 & MSE = 1,234,567

PLS

Adjusted R^2 = 0.83 & MSE = 1,765,432

BPNN

MSE = 123,456,789

Lee, C.-Y., T.-S. Huang, M.-K. Liu, and C.-Y. Lan. 2019. Data Science for Vibration Heteroscedasticity and Predictive Maintenance of Rotary Bearings. Energies., 12 (5), 801.

案例三：PHM & PdM

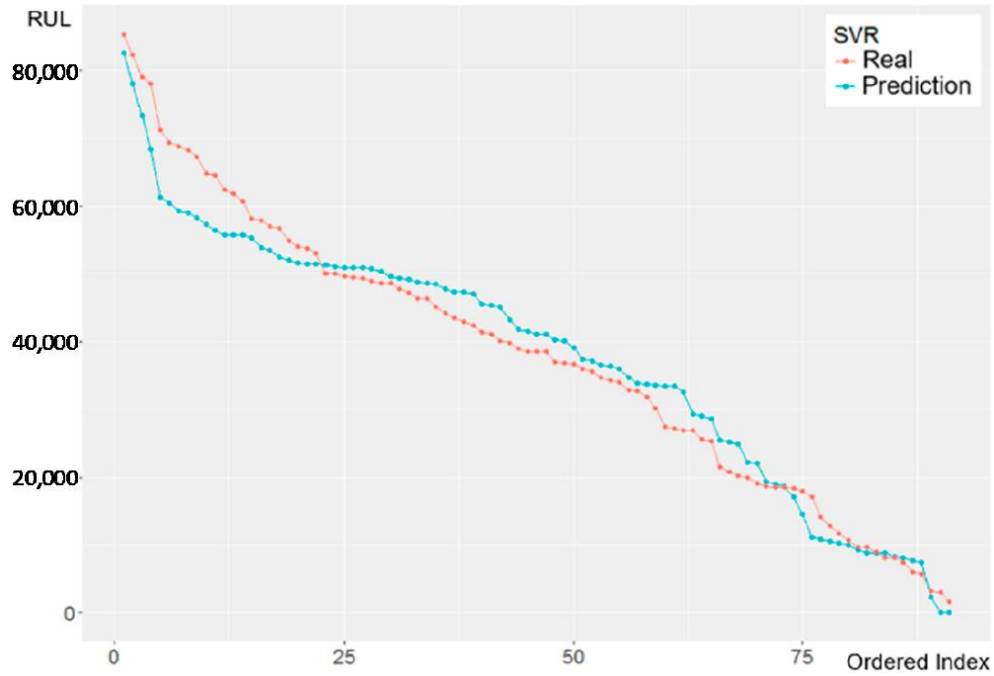
Feature Engineering

Method/ Dimensions	Time-Series Dimension	Change-Point Dimension	Frequency Dimension
Method	OLS	Piecewise linear segmentation	FFT
Features	(1) Mse.ts (2) Slope.ts (3) Intercept.ts (4) Skewness.ts (5) Kurtosis.ts (6) Max.ts	(7) Sd.cp (8) First-point.cp (9) Skewness.cp (10) Kurtosis.cp	(11) Ampl1.f (12) Ampl1-freq.f (13) Ampl2.f (14) Ampl2-freq.f (15) Ampl-mean.f (16) Ampl-var.f (17) Ampl-skewness.f (18) Ampl-kurtosis.f

Feature Selection

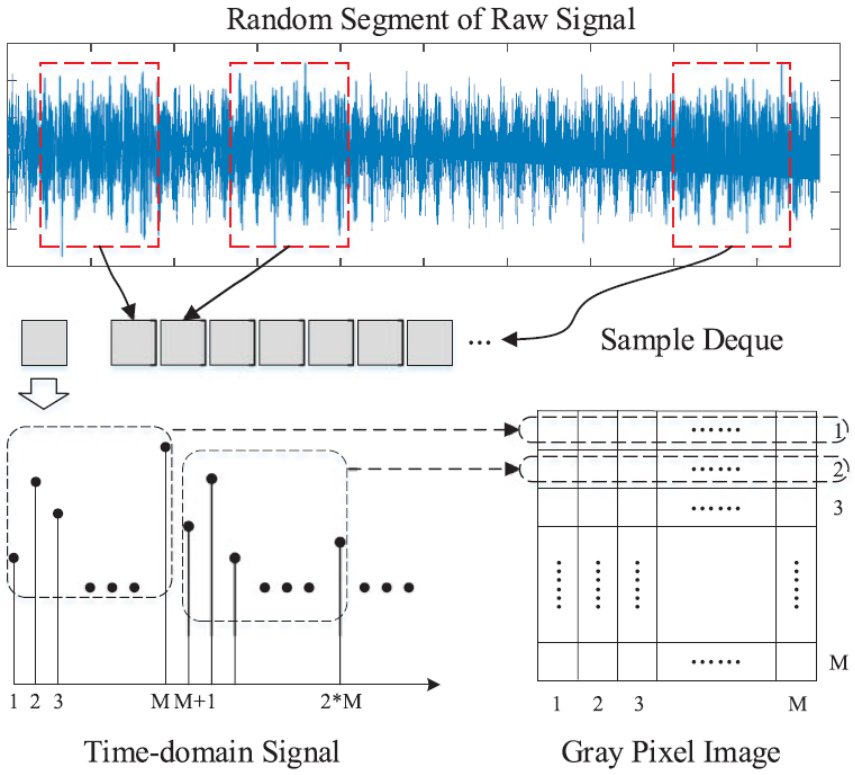
VIF Test		Stepwise Regression	
Features	VIF	Features	State
Mse.ts	>10		
Slope.ts		Slope.ts	out
Intercept.ts	>10		
Skewness.ts		Skewness.ts	out
Kurtosis.ts		**Kurtosis.ts**	**in**
Max.ts		**Max.ts**	**in**
Sd.cp		Sd.cp	out
First-point.cp	>10		
Skewness.cp		Skewness.cp	out
Kurtosis.cp		Kurtosis.cp	out
Ampl1.f	>10		
Ampl1-freq.f		**Ampl1-freq.f**	**in**
Ampl2.f		**Ampl2.f**	**in**
Ampl2-freq.f		**Ampl2-freq.f**	**in**
Ampl-mean.f	>10		
Ampl-var.f		Ampl-var.f	out
Ampl-skewness.f		Ampl-skewness.f	out
Ampl-kurtosis.f	>10		

RUL Prediction

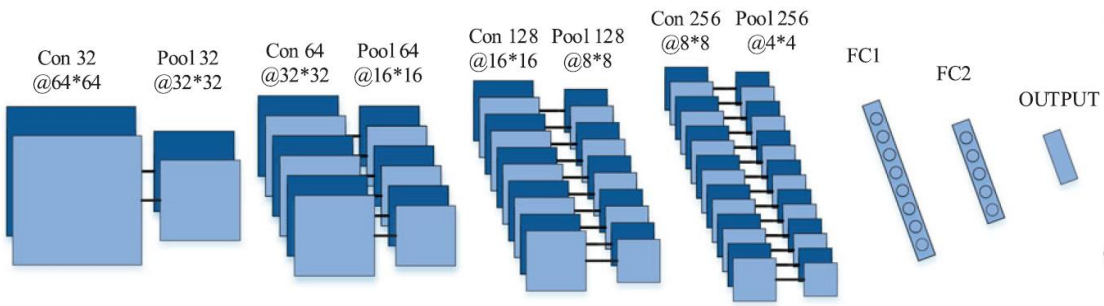


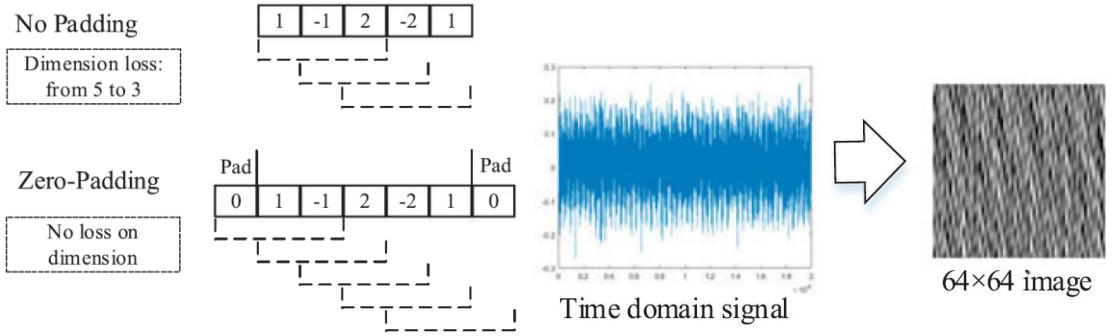
Lee, C.-Y., T.-S. Huang, M.-K. Liu, and C.-Y. Lan. 2019. Data Science for Vibration Heteroscedasticity and Predictive Maintenance of Rotary Bearings. Energies., 12 (5), 801.

Convolutional Neural Network (CNN) Fault Diagnosis

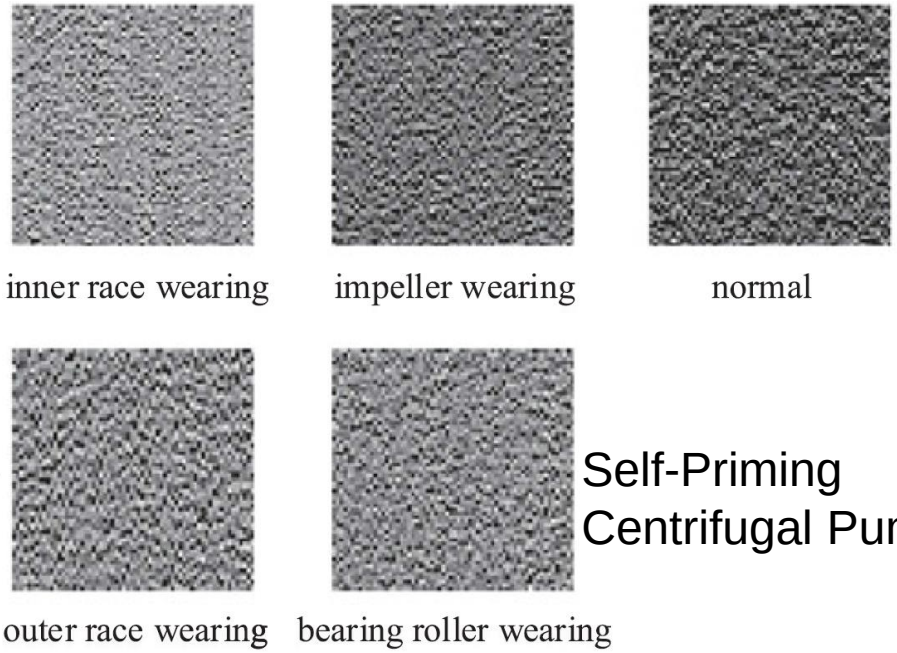


$$P(j,k) = \text{round}\left\{\frac{L\left((j-1)\times M + k\right) - \text{Min}(L)}{\text{Max}(L) - \text{Min}(L)} \times 255\right\}$$





Padding for control the size of feature dimension and the zero-padding for preventing the dimension loss



Self-Priming Centrifugal Pump

Wen, L., Li, X., Gao, L., and Zhang, Y. 2018. A new convolutional neural network-based data-driven fault diagnosis method. IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, 65 (7), 5990-5998.

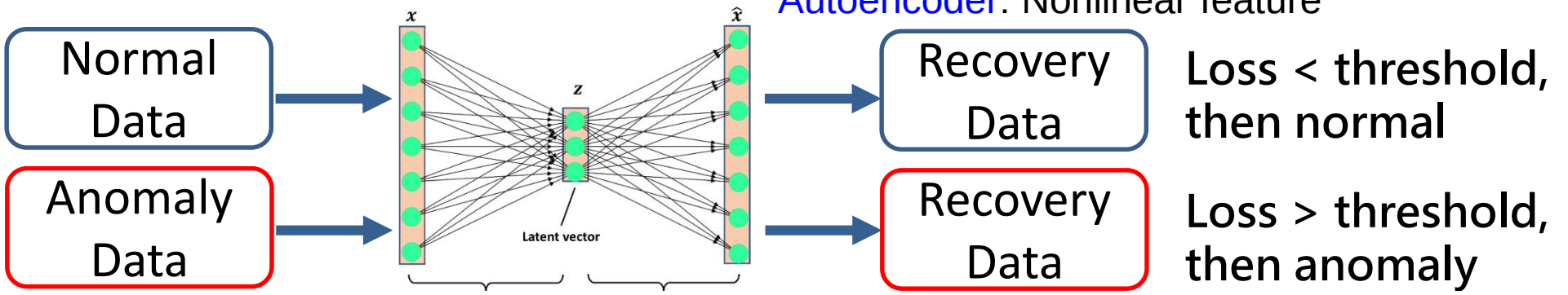
案例三：PHM & PdM

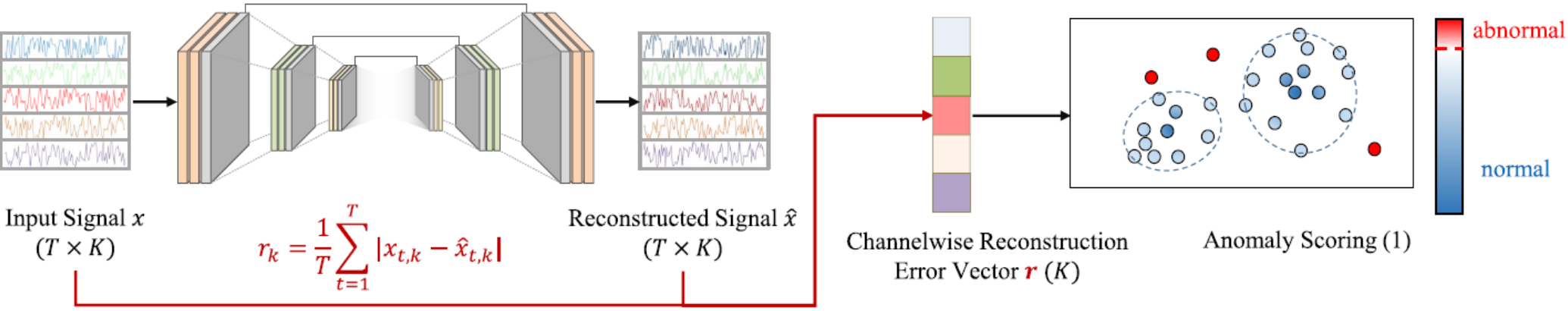
Deep Learning for PdM

- DL has shown superior ability in feature learning, fault classification and fault prediction with multilayer nonlinear transformations.
- Multi-sensory data can be fused via DL-based models. In practice, more than one sensor would be mounted at different positions to acquire a variety of possible fault signals.

Unsupervised Learning

Autoencoder: Nonlinear feature



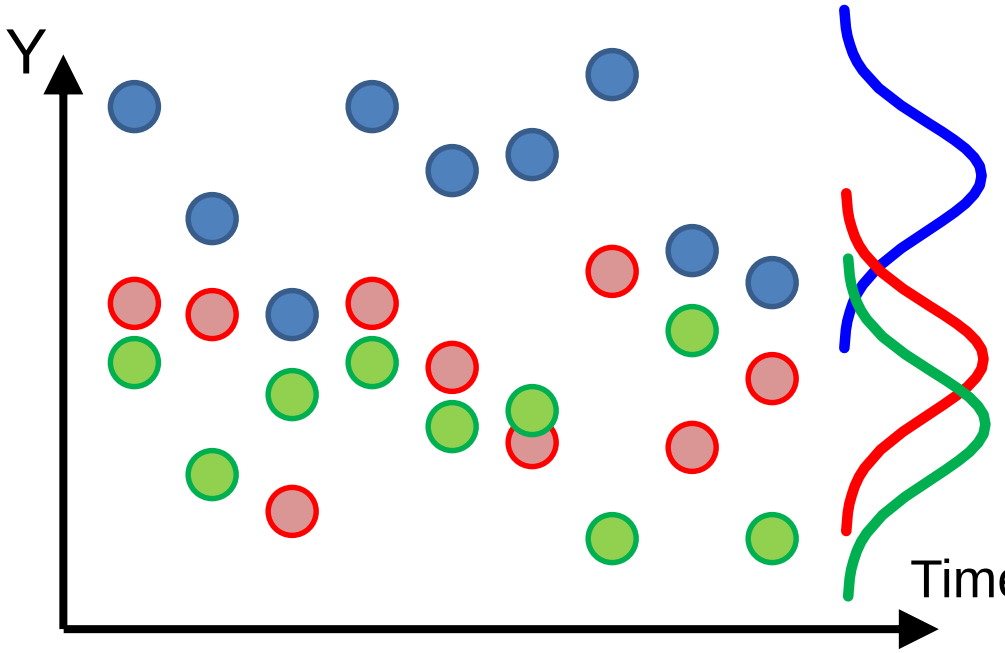


Kwak, M., and Kim, S. B. (2021). Unsupervised abnormal sensor signal detection with channelwise reconstruction errors. IEEE Access, 9, 39995–40007.

Jiang, et al. "A gan-based anomaly detection approach for imbalanced industrial time series," IEEE Access, vol. 7, pp. 143 608–143 619, 2019.

Ran, et al. (2019). A survey of predictive maintenance: systems, pruposes and approaches. IEEE Communications Surveys & Tutorials.

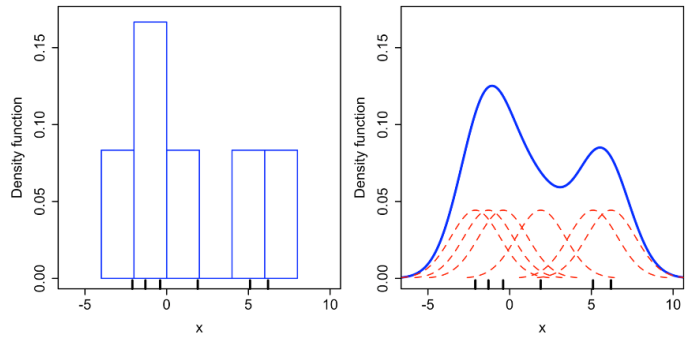
Kernel-based Dynamic Ensemble Technique (KDET)

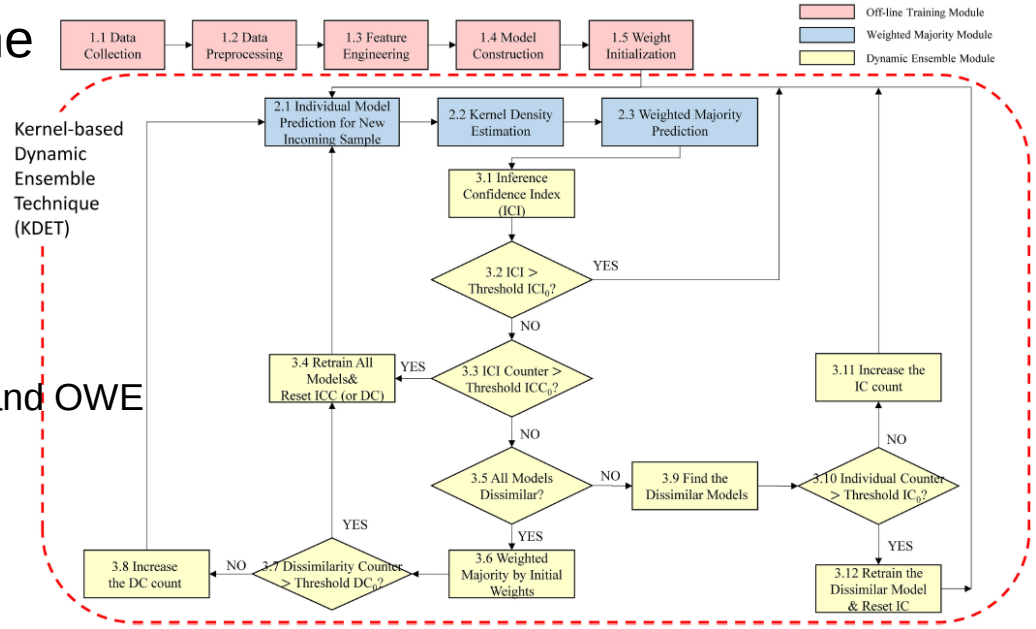


Model1 w_1

Model2 w_2

Model3 w_3



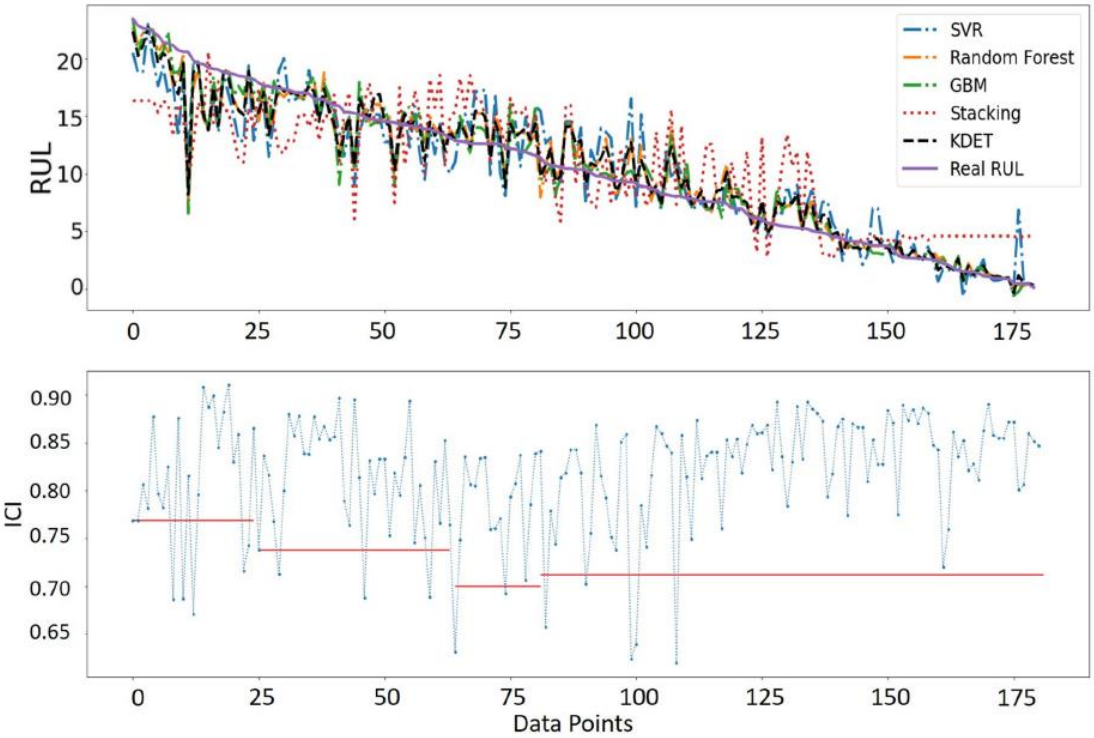


- Base learners
  - Support Vector Regression (SVR)
  - Random forest (RF)
  - Gradient boosting machine (GBM)
- Time complexity $O(n^4 + np^2)$ for KDET, DWM, and OWE
  - dynamic weighting majority (DWM)
  - on-line weighting ensemble (OWE)
  - n is the number of observation and p is feature.

Lu, H.-W., and Lee, C.-Y., 2022. Kernel-based dynamic ensemble technique for remaining useful life prediction. IEEE Robotics and Automation Letters, 7(2), 1142-1149.

KDET for RUL

Random Sampling Dataset



Metrics	Prediction Models					
	SVR	RF	GBM	Weighted Majority	Stacking	KDET
MSE	6.55	4.76	**3.77**	4.81	3.89	3.82
MAPE	24.05	19.26	17.33	18.69	16.98	**16.76**
SMAPE	21.64	17.92	17.32	17.55	17.66	**17.27**

Long-Term Dataset

Metrics (5 replications)	Prediction Models								
	SVR	RF	GBM	*Weighted Majority*	*Stacking*	DWM	K-Fold DWM	OWE	KDET
MSE Avg.	8.34	4.98	4.64	4.96	14.69	0.65	0.38	0.59	**0.33**
MSE Std. Dev.	0.39	0.16	0.18	0.16	1.42	0.08	0.06	0.07	**0.04**
MAPE Avg.	95.12	34.71	45.41	50.35	>100	21.57	20.89	21.42	**20.41**
MAPE Std. Dev.	33.52	7.01	11.53	12.08	36.28	1.65	1.47	1.68	**1.37**
SMAPE Avg.	26.31	17.38	17.69	18.58	37.52	10.15	8.67	9.85	**8.51**
SMAPE Std. Dev.	1.58	1.34	1.39	1.26	2.11	0.71	0.66	0.65	**0.56**

Metrics	Dynamic Weighted Ensemble Methods		
	DWM	OWE	KDET
100% Ground Truth Retraining Triggered Avg.	115	114	**12**
100% Ground Truth Retraining Triggered Std. Dev.	9	9	**5**
60% Ground Truth Retraining Triggered Avg.	73	71	**12**
60% Ground Truth Retraining Triggered Std. Dev.	7	6	**5**
20% Ground Truth Retraining Triggered Avg.	25	24	**12**
20% Ground Truth Retraining Triggered Std. Dev.	**4**	**4**	5

Lu, H.-W., and Lee, C.-Y., 2022. Kernel-based dynamic ensemble technique for remaining useful life prediction. IEEE Robotics and Automation Letters, 7(2), 1142-1149.

案例四： 原料價格預測與採購決策

原料價格預測與採購決策

- 心法1：化被動為主動的資訊透明化
  - 打電話到處詢價 → 第三方報告(?)
  - 掌握主導權：看報告才發現價格異常 → 品管圖監控急升急降pre-alarm
- 原則2：掌握報價的報價、上游的上游
- 原則3：原料請往上游堆
- 作法4：價格預測的因子
  - 總體、個體、Breaking News
- 原則5：採購決策因子
  - 庫存消耗速度、補貨前置時間

原料價格預測與採購決策

- 以油價為例

特徵挑選

Crude Oil

Variable	r.c.	c.c.
X01	17.9591	0.5195
★ X02	18.3465	0.5229

Upstream

Variable	r.c.	c.c.
★ X03	2.2597	0.8511
★ X04	0.8613	0.1990
X05	1.6192	0.5878
X06	-0.3626	-0.1536
X07	2.0611	0.5830
★ X08	-0.4406	-0.4160
X09	0.0002	0.4336

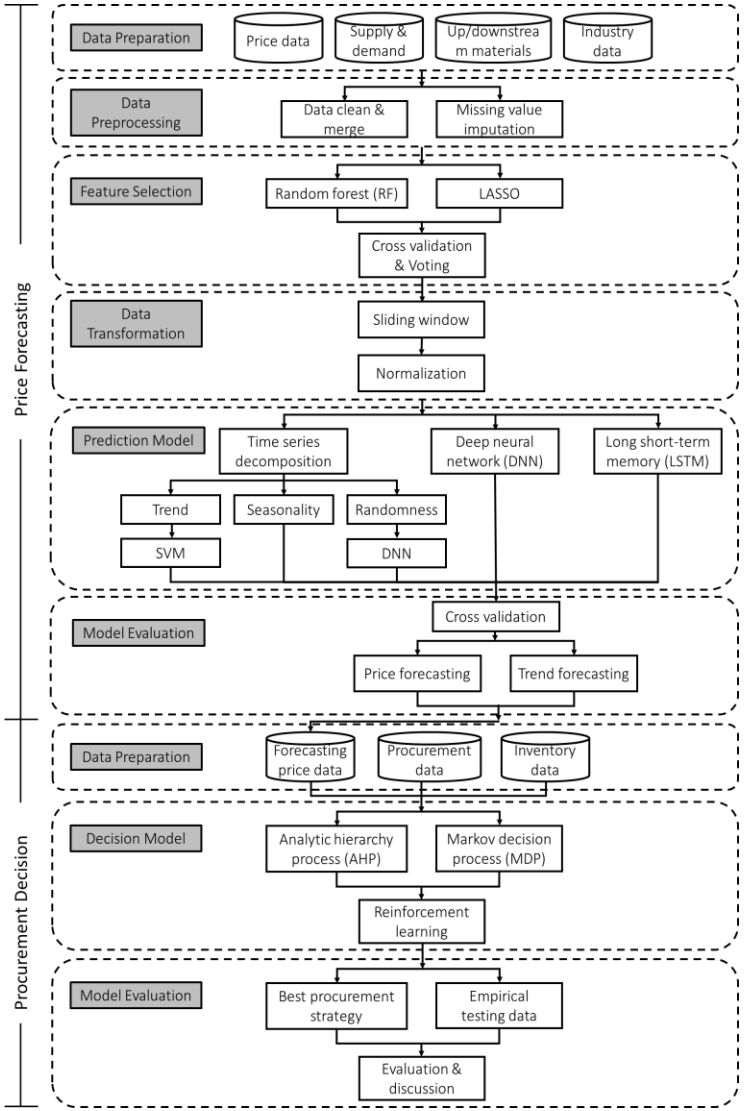
Butadiene

Variable	r.c.	c.c.
Y		
X10	0.9936	0.9997
X11	1.0051	0.9997
X12	0.8651	0.8741
X13	0.9153	0.8584
★ X14	0.8382	0.9401
X15	0.8153	0.9406
X16	0.8615	0.9390
X17	0.8751	0.8425
X18	0.8802	0.9512
X19	0.2148	0.0719
X20	0.3655	0.1411
X21	0.0012	0.4902

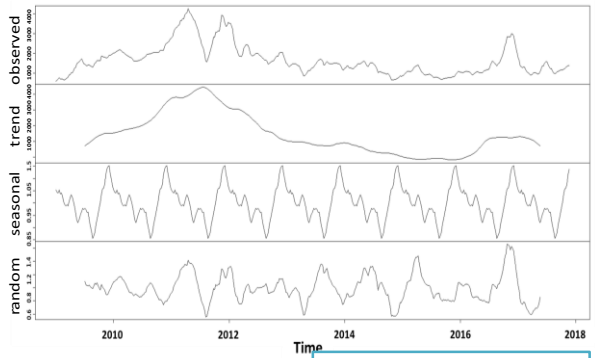
Downstream

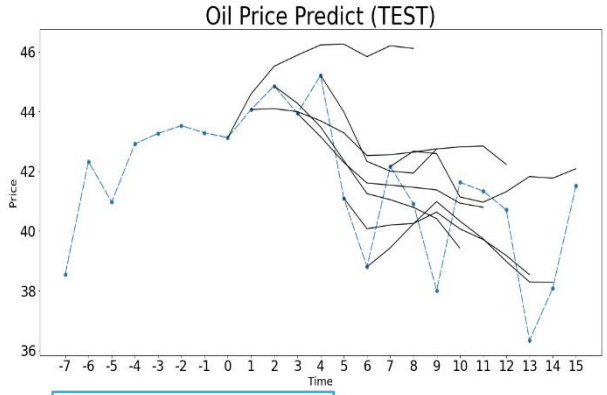
Variable	r.c.	c.c.
★ X22	5.6786	0.7958
X23	0.7643	0.9258
X24	0.8698	0.9424
X25	0.9213	0.7151
X26	0.8003	0.9272
X27	0.8897	0.9313
X28	0.0008	0.5036
X29	0.0005	0.4319
★ X30	1.0112	0.9810
X31	1.3185	0.9753
X32	0.1570	0.1345
★ X33	0.7595	0.3052
X34	1.4520	0.6067

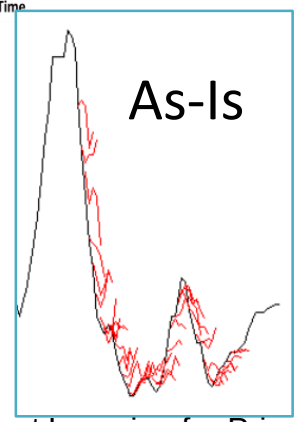
Legend	
	Butadiene(BD)
	r.c. > 1.5
	r.c. < 0
★	Important variables identified by feature selection

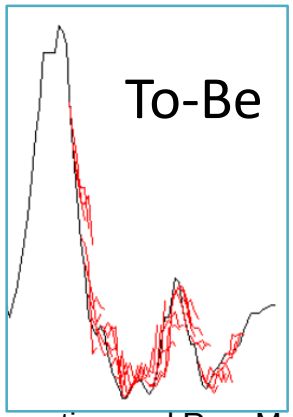


原物料價格預測





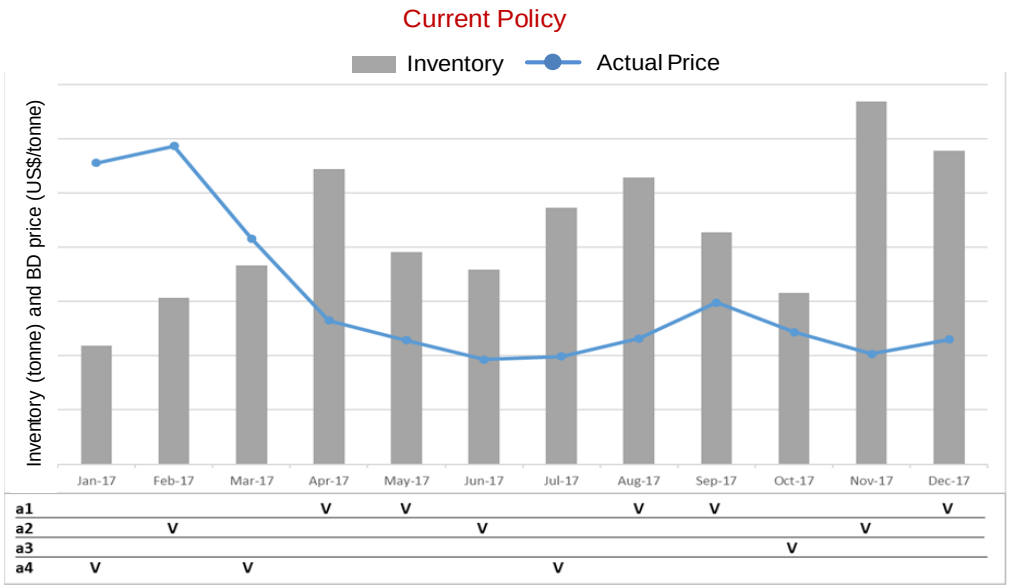


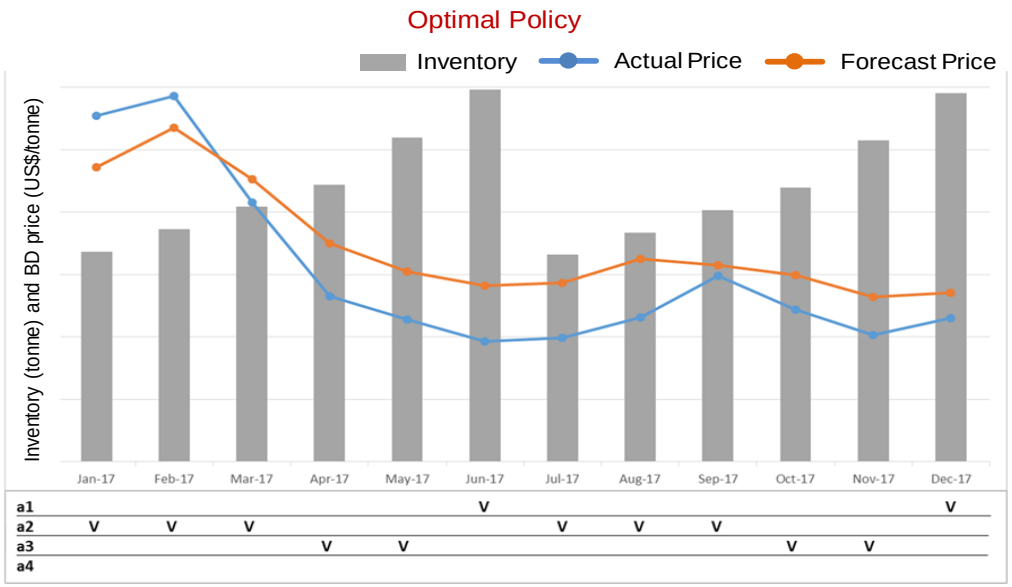


Lee, C.-Y., Chou, B.-J., and Huang, C.-F. 2021. Data Science and Reinforcement Learning for Price Forecasting and Raw Material Procurement in Petrochemical Industry. *Advanced Engineering Informatics*.

原料價格預測與採購決策

強化學習(reinforcement learning)





	Current policy	(s,S) policy	Optimal policy
Average inventory (tonne)	3112	1812	3197
Standard deviation of inventory (tonne)	743	302	489
Amount purchased (tonne)	25,301	35,430	36,835
Total cost (US$)	44,596,113	42,324,694	39,091,618

Cost Down 12.35%

Lee, C.-Y., Chou, B.-J., and Huang, C.-F. 2021. Data Science and Reinforcement Learning for Price Forecasting and Raw Material Procurement in Petrochemical Industry. *Advanced Engineering Informatics*.

還有很多議題...

- 資料科學模型建構的議題還有...
  - 預測要預測什麼?
  - 如果樣本數不夠怎麼辦?
  - 如何決定資料收集的時間區間與數量?
  - 如果資料有些偏差，該如何發展穩健(robust)的模型?
  - Training dataset與testing dataset如何切割與決定?
  - 抽樣所造成的資料不完整與不平衡如何處理?
  - 產品組合持續改變該如何分析?
  - 前後工作站間的交互作用如何衡量?
  - 預測模型何時需要重新修正或重建(re-train)?
  - 預測模型可以實際上線的標準如何訂定?
  - 模型挑選關鍵參數與工程經驗不一致如何處理?
  - 如何確認該關鍵參數是潛在因子?
  - .....

還有很多議題...

- 然而，製造現場的議題還有...
  - 在製品WIP太多如何處理?
  - 批量大小該如何決定?
  - 機台轉速或throughput的調整?
  - 生產排程與派工的法則?
  - 操作員或員工排班的最佳化?
  - 產能彈性如何建構以應變需求波動?
  - 每年度的生產力target該如何訂定與提升?
  - 產品組合product-mix如何決定?
  - 如何減少浪費? 看板式管理如何進行?
  - 專案管理如何Continuous Delivery?敏捷開發?
  - 抽樣檢驗計畫該如何動態調整?
  - 多種零組件與原物料，庫存管理如何訂定?
  - .....

資料科學可否協助解決這些議題?

創業者的世界裡只有兩樣東西

有待解決的問題、正在嘗試的方法

這兩個東西合起來就是一個詞

“**機會**”!!

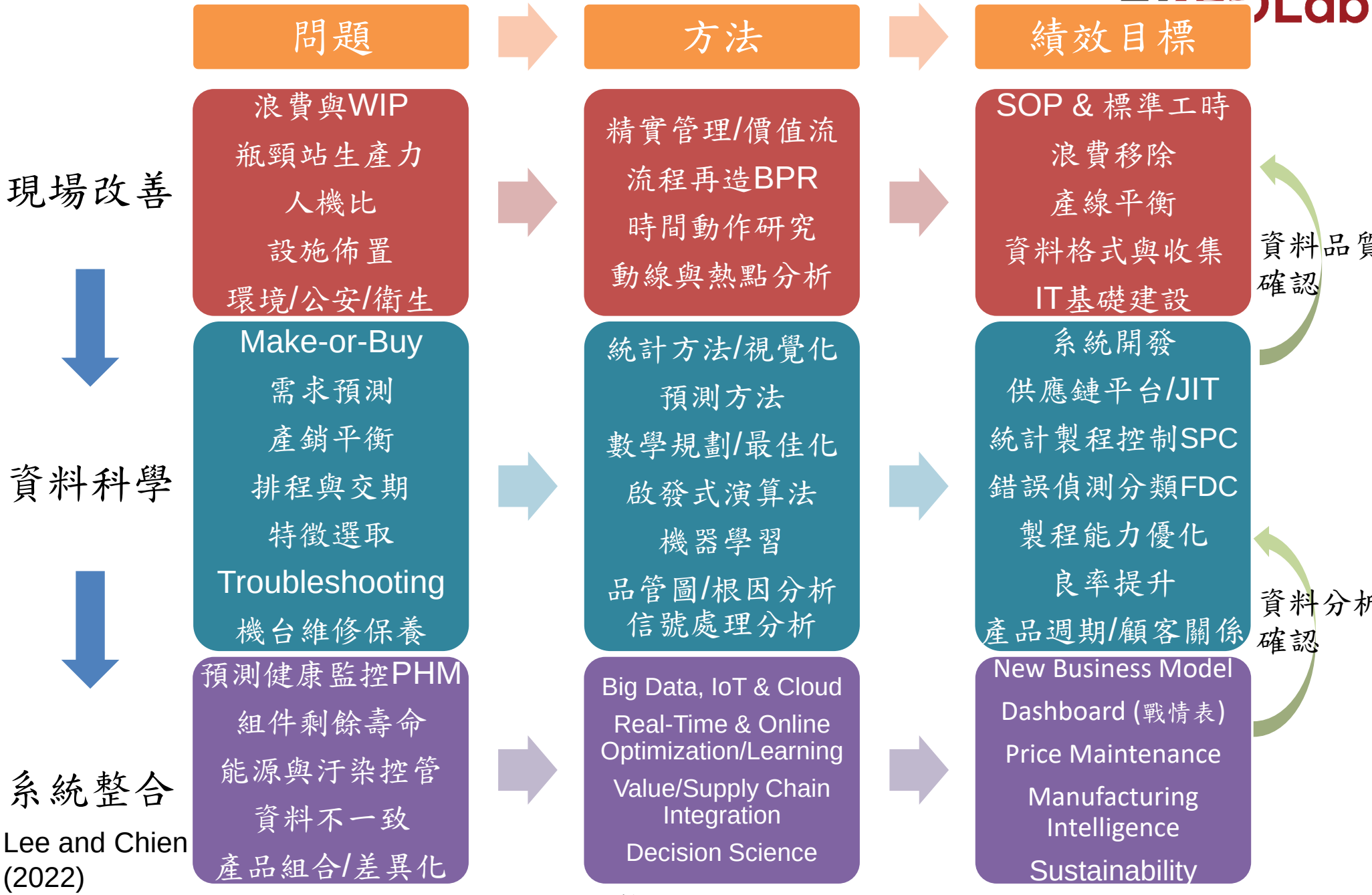
罗振宇 (Dec. 31, 2016)，罗辑思维 "时间的朋友2016" 跨年演讲

自動化生產排程與演算法

Automated Production Scheduling

事實上...

很多時候，我們..
也不知道自己要做什麼題目?


問題
方法
績效目標
現場改善
浪費與WIP
瓶頸站生產力
人機比
設施佈置
環境/公安/衛生
精實管理/價值流
流程再造BPR
時間動作研究
動線與熱點分析
SOP & 標準工時
浪費移除
產線平衡
資料格式與收集
IT基礎建設
資料品質確認
資料科學
Make-or-Buy
需求預測
產銷平衡
排程與交期
特徵選取
Troubleshooting
機台維修保養
統計方法/視覺化
預測方法
數學規劃/最佳化
啟發式演算法
機器學習
品管圖/根因分析
信號處理分析
系統開發
供應鏈平台/JIT
統計製程控制SPC
錯誤偵測分類FDC
製程能力優化
良率提升
產品週期/顧客關係
資料分析確認
系統整合
預測健康監控PHM
組件剩餘壽命
能源與汙染控管
資料不一致
產品組合/差異化
Big Data, IoT & Cloud
Real-Time & Online Optimization/Learning
Value/Supply Chain Integration
Decision Science
New Business Model
Dashboard (戰情表)
Price Maintenance
Manufacturing Intelligence
Sustainability
Lee and Chien (2022)

可能會問...

那...那如果我們什麼資料都沒有，
或資料還沒有標準化地著手收集，
那我們要怎麼開始呢?

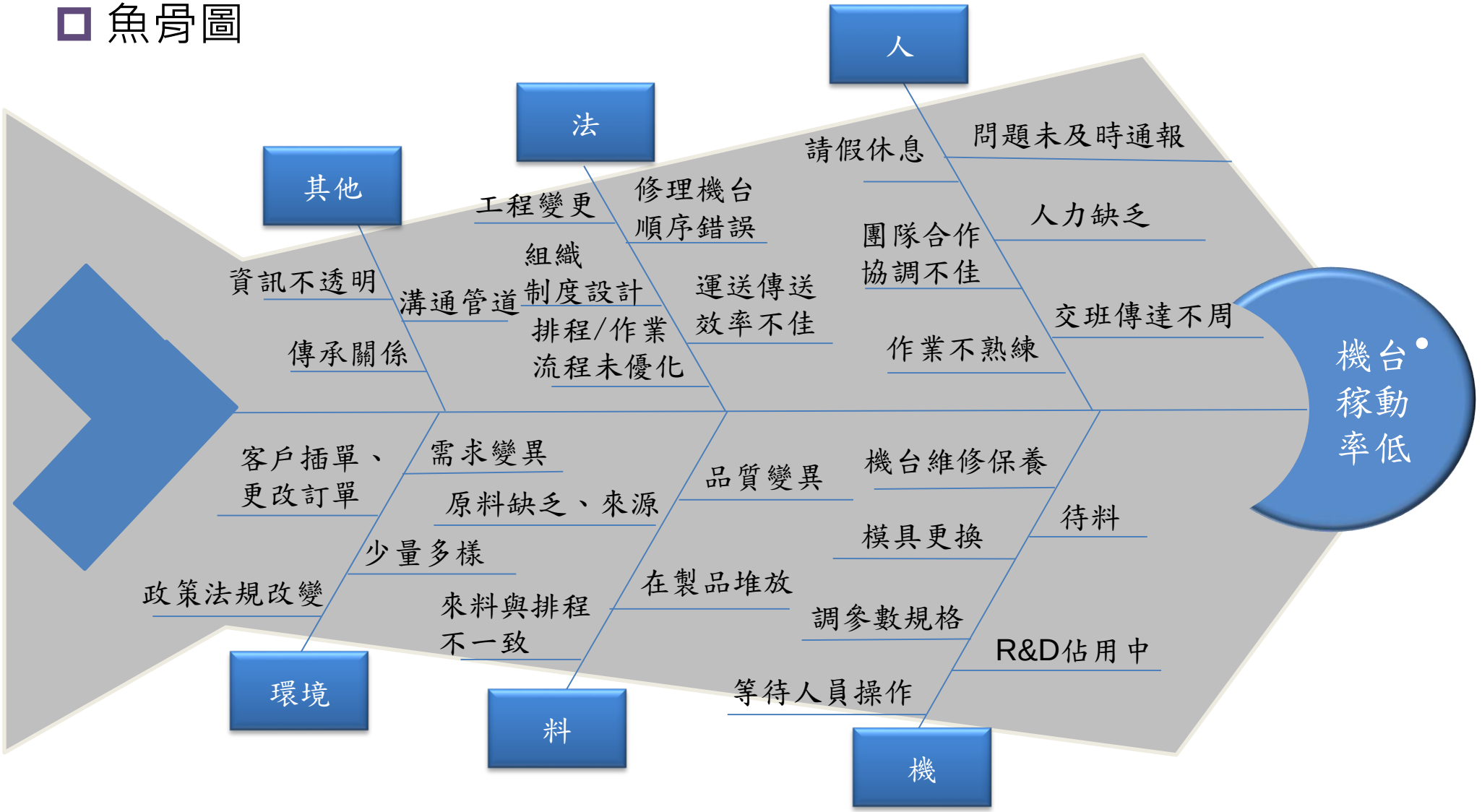
資料科學?

- 資料科學並非要有一堆數學模型或一大堆資料...
- 一開始可以先嘗試，找到問題
- 為了改善，針對這問題無論如何都要收集到資料!
- 方法
  - 資料庫 (但資料可能時間過久、現況已與當時不同、久未校正或有誤差)
  - 詢問專家 (但可能已經離開專案小組、或轉調不同部門組織)
  - 現場觀察
- 現場觀察是一非常強且客觀的方法 → 眼見為憑

話說...

- 於201X年，企業參訪，觀察工廠製造現場與流程
- 某廠區稼動率116/200 = 58%
- 初步參訪的疑惑
  - 為何機台(資金)閒置？
  - 是否是景氣不佳、訂單需求不足？
  - 現場人員數目不足操作機台？
  - 過多機台換模具、調整、維修保養中？
  - 老舊機台(閒置)設備過多？
- 工廠稼動率的合理性驗證

魚骨圖


人
法
其他
環境
料
機
機台稼動率低
請假休息
問題未及時通報
人力缺乏
團隊合作協調不佳
交班傳達不周
作業不熟練
修理機台順序錯誤
工程變更
組織制度設計
運送傳送效率不佳
排程/作業流程未優化
資訊不透明
溝通管道
傳承關係
機台維修保養
品質變異
待料
模具更換
需求變異
客戶插單、更改訂單
原料缺乏、來源
少量多樣
在製品堆放
調參數規格
R&D佔用中
政策法規改變
來料與排程不一致
等待人員操作

人機比與工作研究

人機程序圖

- 紀錄人和機台之間的動作
- 案例：
  - 時間：2017/02/11, 2pm開始觀察3小時 (此處資料為模擬產生，非實際數據)
  - 對象：製造部A員操作3台機台
  - 記錄人的操作行為與機台做動的時間
  - 計算機台稼動率 = (機台作業生產時間) / (總觀察時間)
  - eg. (56+160+138 mins)/(180+180+180 mins)
    =65.6%

人機比與工作研究

- 人
  -
  -

			機台A		機台B		機台C	
時間	操作員作業	耗時(分)	作業	耗時(分)	作業	耗時(分)	作業	耗時(分)
14:00-14:11	調整機台參數規格	11	機器加工(產品A)	43	停機調規格	11	機器加工(產品C)	88
14:11-14:16	將不良品移置廢品區	5						
14:16-14:27	填寫機台檢查紀錄表	11						
14:27-14:30	產品品質檢測	3						
14:30-14:43	電腦資料輸入	13						
14:43-14:50	停機、量測產品尺寸	7	停機等待換規格、換模	124	機器加工(產品B)	140		
14:50-14:54	電腦工程分析	4						
14:54-15:00	領取原物料	6						
15:00-15:15	休息	15						
15:15-15:28	領取模具	13						
15:28-15:33	產品品質檢測	5					停機待料	42
15:33-15:43	填寫機台檢查紀錄表	10						
15:43-15:48	換模具	5						
15:48-16:01	填寫機台檢查紀錄表	13						
16:01-16:10	領取模具	9					機器加工(產品C)	50
16:10-16:17	產品品質檢測	7						
16:17-16:22	存放載具	5						
16:22-16:31	產品品質檢測	9						
16:31-16:40	調整機台參數規格	9			停機調規格	9		
16:40-16:47	產品品質檢測	7			機器加工(產品B)	20		
16:47-16:52	填寫機台檢查紀錄表	5	機器加工(產品D)	13				
16:52-16:55	領取原物料	3						
16:55-17:00	電腦資料輸入	5						

據)

人機比與工作研究

- 工廠稼動率條件
  - 強假設：人員動 → 車台動 → 物料動
  - 車台的稼動率基本上會低於人員的工作效率

- 觀察操作員的時間分解
  - 人員工作效率：80% ~ 85%
  - 因此，機台稼動率之上限即為人員工作效率(80% ~ 85%)
  - 200 * 80% = 160 (台) 到 200 * 85% = 170 (台) 之間為理想機台運作數

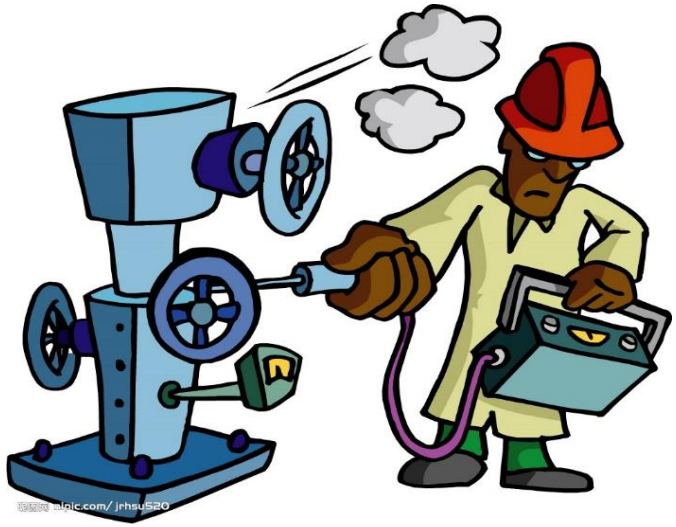
- 小結
  - 每天若在戰情表(Dashboard)上看到機台只有160台在Run (並不糟喔)

- 改善
  - 改善人員操作的作業順序 (eg. 有機台停機時要先處理，而非填表單)

人機比計算方法

- $= \frac{\text{供給→人}}{\text{需求→機}}$
- $= \frac{\text{人力實際供給時數/天}}{\text{單位機台人力需求時數/天}}$
- $= \frac{\text{單位人力工作時長×工作效率}}{\text{此時長×機台於此時長內需要人力之比率}}$
- $= \frac{\text{工作效率}}{\text{機台需要人力之比率}}$
- $\cong \frac{\text{工作效率(Labor Eff)}}{\text{1−稼動率(Machine Util)}}$

$$= \frac{0.8}{1-0.656} = 2.33 \text{ (台)}$$



- 因此長官可以知道買多少機台，需要搭配多少人力。

人機比與工作研究

- 收集資料 → 現場觀察 (工作研究 / time-motion study)

- 優點
  - 資料準確客觀
  - 為當下現況資料 (較即時)

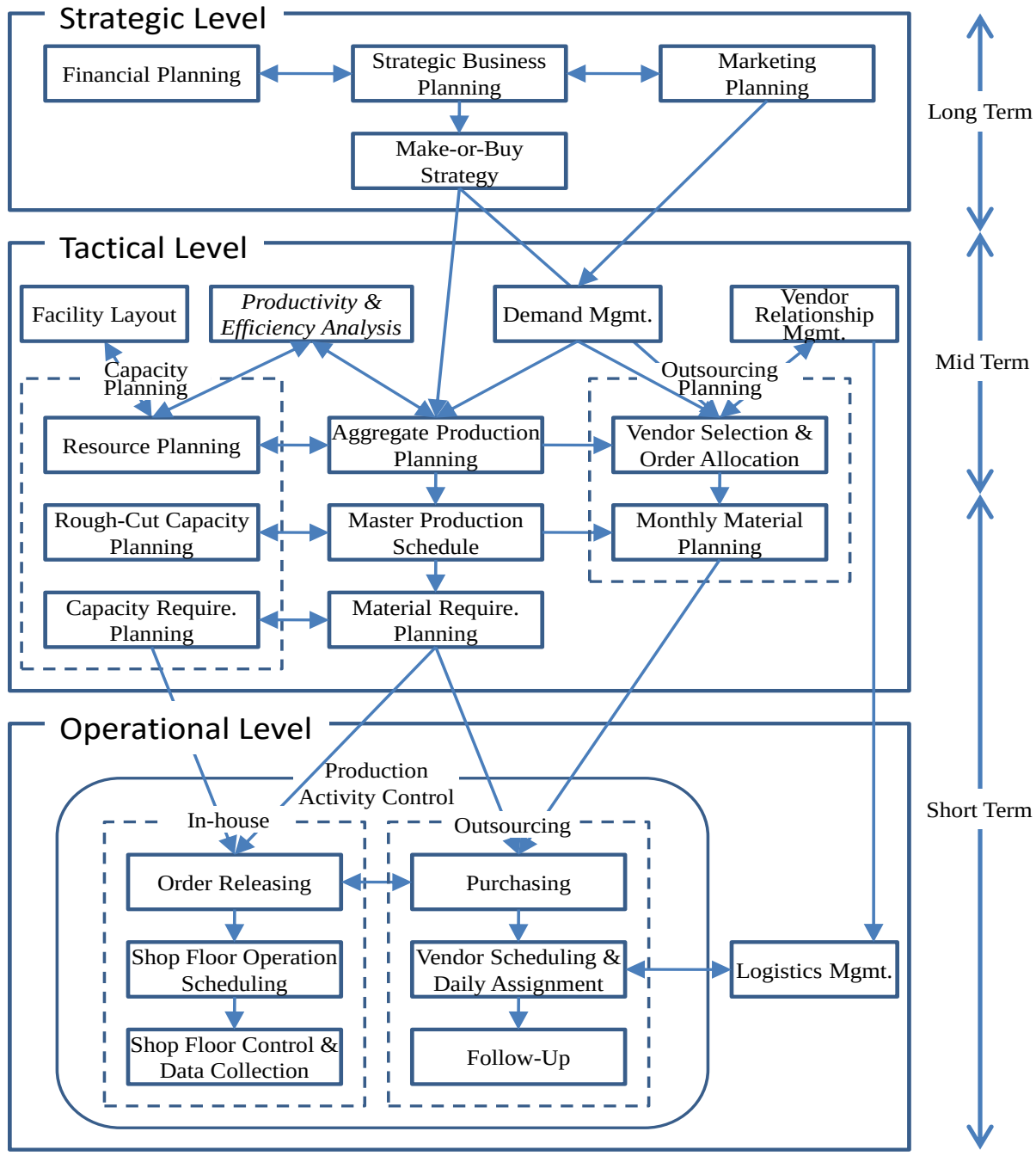
- 缺點
  - 很花時間
  - 觀察的時間會很分散片段 (某製程/工序這次沒觀察到，要等下次)
  - 缺少現場實務經驗，資料解釋不易 (需現場人員協助)

- 建議可與學校合作~
  - 學校不只是只有理論與方法的地方
  - 更是培育人才的地方 (其實對現場來說，就是因為學生很多不懂 → 才能把觀察到的事實講出來 → 藉機學習、也與業界腦力激盪)

生產排程Scheduling

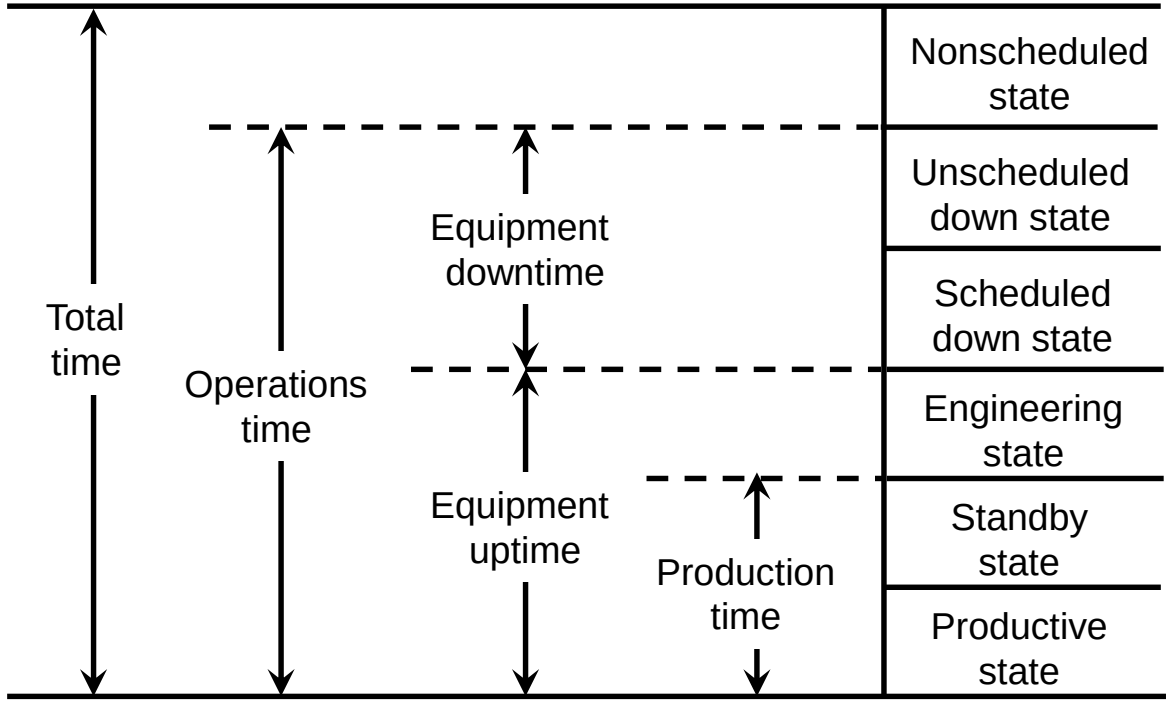
- 老師...我要做排程..
  - Q: 那..那一個層級排程呢?
  - A: 全部....
  - 現場 → 瓶頸站
  - 排程也不單只有現場
  - 現場應該先導Lean...
- Sales vs. 排程人員
  - Sales → 只管接單
  - 排程 → 只管達交
  - 目標的衝突
- 排程 vs. 稼動率(utilization)

Lee and Johnson (2013)



Overall Equipment Effectiveness (OEE) revisited

- Nakajima (1988); de Ron and Rooda (2005):



$$\text{OEE} = \frac{\text{Theortical production time for effective units}}{\text{Total time}}$$

$$= \frac{\text{Equipment uptime}}{\text{Total time}} \times \frac{\text{Production time}}{\text{Equipment uptime}} \times \frac{\text{Theortical production time for actual units}}{\text{Production time}} \times \frac{\text{Theortical production time for effective units}}{\text{Theortical production time for actual units}}$$

$$= \text{Available Eff} \times \text{Operational Eff} \times \text{Rate Eff} \times \text{Quality Eff}$$

- Machine idleness is identified explicitly through this definition

半自動化多目標生產排程

現場生產排程系統困難與挑戰

顧客/訂單/產品

交期變動/插單

工程變更

少量多樣/加工時間不一

訂單優先順序/顧客重要性

等批/等候時間限制

操作員

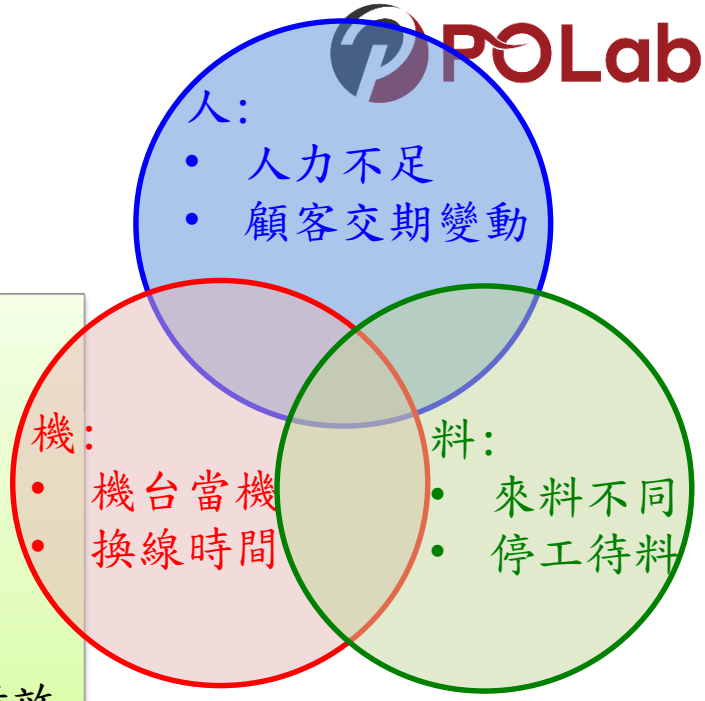
人力不足

MO

訓練不足/換模技術不一

人員配置

個人績效(競合)影響整體績效



機台/設備/廠務

製程(瓶頸)加工時間變異大

不確定性(當機/維修/保養)

特定產品/機台能力不同/模具僅通用於特定機台

換線/機台整備/模具耗損

廠區間的Backup

料件/模具/供應商

來料與公司排程不同

停工待料

不允許料閒置太久(先進先出)

外包時程變異

進料品質變異

好的排程

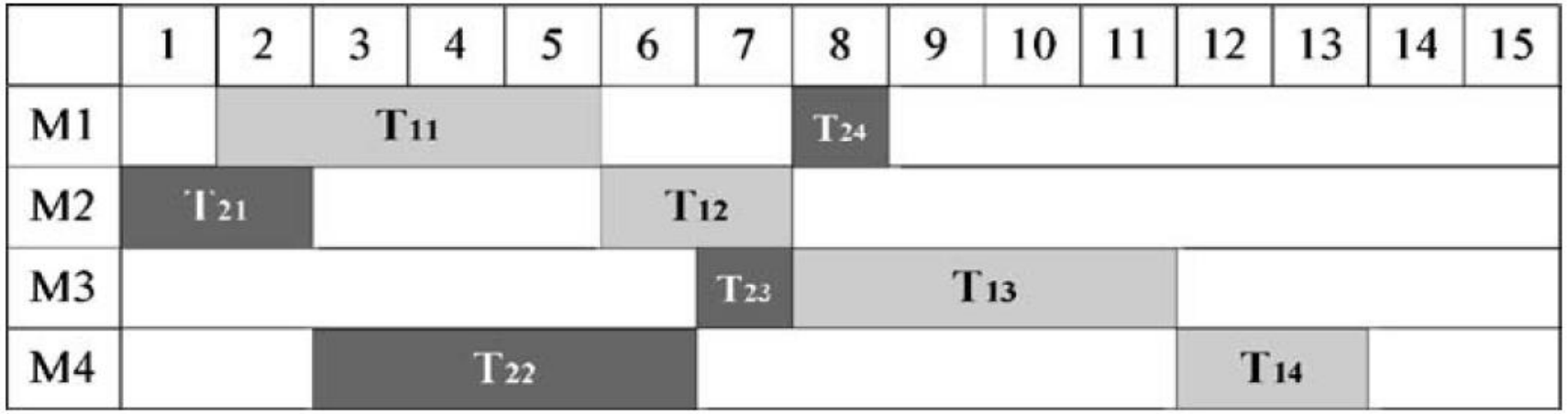
- 有效提升機台稼動率/利用率 (utilization)
- 有效縮短生產週期/前置時間 (cycle time)
- Time-to-Market/ 產品達交

Wu, Min-You (吳民友) and Chia-Yen Lee, 2015. Sampling-based NSGA-II for Stochastic Scheduling in Auto Parts Manufacturer (抽樣多目標遺傳演算法於汽車零組件製造商之隨機排程最佳化). 2015 Chinese Institute of Industrial Engineers (CIIE) Conference & Annual Meeting, Taichung, Taiwan.

生產排程Scheduling

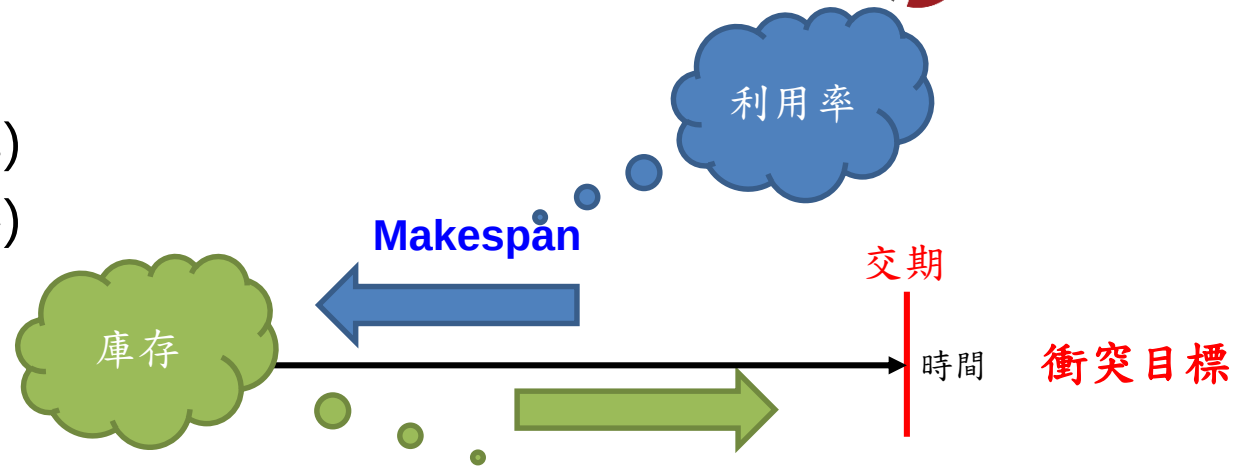
- 排程 (Scheduling) (Graves, 1981)
  - 『在一段時間內，配置可用的資源來處理一群工作，以達成所設定的**目標**』
  - Scheduling is the allocation of limited resources over time to perform a given set of jobs or activities. 換言之，是決定所有工作在機器上加工的起始時間以及加工順序，所以乃是**同時考慮資源限制和執行限制之最佳化問題**。
  - 排程重點：針對對現場特定**績效指標**對不同工作做最佳的資源配置

Chien and Chen (2007)



生產排程Scheduling

- 目標概念
  - 加工時間最短(每個訂單)
  - 先進先出(未照排程到料)
  - 優先順序
  - 日期達交



- 可量化(最小化)
  - 最小最大完成時間(Makespan)
  - 總加權完成時間(The total weighted completion time)
    - Cycle time/ machine idleness
  - 總整備時間 (The total sequence-dependent setup time)
  - 生產線平衡(Line Balancing)
  - 最少換模換線次數/時間
  - 延遲訂單數量(The number of tardy jobs)
  - 總加權延遲時間(The total weighted tardiness)- Meet due date
  - 總加權提早及延遲時間(The total weighted earliness and tardiness)
    - On-time delivery/ WIP reduction

The total weighted earliness and tardiness (TWET)

吳民友、李家岩 (2015)

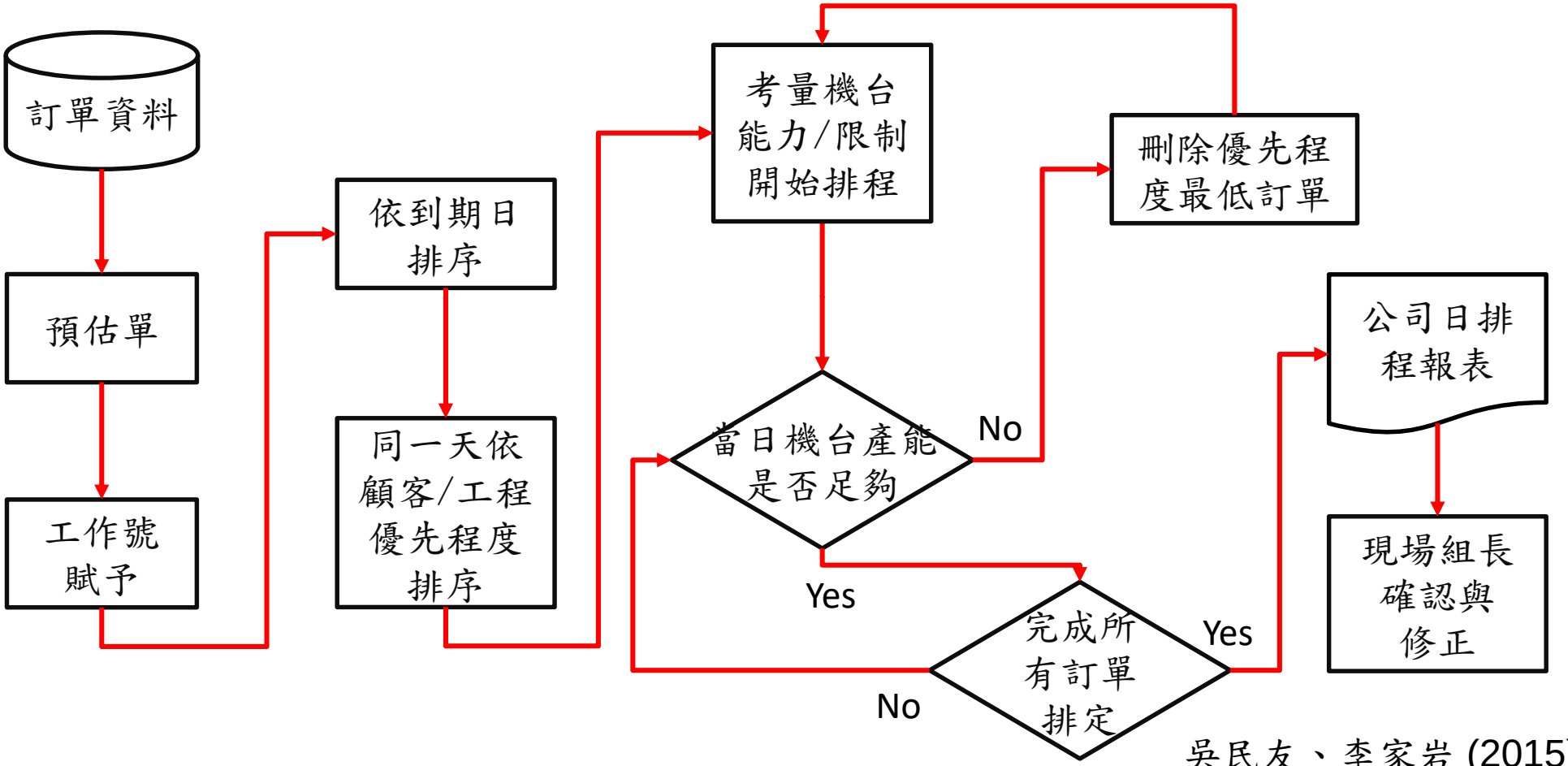
排程應用範疇

- 航空公司機師/空服員排班
- 機場飛機起降
- 車輛路徑派遣 (Vehicle Routing)
- 高鐵/火車/公車排班
- 電梯設定
- 微處理器系統
- 醫院排班
- 醫院復健排程
- 醫師手術排班
- 預約系統 (eg. 看病/餐廳/航班等)
- 對於服務顧客的管制
- 人機料的生產排程(協調多重資源的排程)

人工排程邏輯

現場人工排程

- MRP後，按照設定加工時間(processing time)，推算預計投料時間點
- 排程目標：滿足達交率 → 依到期日(Due day)排序工單



吳民友、李家岩 (2015)

優先順序法則

- Dispatching
  - is to release of orders and instructions for starting of the production for an item in accordance with the 'route sheet' and schedule charts.

- Dispatching Rule (優先順序法則): 用來選擇欲處理工作次序的一種簡單啟發式方法 .
  - FCFS (First Come, First Served) 先到先服務
  - SPT (Shortest Processing Time) 最短處理時間
  - EDD (Earliest Due Date) 到期日
  - Moore (Moore's Algorithm) 到期日+
  - CR (Critical Ratio) 關鍵性比率
  - S/O (Slack per Operation) 每個作業的寬裕時間
  - Rush 緊急事件

$$CR = \frac{(\text{到期時間}) - (\text{現在時間})}{\text{現場需要加工時間}}$$

$$S/O = \frac{(\text{到期時間}) - (\text{現在時間}) - \text{現場需要加工時間}}{\text{剩餘作業數}}$$

N Jobs on 1 Machine

- Examining the scheduling of n jobs on 1 machine (or the handling of the bottleneck machine)

- Performance Metrics
  - Mean Flow Time
  - Average Job tardiness
    - Tardiness is nonnegative; however, the lateness can be negative.
  - Number of Tardy Jobs

- Lateness vs. Tardiness
  - $L_j = c_j - d_j$, where c_j is completion time and d_j is due date
  - $T_j = \max\{0, L_j\}$

- Let's try FCFS, SPT, EDD and CR

N Jobs on 1 Machine

Example (Nahmais, 2005)

- Machine shop has 5 unprocessed jobs (J1, J2, J3, J4, J5) numbers by order they entered Bottleneck machines queue:

Job #	Process Time (p_i)	Due Date (d_i)
1	11	61
2	29	45
3	31	31
4	1	33
5	2	32

- Notations
  - p_j: process time
  - c_j: completion time
  - d_j: due date

N Jobs on 1 Machine

FCFS

Sequence	P. Time	Comp. Time	D. Date	Tardiness
J1	11	11	61	0
J2	29	40	45	0
J3	31	71	31	40
J4	1	72	33	39
J5	2	74	32	42
Totals	74	268		121

- Mean Flow Time: (268)/5 = 53.4
- Avg Tardiness: (121)/5 = 24.2
- # Tardy Jobs: 3

The "makespan" is fixed in this case (N jobs on 1 machine). Only consider the "job sequence".

N Jobs on 1 Machine

SPT

Sequence	P. Time	Comp. Time	D. Date	Tardiness
J4	1	1	33	0
J5	2	3	32	0
J1	11	14	61	0
J2	29	43	45	0
J3	31	74	31	43
Totals	74	135		45

- Mean Flow Time: (135)/5 = 27
- Avg Tardiness: (43)/5 = 8.6
- # Tardy: 1

N Jobs on 1 Machine

EDD

Sequence	P. Time	Comp. Time	D. Date	Tardiness
J3	31	31	31	0
J5	2	33	32	1
J4	1	34	33	1
J2	29	63	45	18
J1	11	74	61	13
Totals	74	235		33

- Mean Flow Time: (235)/5 = 47
- Avg Tardiness: (33)/5 = 6.6
- # Tardy: 4

N Jobs on 1 Machine

CR: Iterative Process

- looks at time remaining between current time and due date
- considers processing time as a percentage of remaining time
  - CR = 1.0 means just enough time
  - CR > 1 .0 more than enough time
  - CR < 1.0 not enough time
- Compute:

$$CR = \frac{(Due\_Date) - (Cur\_Time)}{Processing\_Time}$$

- Current time updates after each selection by adding scheduled Process Time to current time

N Jobs on 1 Machine

CR

JOB	Pr. Time	D. Date	CR
Current Time = 0			
1	11	61	5.546
2	29	45	1.552
3	31	31	1.00
4	1	33	33
5	2	32	16

JOB	Pr. Time	D. Date	CR
Current Time = 31			
1	11	61	2.727
2	29	45	.483
4	1	33	2
5	2	32	0.5

N Jobs on 1 Machine

CR

JOB	Pr. Time	D. Date	CR
Current Time = 60			
1	11	61	0.091 do last
4	1	33	-27*
5	2	32	-14**

Tie: use SPT

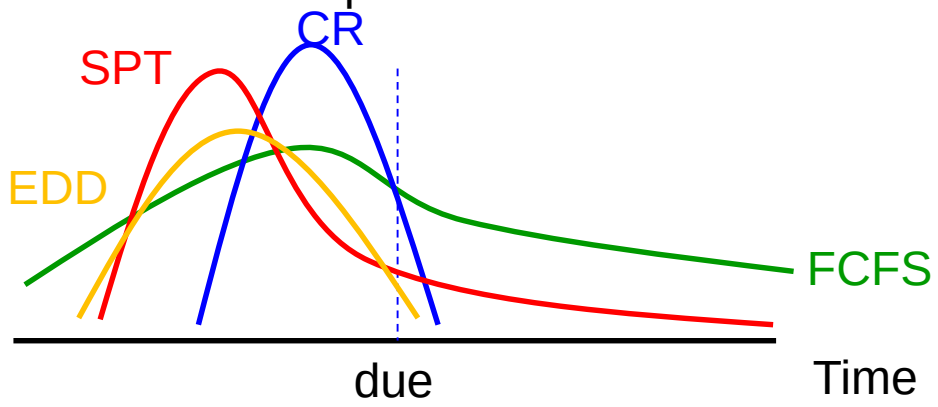
JOB	C. Time	D. Date	Tardy
Summary			
3	31	31	0
2	60	45	15
4	61	33	28
5	63	32	31
1	74	61	13
Total:	289		87

- Mean F. Time: (289)/5 = 57.8
- Mean Tardiness: (87)/5 = 17.4
- # Tardy: 4

Sequencing Rules

Performance Comparison

- FCFS:
  - Does not consider job attributes (due dates, processing times) and not do well
- SPT
  - Minimizes total time jobs spend in the system (mean flow time)
  - Given great mean flow time and does well relative to tardiness but does not sider due dates at all (Note that some job may queue forever!)
- EDD
  - Minimizes the Maximal Tardiness (Tmax), $T_{max} = \max\{0, L_j\}$
  - Does well relative to due dates (not optimal in any case but intuitively attractive)
- CR
  - Does worse in this example than usual



然而...

- EDD or SPT是現場常用的rules
- 然而，各有缺點
  - EDD缺點：現場一直救火，急件插單，滿足大客戶，放棄小客戶
  - SPT缺點：有些job可能永遠都沒機會加工
- 此外，簡單的Dispatching rule未考慮到
  - ”換線換模”的時間與成本
  - 生產線平衡(Line Balance)
- 延伸方法
  - 快速換模技術(Single-Minute Exchange of Die, SMED)
  - 生產線平衡技術 (Line Balancing)

Lee and Johnson (2013)

快速換模技術

- Single-Minute Exchange of Die, SMED (新鄉重夫Shingo, 1985)
  - Rapid changeover and setup time reduction in converting current manufacturing process to manufacture the next product; improves production flow and reduces lot sizes.
  - Long setup time leads to a small number of setups, larger batch sizes, larger WIP inventories and poor process flow.
- 思維的改變
  - 新鄉重夫：「快速換模絕對不是 "技巧的問題"，而是 "思維的問題" 」
  - 豐田汽車副社長大野耐一：「 生產現場中，”人的智慧"是成敗關鍵」

Shingo, S. (1985). A Revolution in Manufacturing: The Smed System, Productivity Press.

快速換模技術

SMED流程

- 1.記錄整個換模(線)現況過程和時間
  - 工作研究：人機程序圖、時間與動作研究(time-motion study)
- 2.區分內部換模與外部換模
  - 內部換模：指必須在機器停止生產狀態下，才能進行的換模動作。
  - 外部換模：指機器在生產運轉中，仍然可以進行的換模動作。
- 3.將內部換模作業儘可能轉到外部換模作業
  - 工具、模具、零組件標準化，不尋找、不移動、不多用
  - 工具預熱、預裝配、預設定、預清潔、預熱等等
- 4.改善內部換模
  - 平行作業、
  - 工具放置的方法/位置統一/尺寸統一
- 5.改善外部作業
  - 把工具/規尺存放在機器旁邊
  - 備好工具更換準備的核查清單、提供詳細的工具更換流程記錄單
- 6.標準化新的換模準備作業

科建顧問(2009)，"少量多樣生產的關鍵-快速換模(線)技術"，http://www.kind.com.tw/main.php?action=article_intro&id=52.

Scheduling Methodology

- JSP is among the hardest combinatorial optimization problems.
  - NP-hard problem

- Heuristic Method (Priority Rule)
  - Shortest processing time (SPT), earliest due date (EDD), etc.
  - Pros: easy to understand
  - Cons: poor performance for complicated production line

- Meta-Heuristic Algorithm (**Tabu**, Simulated Annealing, **Genetic Algorithm**)
  - Approximated-optimization approach
  - Pros: provide a good solution efficiently
  - Cons: cannot guarantee the global optimum

- Mathematical Programming
  - Optimization-based approach formulated by mixed integer programming
  - Pros: Guarantee global optimum
  - Cons: computational burden for large-scale problem

Local optimum
Short running time

Global optimum
Long running time

Meta-heuristics

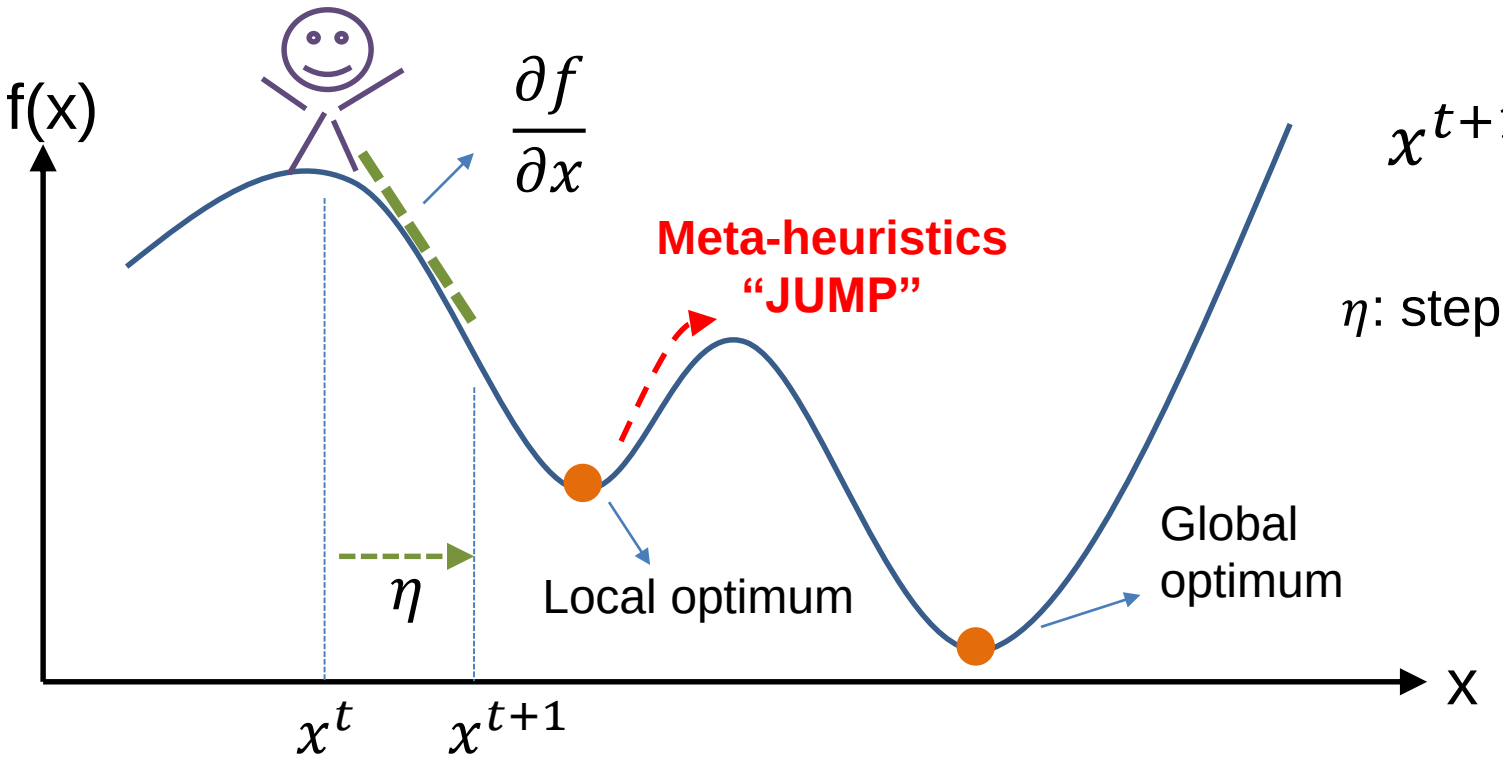
Definition of Meta-heuristics (Glover and Laguna 1997)

- A meta-heuristic refers to a master strategy that guides and modifies other heuristics to produce solutions beyond those that are normally generated in a quest for local optimality.
- For the "Minimization Problem"…

Gradient Descent (梯度下降法)

$$x^{t+1} \leftarrow x^t + \eta \frac{\partial f}{\partial x}$$

η: step size (learning rate)



Tabu Search (禁忌搜尋法)

Basis

- Tabu Search (TS) has its roots in methods that cross boundaries of feasibility and local optimality
- TS was first proposed by Glover (1977)
- The word tabu (or taboo) comes from Tongan, a language of Polynesia, where it indicates things that cannot be touched because they are sacred. Now it means “a prohibition imposed by social custom”
- In TS, tabu status of forbidden elements shift according to time and circumstance, based on an evolving memory.
- Tabu status can be overruled for a preferrable alternative.
- Hence TS uses adaptive (flexible) memory (long-term and short-term)
- Neighborhood Search
- exploitation (開採) of good solutions and exploration (探索) of new promising regions
- Stopping criteria (to terminate the searching procedure)
  - The maximal number of iteration/ The objective function is unchanged given a number of iteration/ Running time

Tabu Search Algorithm (Glover and Laguna, 1997)

- 1. Find an initial solution $x_0 \in X$, set $x^{now} = x^{best} = x_0$, initialize memory
- 2. Intensification phase:
  - 2.1 If termination condition (e.g. simple iteration count, no admissible improving move, no change in x^{best} in so many iterations) is satisfied, then go to step 3
  - 2.2 Choose the best $x^{next} \in N(x^{now})$ such that x^{next} is not tabu or satisfies aspiration criterion
  - 2.3 Move from x^{now} to x^{next}, i.e. set $x^{now} = x^{next}$
  - 2.4 If x^{now} is better than x^{best}, then set $x^{best} = x^{now}$
  - 2.5 Update recency based memory (tabu classifications), frequency based memory and/or critical event memory (elite solutions), return to step 2.1
- 3. Diversification phase:
  - 3.1 If termination condition is satisfied, then stop
  - 3.2 Using frequency based memory and/or critical event memory, find a new starting point x^{now}, return to step 2

- Single-machine total weighted tardiness problem (Chern, 2004)

Jobs	Process Time (p_j)	Due Date (d_j)	Weights (w_j)
1	10	4	14
2	10	2	12
3	13	1	1
4	4	12	12

  - Exhaustive enumeration method (窮舉法): 4! Cases

- Iteration 1: Initial solution (2,1,4,3) with total weighted tardiness
  - $T(2,1,4,3) = w_2 \max\{p_2 - d_2, 0\} + w_1 \max\{(p_2 + p_1) - d_1, 0\}$
    $+w_4 \max\{(p_2 + p_1 + p_4) - d_4, 0\} + w_3 \max\{(p_2 + p_1 + p_4 + p_3) - d_3, 0\}$
    $= 12 \times (10 - 2) + 14 \times (10 + 10 - 4) + 12 \times (10 + 10 + 4 - 12)$
    $+1 \times (10 + 10 + 4 + 13 - 1)$
    $= 500$
  - Set initial Tabu list, TABU = < >, and size of tabu list = 2

- Iteration 2: neighborhood search at (2,1,4,3).
  - Schedules obtained by pairwise interchanges are:

    $(1,2,4,3)$, $(2,4,1,3)$, and $(2,1,3,4)$

  - $T(1,2,4,3) = 480$, $T(2,4,1,3) = 436$, and $T(2,1,3,4) = 652$
  - (2,4,1,3) is the best from the non-tabu results
  - Update Tabu list, TABU = < (1,4) >

- Iteration 3: neighborhood search at (2,4,1,3).
  - Schedules obtained by pairwise interchanges are:

    $(4,2,1,3)$, $(2,1,4,3)$ TABU!, and $(2,4,3,1)$

  - $T(4,2,1,3) = 460$, $T(2,1,4,3) = 500$ TABU!, and $T(2,4,3,1) = 608$
  - (4,2,1,3) is the best from the non-tabu results
  - Update Tabu list, TABU = < (2,4), (1,4) > (size of tabu list = 2)

Single-Machine Scheduling Problem

- Iteration 4: neighborhood search at (4,2,1,3).
  - Schedules obtained by pairwise interchanges are:

    $(2,4,1,3)$ TABU!, $(4,1,2,3)$, and $(4,2,3,1)$

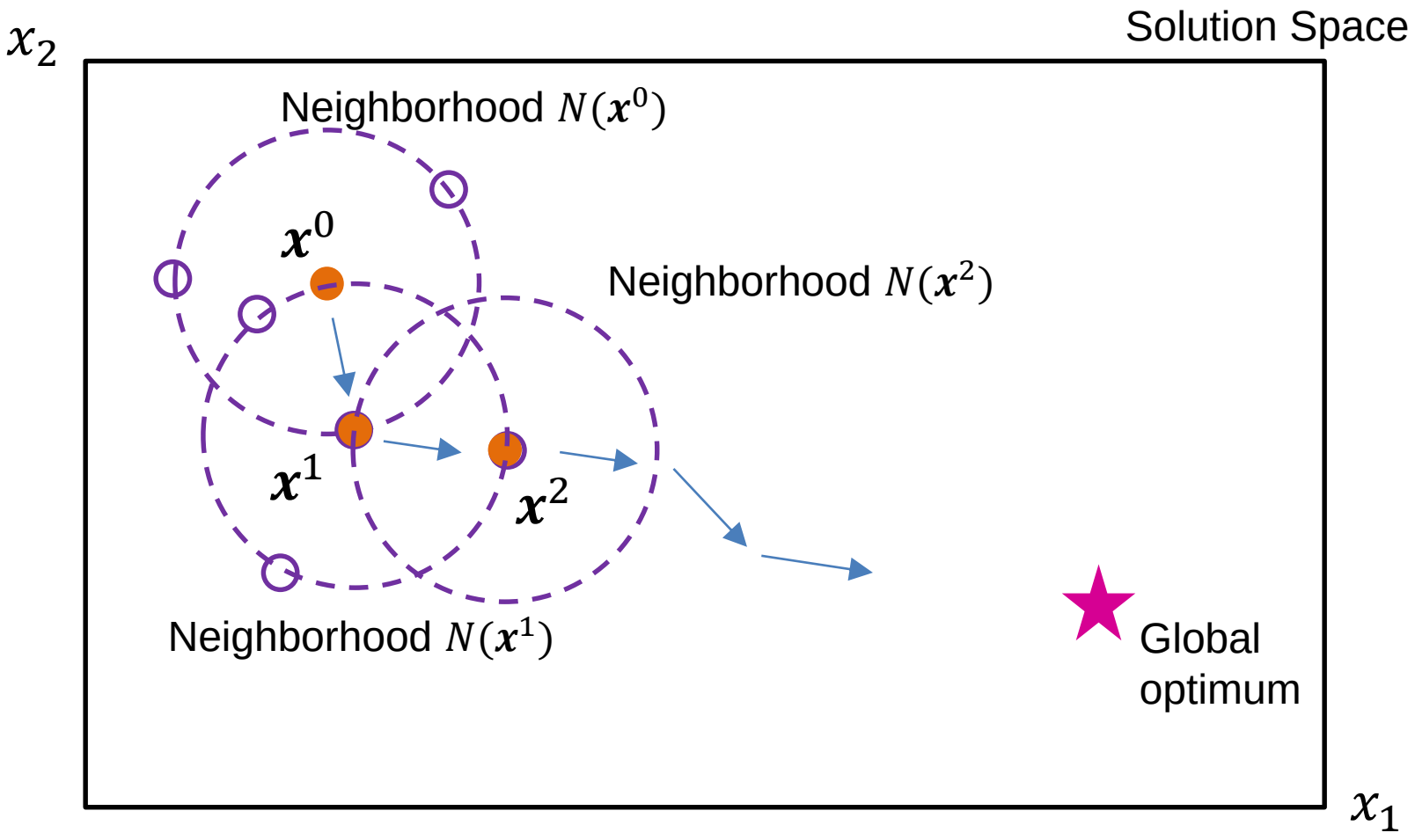
  - $T(2,4,1,3) = 436$ TABU!, $T(4,1,2,3) = 440$, and $T(4,2,3,1) = 632$
  - (4,1,2,3) is the best from the non-tabu results
  - Update Tabu list, TABU = < (2,1), (2,4) >

- Iteration 5: neighborhood search at (4,1,2,3).
  - Schedules obtained by pairwise interchanges are:

    $(1,4,2,3)$, $(4,2,1,3)$ TABU!, and $(4,1,3,2)$

  - $T(1,4,2,3) = 408$, $T(4,2,1,3) = 460$ TABU!, and $T(4,1,3,2) = 586$
  - (1,4,2,3) is the best from the non-tabu results
  - Update Tabu list, TABU = < (4,1), (2,1) >

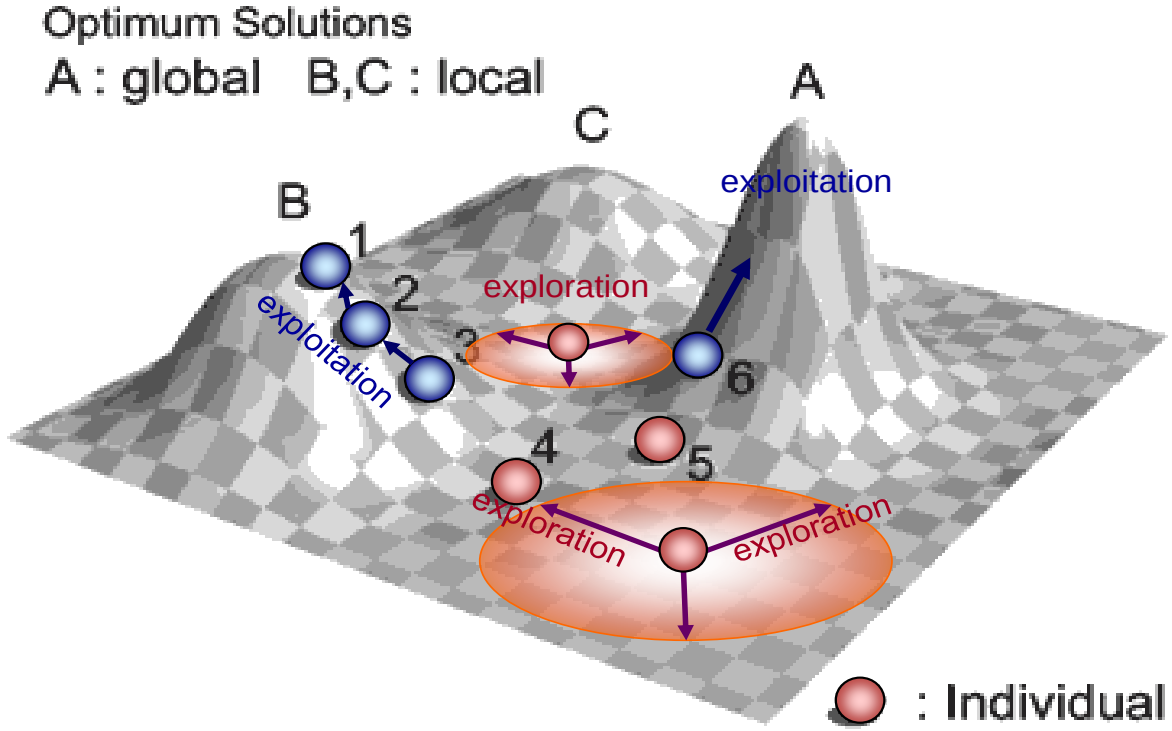
Stochastic (Local/Random) Search



Exploitation and Exploration

Intensification and diversification

- Intensification: a form of exploitation (開採)
  - Based on modifying choice rules to encourage good move combinations and solution attributes, and it may lead to return to attractive regions
  - Examines neighbors of prerecorded elite solutions
- Diversification: a form of exploration (探索)
  - Examines unvisited regions, generates different solutions

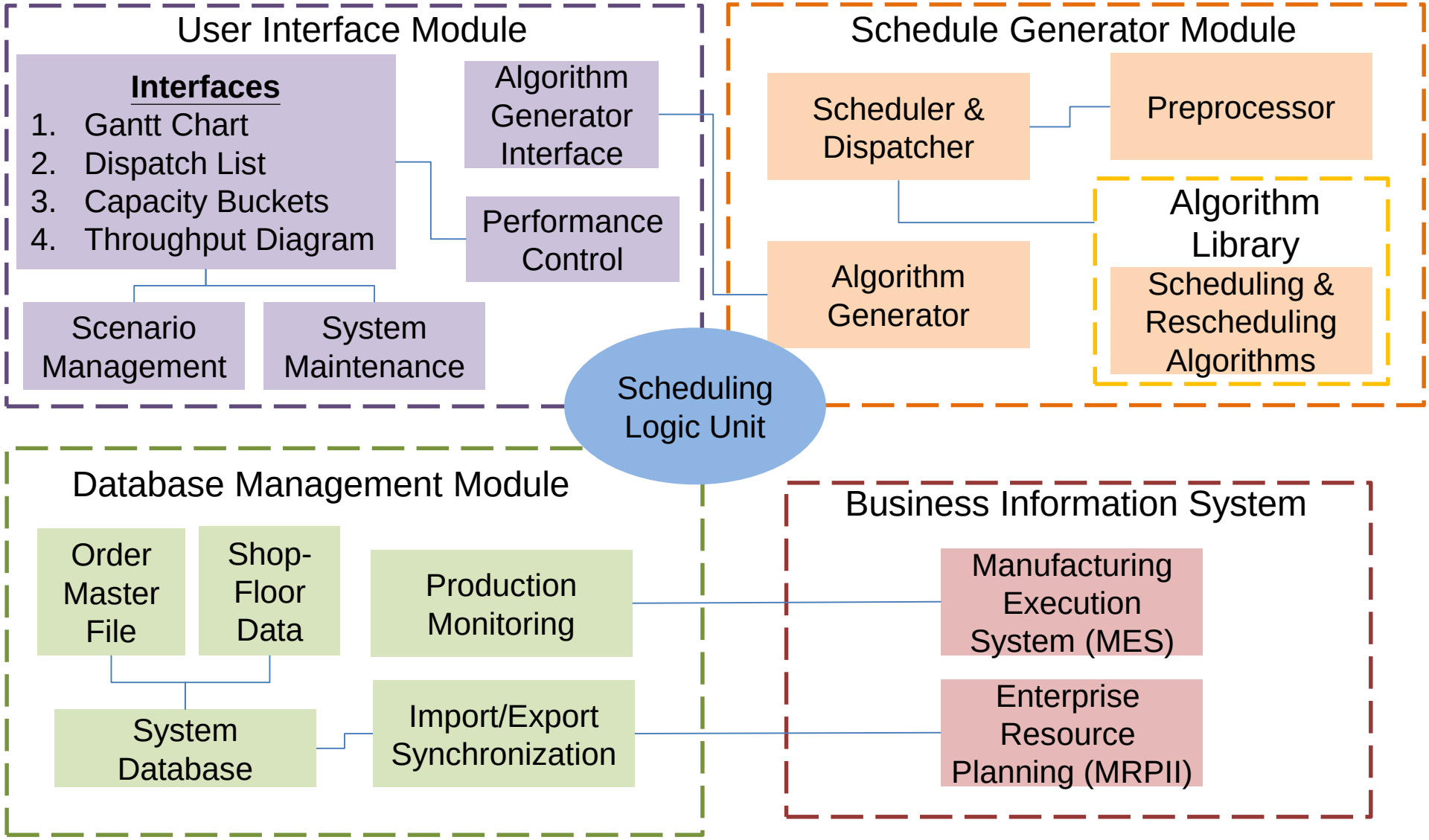


(Gen, 2005)

If you change the size of TABU list, what's the result?

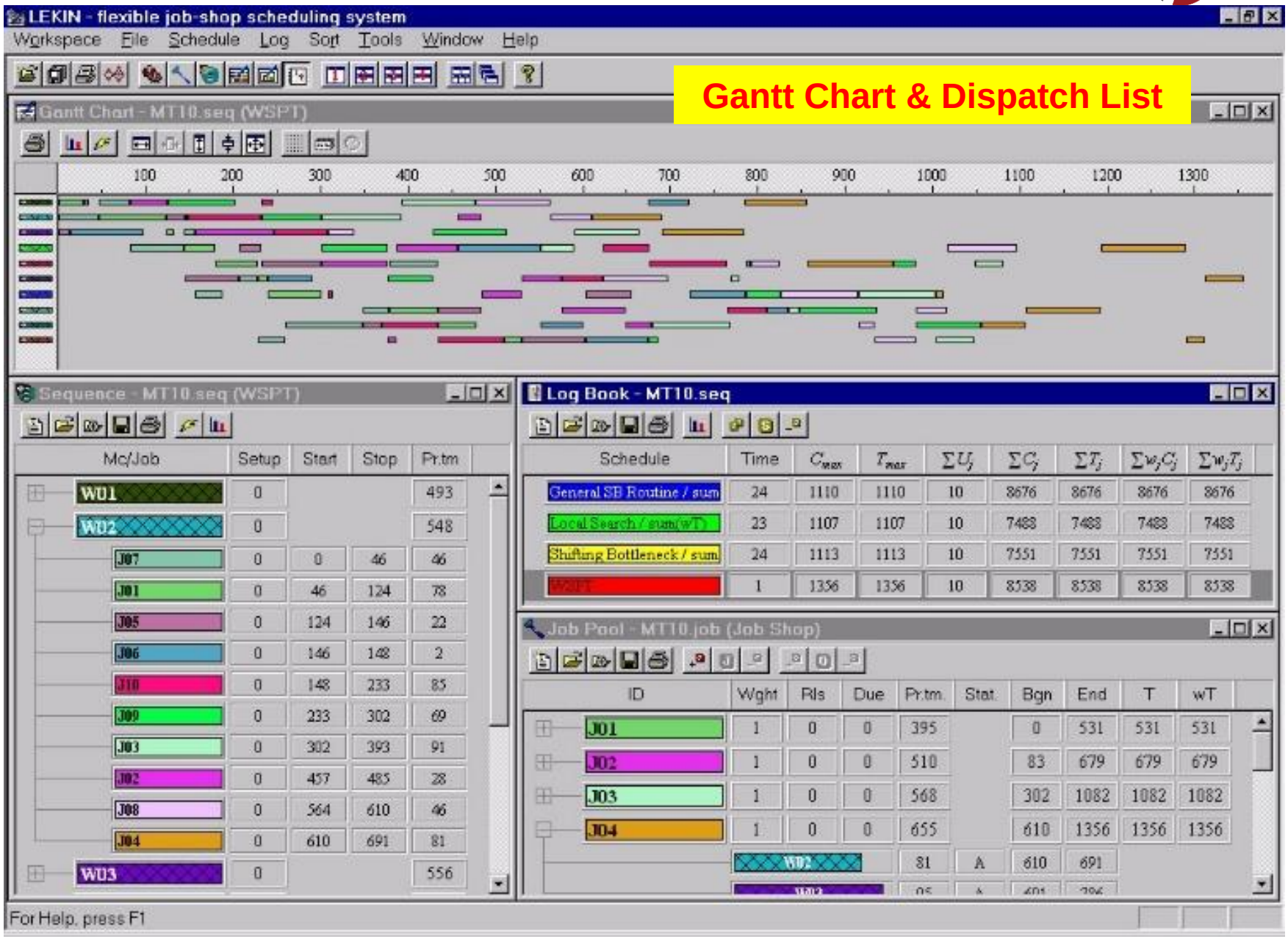
A trade-off between exploitation and exploration!!!

Module Architecture of MFG Scheduling Systems



revised from Framinan and Ruiz (2010)

LEKIN (http://web-static.stern.nyu.edu/om/software/lekin/)



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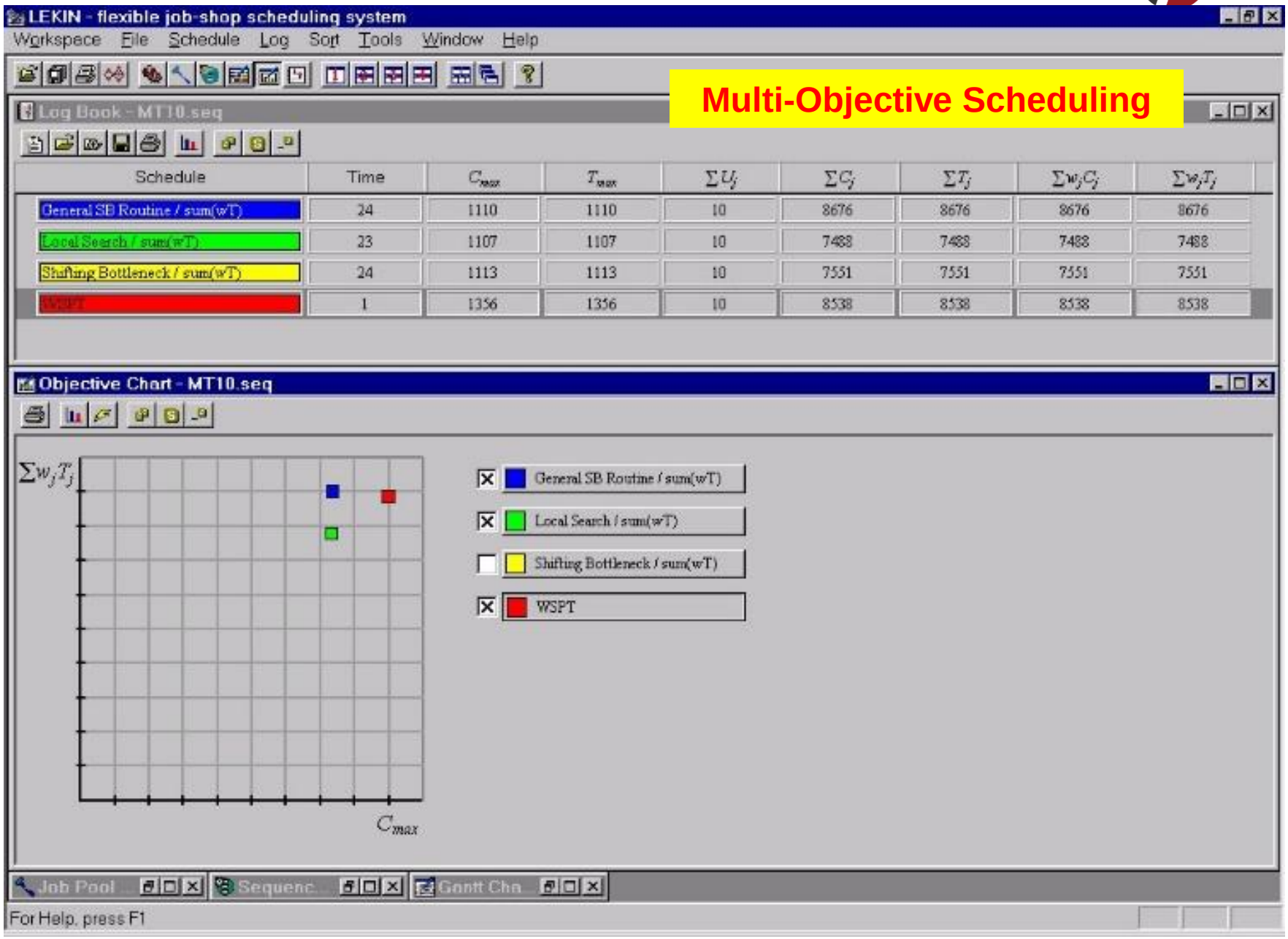
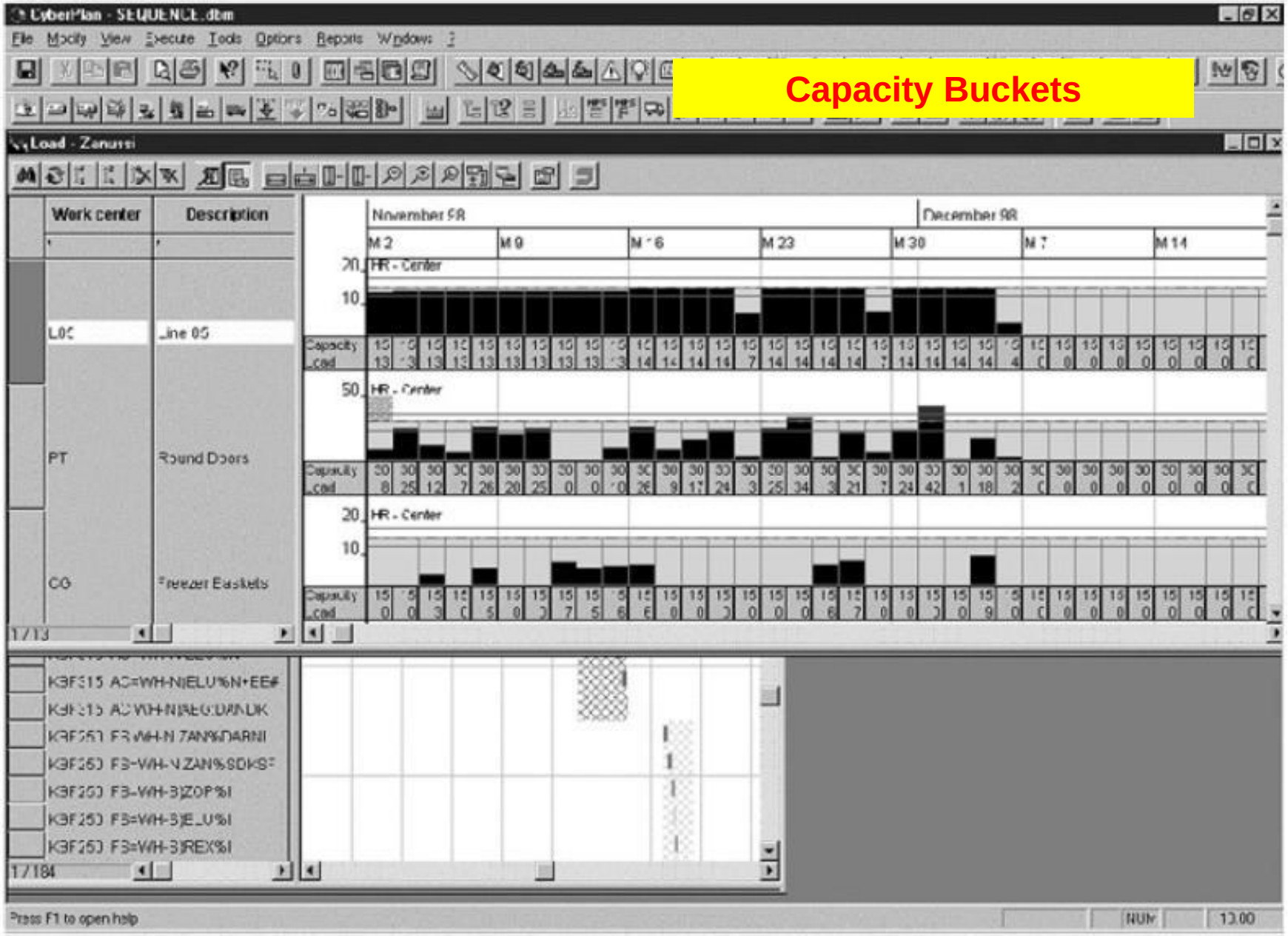
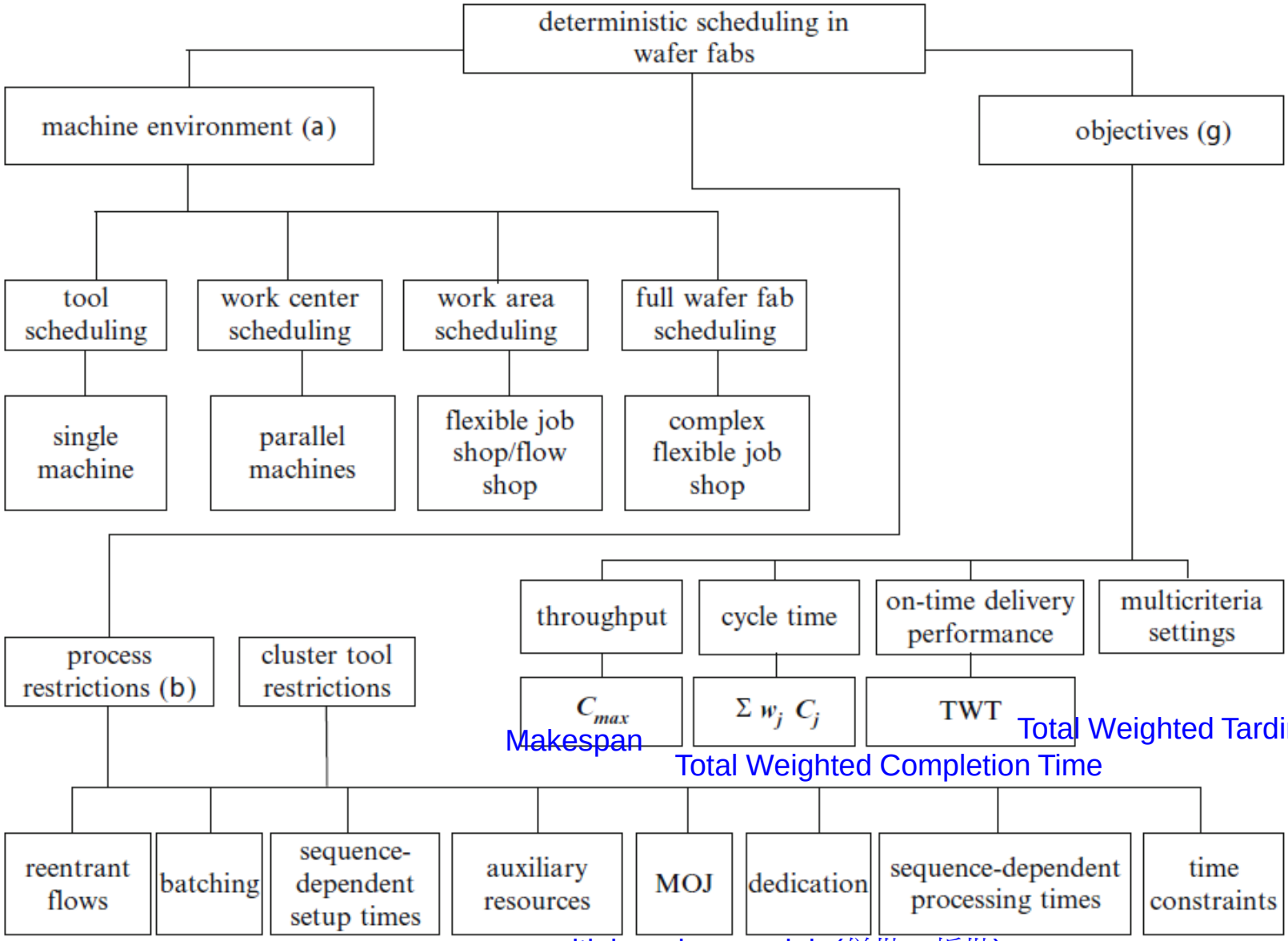


Cyberplan System (Pinedo, 2012)



Scheduling in Wafer Fabs



Monch, L., Fowler, J. W., and Mason, S. J. (2013). Production Planning and Control for Semiconductor Wafer Fabrication Facilities: Modeling, Analysis, and Systems. Springer New York Heidelberg Dordrecht London.

生產排程Scheduling

- 排程的好處多多
  - 先從某站點A開始做(可能是瓶頸)
  - 做完上下游的問題自然會浮出來
    - 上游變卡了，WHY? 下游變卡了，WHY?
    - 改善的機會!!
    - 但並不是把A產出極大化→ 上游慢，則A的稼動率會很低..下游慢，則會堆貨

- 講究的是synergy
  - 排程需整合人、機、料、法、環等資源
    - 人員技能、機台能力、模具原料庫存、批次工作站、Queue time limit
  - 部份手動排程調整rescheduling大部分有其必要 → 半自動化
  - Web-based scheduling system
  - 排程系統長期發展應與其他系統整合
    - 庫存管理、人員排班、維修保養排程、產能規劃與定價(?)
    - 供應鏈上下游的系統整合 (資訊透明化)

自動化時實務與學理的排程差異(Pinedo, 2012)

- 靜態n個工作排程最佳化
  - 實務上是動態的，因此當新的工作(job)來，必須要rescheduling
  - Note1: 設定一個未來時段排程不可變動，eg. 未來6hrs內的排程固定
  - Note2: 插入空隙(slack time)於排程中，以防止急單或機台當機狀況
- 複雜的現場環境
  - 機台能力(eg. 機差)、製程限制(eg. 綁機)、訂單相關(eg. 優先權)、工序相關(eg. 前置時間)、時間相關(eg. 等候限制)、機台狀況(eg. 當機、維修保養)
- 工作優先權的動態調整
  - 學理上會固定工作/工單的優先權，然而實務上權重會動態調整，甚至最低優先權的工作突然變成最高優先權的工作
- 目標函數/懲罰函數通常不是"線性"的
  - 線性：Penalty function $= \max\{0, c_j - d_j\}$
  - 非線性： Penalty function $= \max\{0, (c_j - d_j)^2\}$

自動化時實務與學理的排程差異(Pinedo, 2012)

- 多個目標函數，且每個目標函數的權重會隨時間動態調整
  - A. 最小化 sum of the sequence dependent setup times → increase throughput
  - B. 最小化 total weighted tardiness → maintain quality of service
  - If workload is relatively heavy, then A; otherwise, B.

- 排程常跟人員排班與加班有密切關係

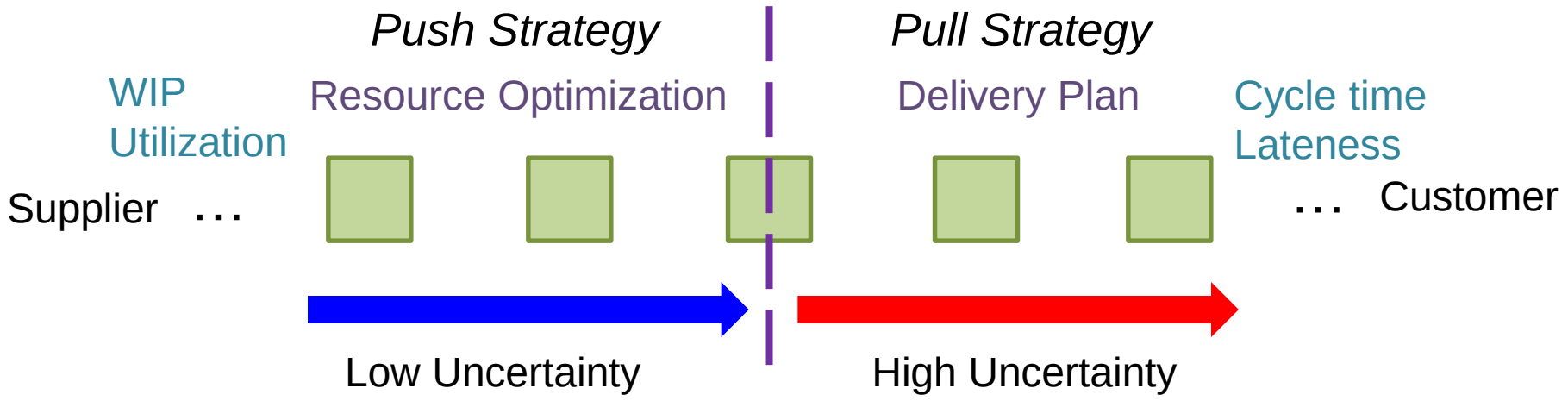
由於眾多因素的複雜關係，排程基本上都是”客製化”

- 加工時間的隨機性不易建模
  - 98%是固定值(eg. 10mins); 2%會加上平均數相當大的指數分配時間
  - 自動化製造與組裝現場尤其常發生
  - 機台或機器人平常加工很順；但突發狀況會立即造成非常糟的加工時間
  - 加工時間也常受到人員訓練(經驗曲線)以及模(刀)具耗損的影響

- 排程系統開發過一陣子就…
  - Out-of-fashion database without updated order, upgraded-version machine (throughput change), labor (learning curve), …
  - Rescheduling

生產排程Scheduling

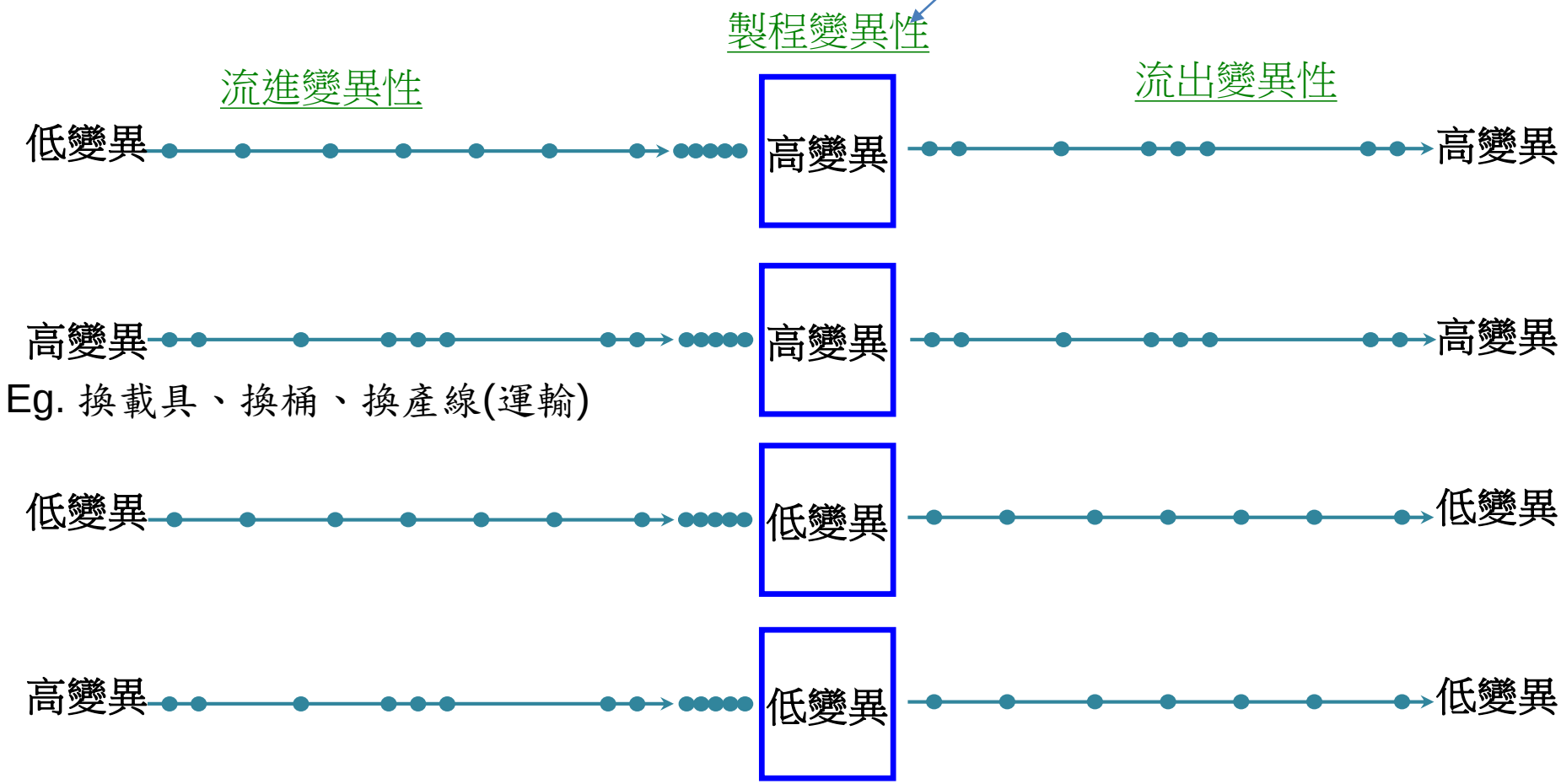
- 如果現場的「剩餘」產能是足夠的
  - 某工作可以在這機台處理，也可再另外一個機台 (有選擇性)
  - 先考慮Setup time與due date → high priority
  - 再考慮flexibility (有多少機台可以做這job) → low priority
- 如果現場有兩個瓶頸，下游的瓶頸排程先處理! (WHY?)
  - Hint: WIP
  - 但下游若是偏向組裝線 (i.e. delayed differentiation)，人為調整因素較多，自動化導入也就愈加困難
  - 推拉界限(push-pull boundary)視角



製造系統的變異

- 流動變異性
  - 瓶頸站(high utilization station)的重要性

Must check the variance of processing time

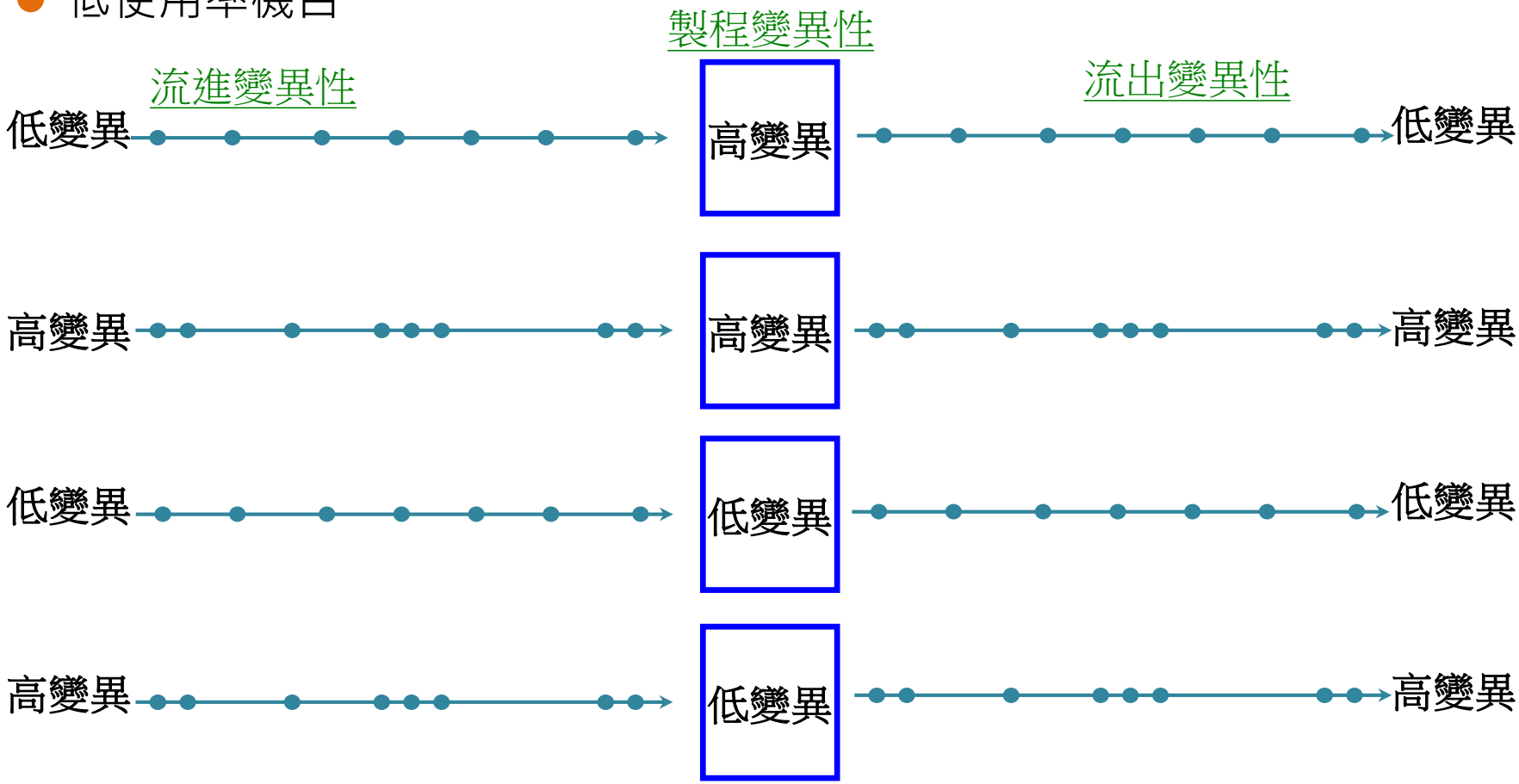


Eg. 換載具、換桶、換產線(運輸)

Check the **process variability** of (1) processing time (product); (2) MTTR & MTBF (equipment).

製造系統的變異

- 流動變異性
  - 低使用率機台



Check the **flow variability** out of a low utilization station is determined primarily by flow variability into that station.

迷思

- 1. 開發資訊系統連結資料庫、ERP、MES串起來，導入人工智慧AI演算法優化(eg. 基因演算法GA)，排程就「成功」了?
- 2. 排程有沒有一般化(generalized)的模組?
- 3. 排程系統真正關鍵在交接、維護、與持續更新
  - 教育訓練
    - 排程是組合最佳化(Combinatorial optimization)的問題，通常為NP-hard
    - 一旦學會解這類題目，應用範圍就變廣了
      - 運輸最短路徑問題 (eg. travelling salesman problem, TSP)
      - 網路結構最佳化問題 (eg. minimum spanning tree, MST)
      - 財務投資組合問題/ 人員排班問題/ 資源優化的問題/ 設施規劃/廠址選擇
      - 產能規劃/庫存管理/ 電信基地台架設 選址問題/ 車輛配送路徑問題等
  - 現場動態調整

排程光譜

Mindset：不得不

手動　　半自動　　全自動

- 特殊化/客製化
- 樣本
- 各廠有自己的
- 工程師經驗
- Rule-based

前期	後期
處方性構析	預測性構析
靜態	動態
LP、Tabu	DL、模擬
小工具、小指標	小工具、小未來
輔助決策	掌握環境變化

- 一般化/標準化
- 母體
- 各廠統一
- 電腦自動優化
- AI-based

Mindset：不一定

一樣米養百樣人
看每個人的造化

- 到這裡..可以發現...
- 排程...好像不是要預測些什麼!?
- FCFS, SPT, EDD, CR 哪一個好?
- 製造資源的最佳化 → 處方性分析

From Predictive to Prescriptive

- 再過一陣子..

「業界缺的就不是Data Scientist，而是如何將Model產生的Pattern或預測結果，與公司、現場、內部、外部的資源整合，以進行Prescriptive Analysis」

(范治民博士，2017)

- 預測但不做決策..預測就可惜了..
  - 然而，決策是根據「資源」來做判斷

在製造業中

自動化程度愈高...

排程需求就愈重要!

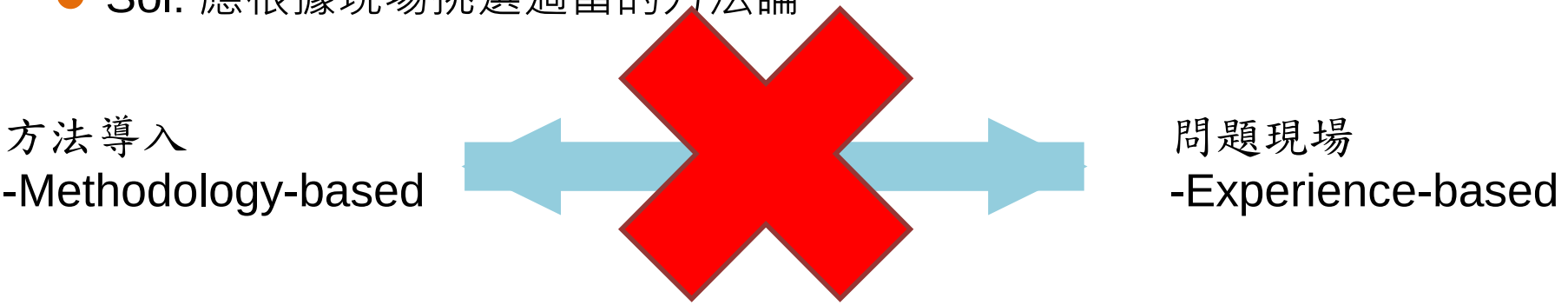
而排程就是一種

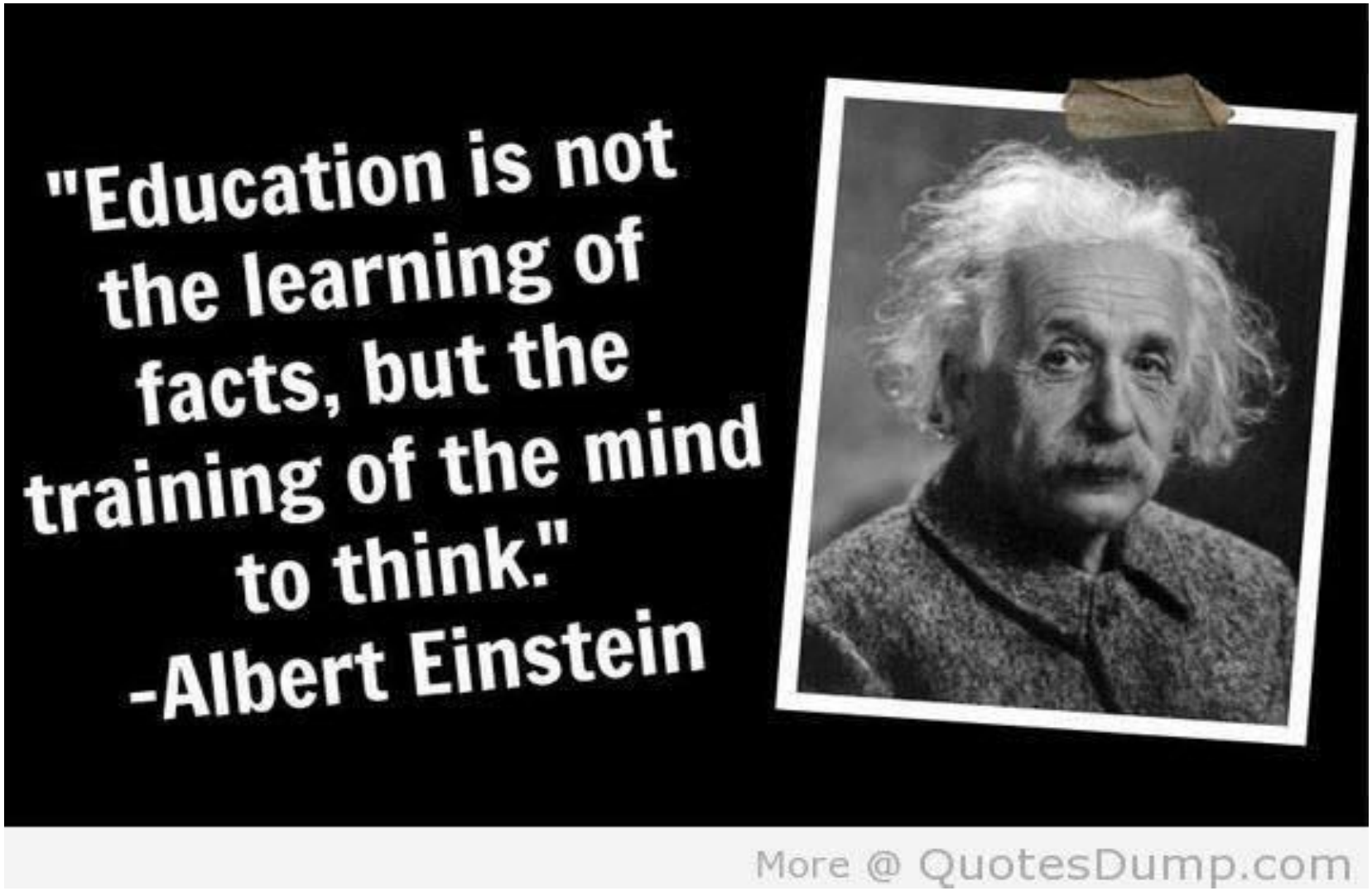
Prescriptive Analysis (處方性分析)

根據資源"人機料法環"達成的綜效synergy

失敗案例與注意事項

- 主管對現場認知的落差(垂直)、跨部門資料取得與整合(水平)
  - PPT製作、KPI達成、報喜不報憂、組織間的競合
  - Sol: 總經理辦公室、特助出來協調
- 數據、資訊系統與IT基礎建設
  - 進去找到問題點後，發現沒有數據 (現場都是有問題後才開始收集數據)
  - Sol: 小數據Pilot-run的重要性、分階段進行、初步試驗性質的問題診斷
- 「解」問題過程
  - 為AI而AI? 為自動化而自動化?
  - Sol: 應根據現場挑選適當的方法論




"Education is not
the learning of
facts, but the
training of the mind
to think."
-Albert Einstein
More @ QuotesDump.com

從預測性思維到處方性決策

From Predictive to Prescriptive

預測要愈準愈好?

迷思

- 這是當然的..
- 但另一方面，預測的本質是...
  - 找出關鍵因子
  - 建構因果關係
  - 把正或負的影響(趨勢)抓到
    - eg. 線性回歸中的獨立變數的係數
  - 協助決策制定，以趨吉避凶

讓我們一起來想一下...

- 為什麼要預測?
- 預測的目的是什麼?
- 下一步為何?

預測像...

預測像...

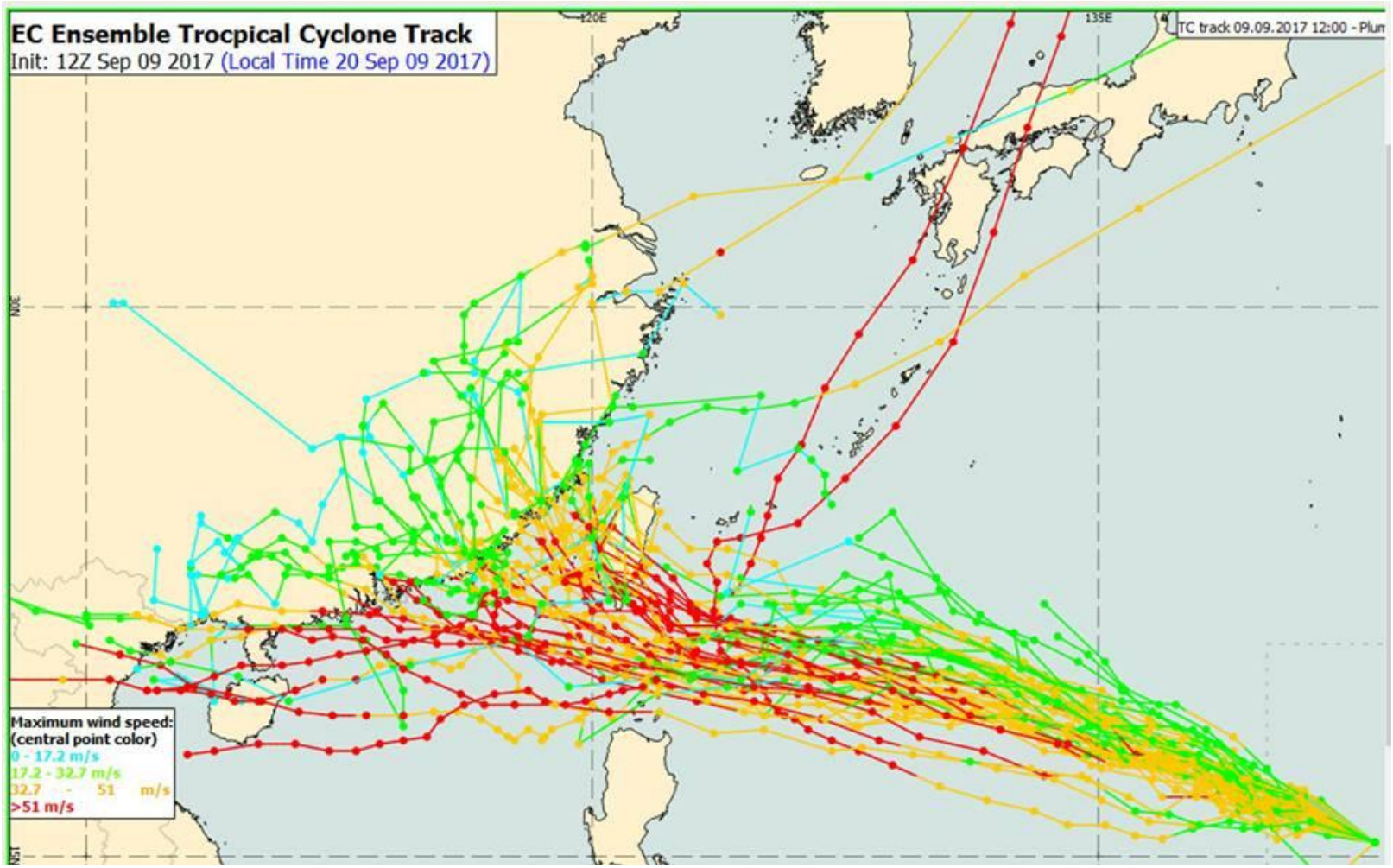
http://www.zou1.com/news/show-97765.html

http://thewhen.pixnet.net/blog/post/42532195-%E5%A1%94%E7%BE%85%E5%8D%A0%E5%8D%9C%3A%E6%88%91%E8%A9%B2%E5%A6%82%E4%BD%95%E5%A2%9E%E5%8A%A0%E8%B2%A1%E9%81%8B%3F

但...其實是...

衡量風險與不確定性

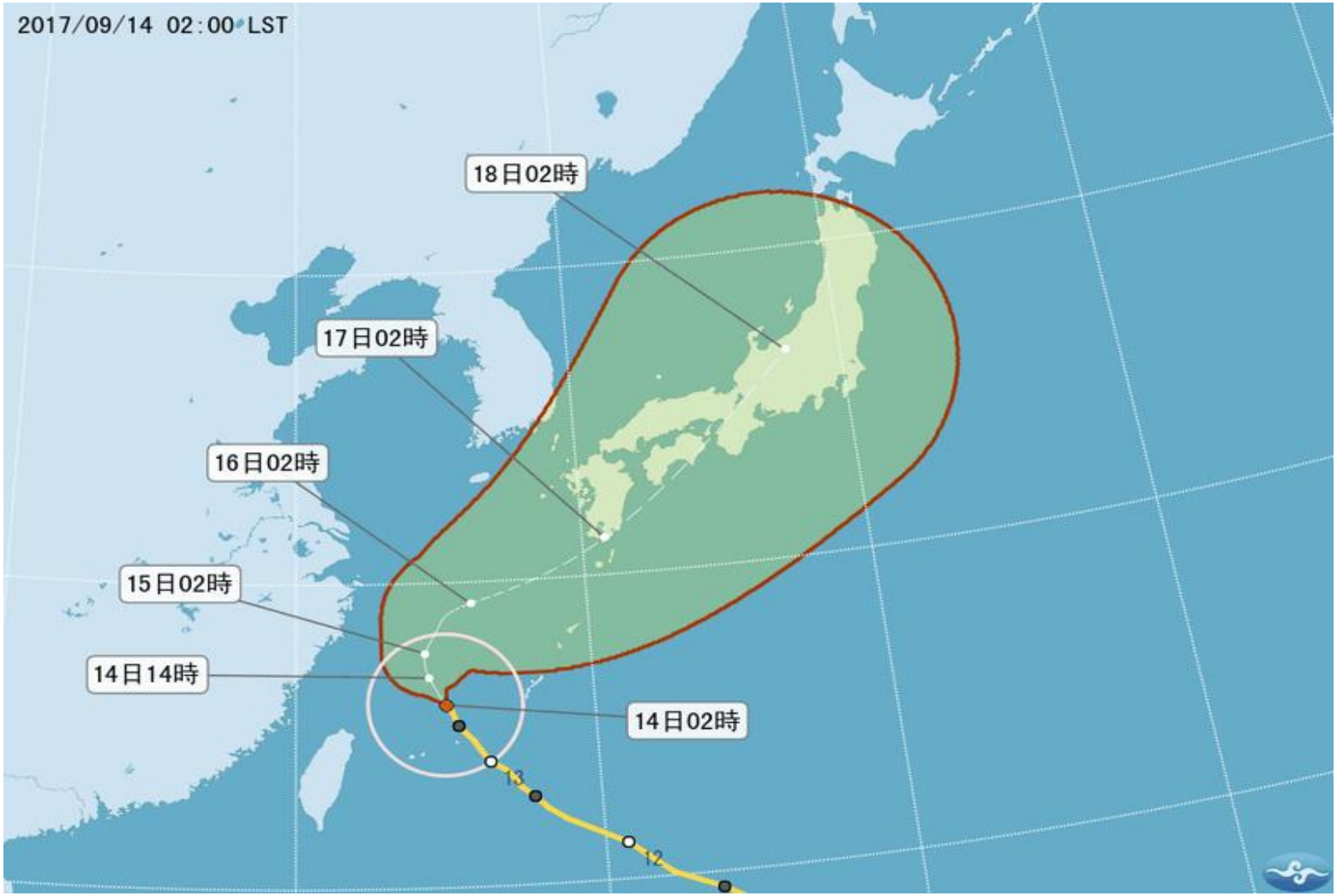
2017/09/09 歐洲模式中心的五十幾種氣象模式的颱風路徑預測結果，泰利侵台機會頗高。



http://news.ebc.net.tw/news.php?nid=77898

衡量風險與不確定性

2017/09/14 中颱泰利「髮夾彎」 北部、東北部風雨較大



http://www.cna.com.tw/news/firstnews/201709140012-1.aspx

所以「決策」很.....難做....

瞭解這就...

不要太為難你的長官 XD

因此...說穿了...

「推論(預測)」就是

透過分析資訊來降低未來不確定性

的一種方法

以利決策的進行!

重點不在於「預測」本身

重點在於我們開始「動起來」

透過「收集資訊」來降低所面對的不確定性

決策的類型

- 根據「資訊」收集的狀況，**決策**的類型可以簡單分成下面三種
- 確定性下決策 (Decision under Certainty)
- 風險下決策 (Decision under Risk)
- 完全不確定下決策 (Decision under Strict Uncertainty)

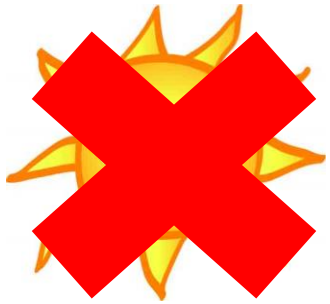
小試身手...

天氣與決策

	不帶傘	帶傘
晴天	○	✕ 1. 笨重 (不方便) 2. 弄丟 (再買一支)
雨天	✕ 1. 落湯雞 (感冒) 2. 搭計程車 (支出) 3. 拿別人的傘 !! (良心不安)	○

小試身手...

- 確定性下決策 (Decision under Certainty)

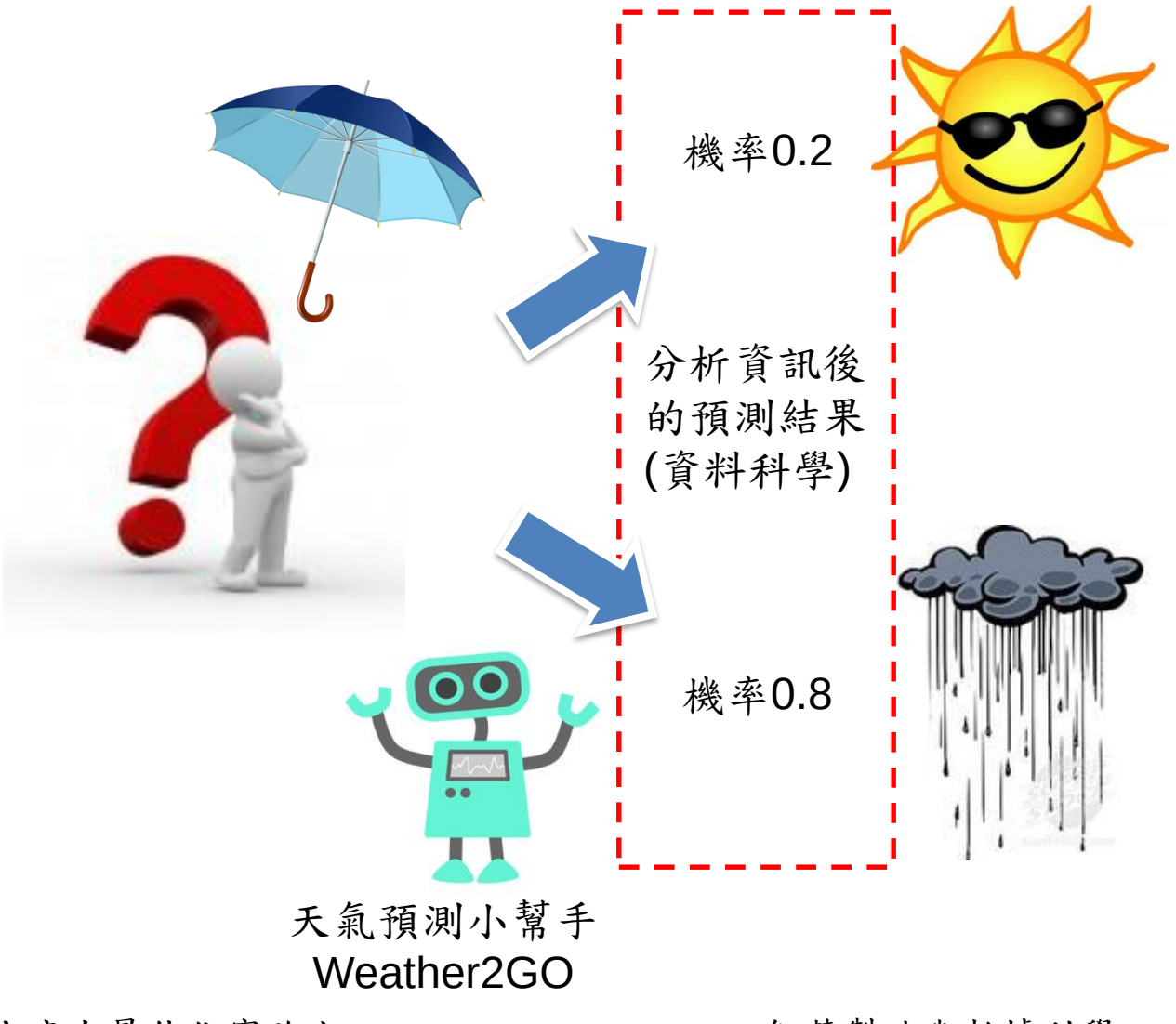


明天一定(100%)下雨...

神預測
God2GO

小試身手...

風險下決策 (Decision under Risk)



- 方法一：期望值

0.2 x太陽+0.8 x 下雨 (!?)

迷思- 骰子六個面

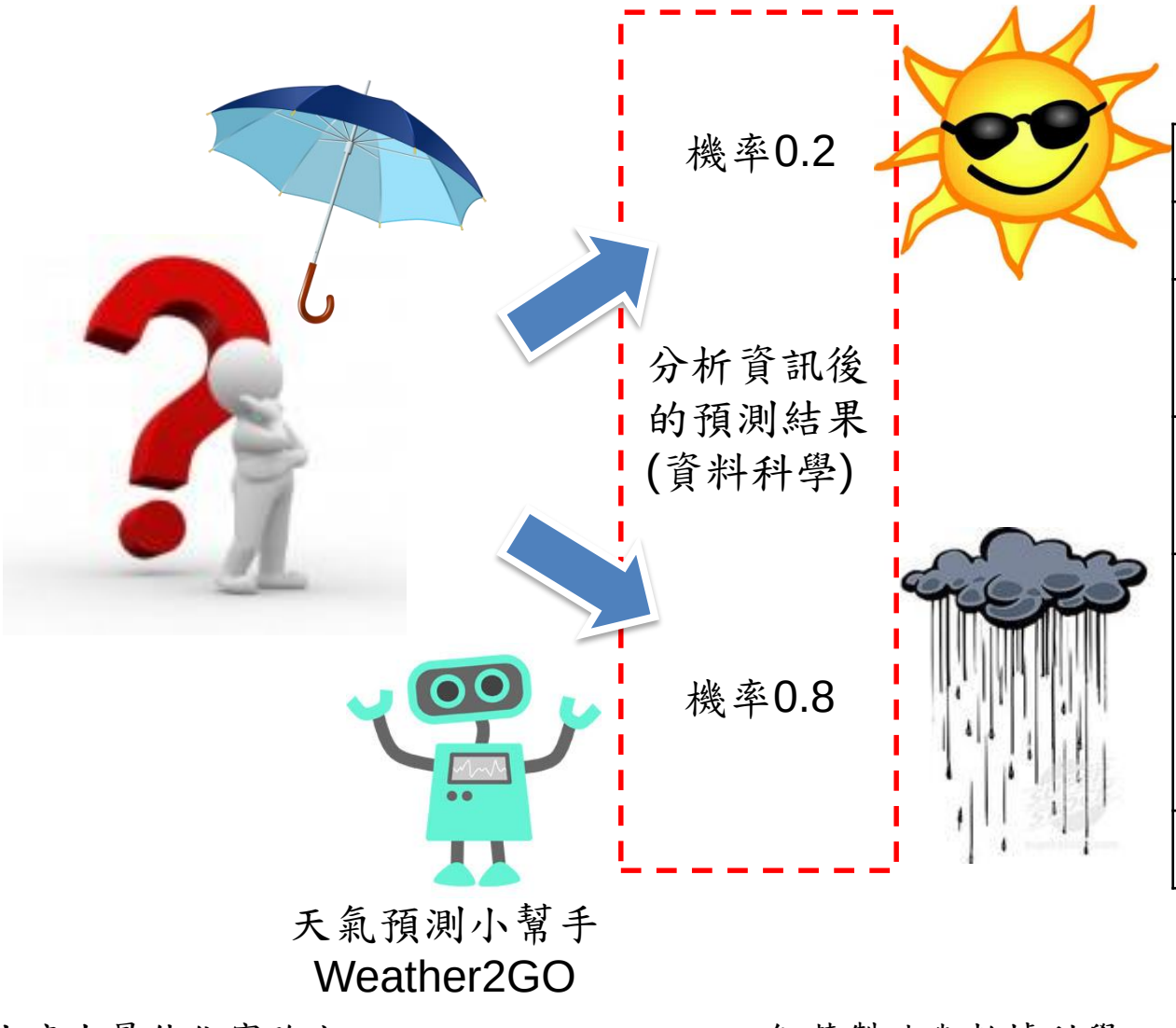
每一面1/6, 期望值為3.5

賭骰子應該出現3.5 (!?)

- 方法二：決策風險

小試身手...

風險下決策 (Decision under Risk)



- 方法二：決策風險
  - 處方性的分析

	風險成本矩陣	
	不帶傘	帶傘
晴天	成本 $0	成本 $100 (弄丟)
雨天	成本 $200 (感冒)	成本 $0
期望成本	0.2x0 +0.8x200 =160	0.2x100 +0.8x0 =20
決策：帶傘		

風險下決策 (Decision under Risk)

切記...
不是因降雨機率0.8，所以我們才帶傘，
主要是因為決策風險(成本)的考量後，
我們才決定帶傘。

又或...
我們可以想想這件事，
若弄丟後買一把傘成本為100,000元，
我們還會決定帶傘嗎?

- 方法二：決策風險
  - 處方性的分析

	風險成本矩陣	
	不帶傘	帶傘
晴天	成本 $0	成本 $100 (弄丟)
雨天	成本 $200 (感冒)	成本 $0
期望成本	0.2x0 +0.8x200 =160	0.2x100 +0.8x0 =20
決策：帶傘		

由此可知...

預測(降雨機率)很重要，

決策風險(帶不帶傘的後果)也很重要

互為表裡、相輔相成

Lee (2019)

小試身手...

- 完全不確定下決策 (Decision under Strict Uncertainty)

方案1：沒有帶傘的習慣耶

方案2：就每天帶把小傘吧~

Based on your Preference Structure

沒有任何資訊
I2GO

完全不確定下決策 (Decision under Strict Uncertainty)

- 公司規劃投資產能擴充，希望明年銷量愈高愈好
  - 目前公司年度營業利益約25億元
  - 根據明年景氣狀況，營業利益預估如下

	明年景氣變化情境		
方案	景氣好	景氣持平	景氣差
併購公司A	42	21	8
購置機台	35	28	13
外包	28	25	23

你會選哪一個方案?

Revised from Chien (2005)

完全不確定下決策 (Decision under Strict Uncertainty)

- 悲觀準則 (The Maximin Payoff Criterion)
  - 小中取大報酬準則
  - 作最壞的打算，再由各最壞的報酬中選擇最好的結果

	天氣情境			
方案	景氣好	景氣持平	景氣差	Min Return
併購公司A	42	21	8	8
購置機台	35	28	13	13
外包	28	25	23	**23**

樂觀準則 (The Maximax Payoff Criterion)

- 又稱大中取大報酬準則
- 作最好的打算，再由各最好的報酬中選擇最好的結果

	天氣情境			
方案	景氣好	景氣持平	景氣差	Max Return
併購公司A	42	21	8	**42**
購置機台	35	28	13	35
外包	28	25	23	28

完全不確定下決策 (Decision under Strict Uncertainty)

- 薩維基準則 (The Minimax Regret Criterion) (Savage, 1951)
  - 又稱最小最大悔惜準則
  - 悔惜定義為「一決策方案之報酬與相同自然狀態下可以產生最大報酬之決策方案，兩者報酬的差額」
  - Step 1：建立悔惜償付表
  - Step 2：在悔惜償付表中採大中取小準則(minimax)

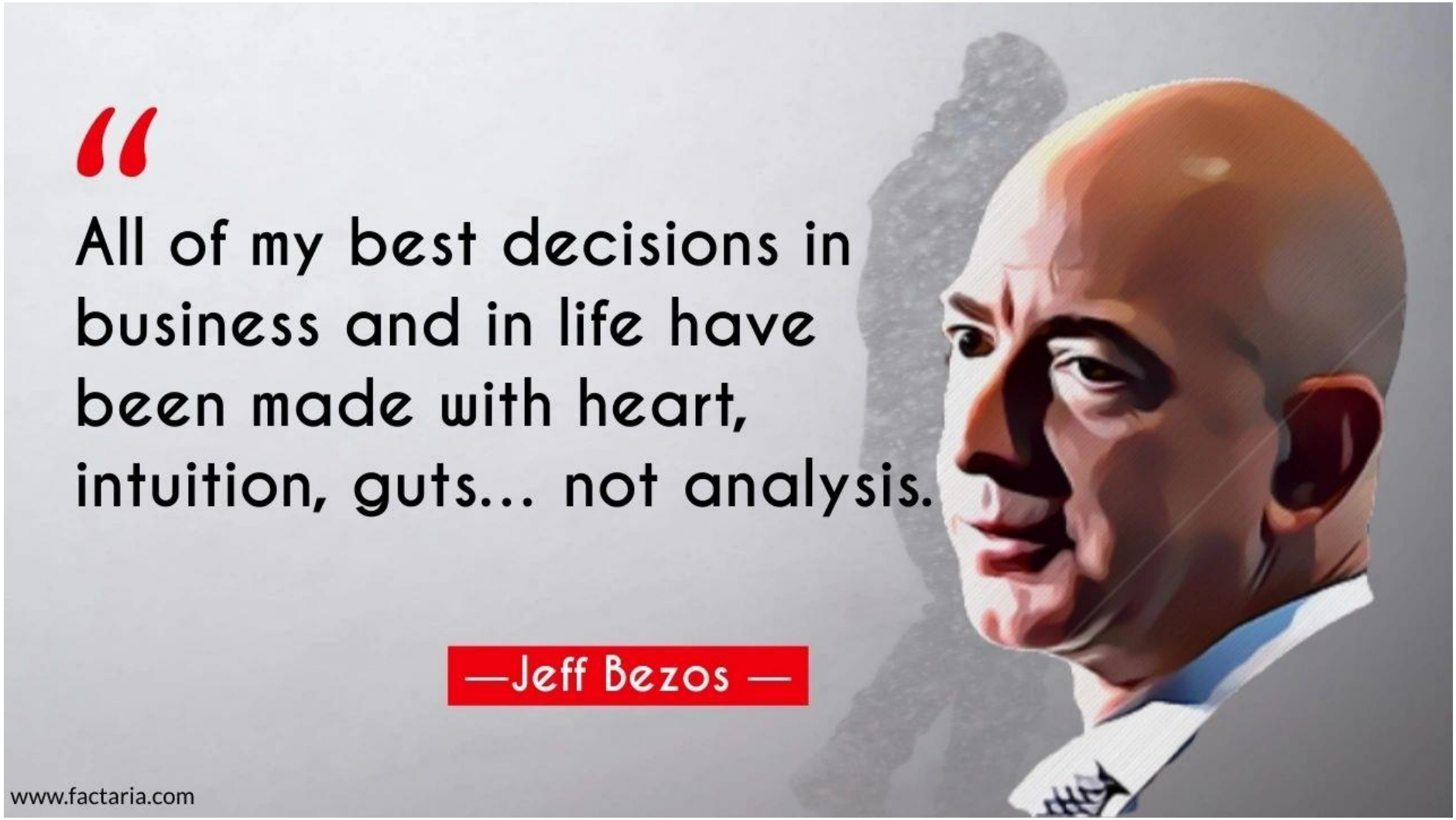
	天氣情境			悔惜矩陣			
方案	景氣好	景氣持平	景氣差	景氣好	景氣持平	景氣差	Max Regret
併購公司A	42	21	8	0	7	15	15
購置機台	35	28	13	7	0	10	**10**
外包	28	25	23	14	3	0	14

完全不確定下決策 (Decision under Strict Uncertainty)

- 公司規劃投資產能擴充，希望明年銷量愈高愈好
  - 無資訊情況下，理性決策並**沒有**對跟錯的差別
  - 只是根據每個人的「**喜好結構 (preference structure)**」所呈現決策結果

	天氣情境		
方案	景氣好	景氣持平	景氣差
併購公司A	42	21	8
購置機台	35	28	13
外包	28	25	23

你會選哪一個方案?


"
All of my best decisions in business and in life have been made with heart, intuition, guts... not analysis.
—Jeff Bezos —
www.factaria.com

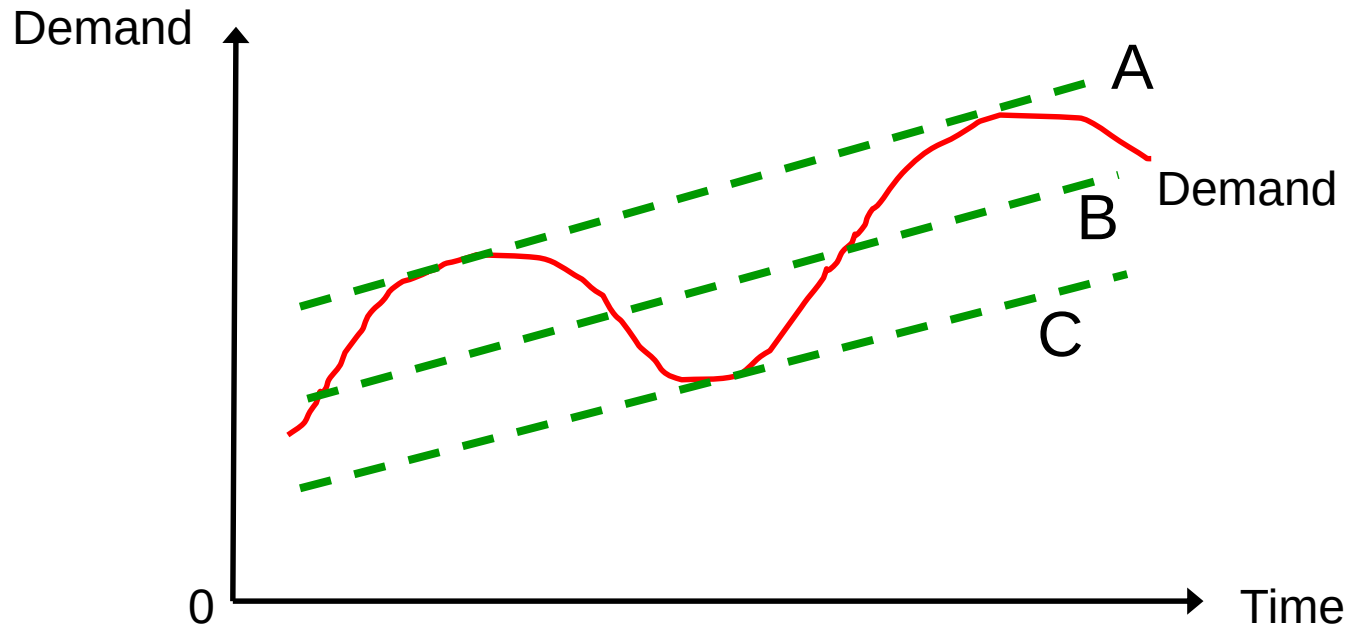
既然決策很難做...

就想辦法在做決策之後

讓它變成一個好的決策!

大試身手...

- Capacity Planning Problem (Newsboy problem over time)

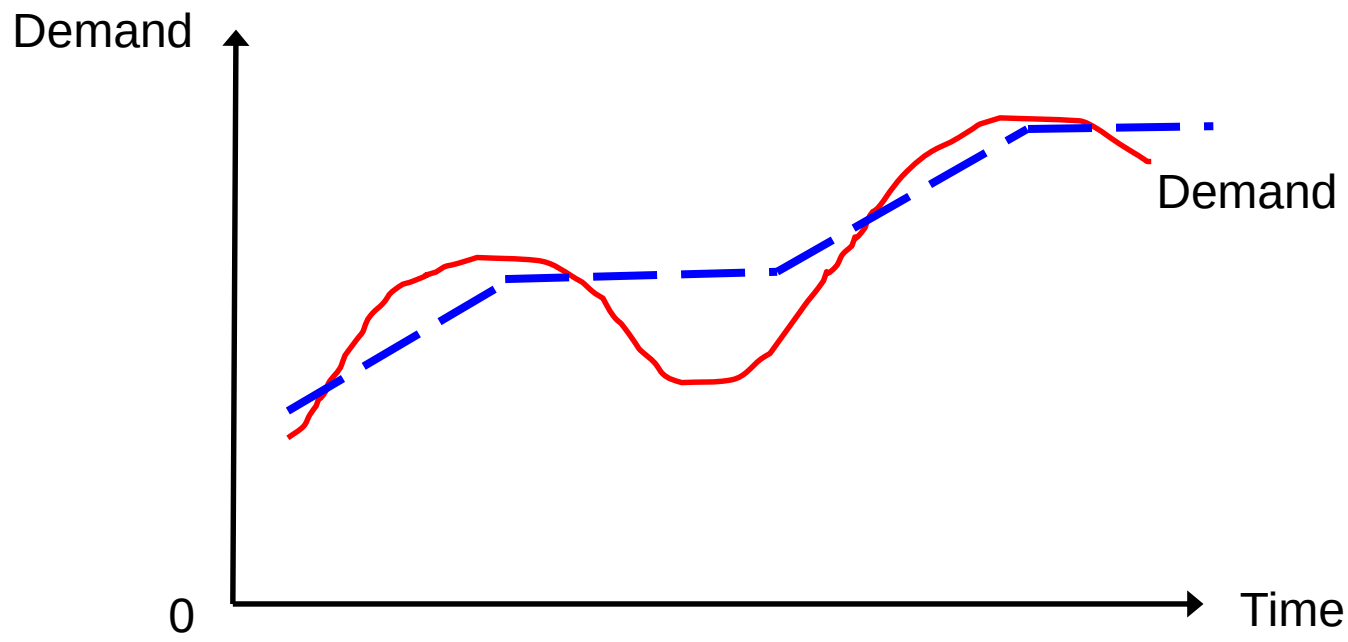


- Capacity Plan: A, B, C or D (demand)?

- Two Types of Risk
  - Capacity Shortage 產能短缺: loss of sales, loss of market share
  - Capacity Surplus 產能過剩: machine idleness, inventory, holding cost

衡量風險與不確定性

- Capacity Planning Problem (Newsboy problem over time)
  - 其實，產能規劃經常是…



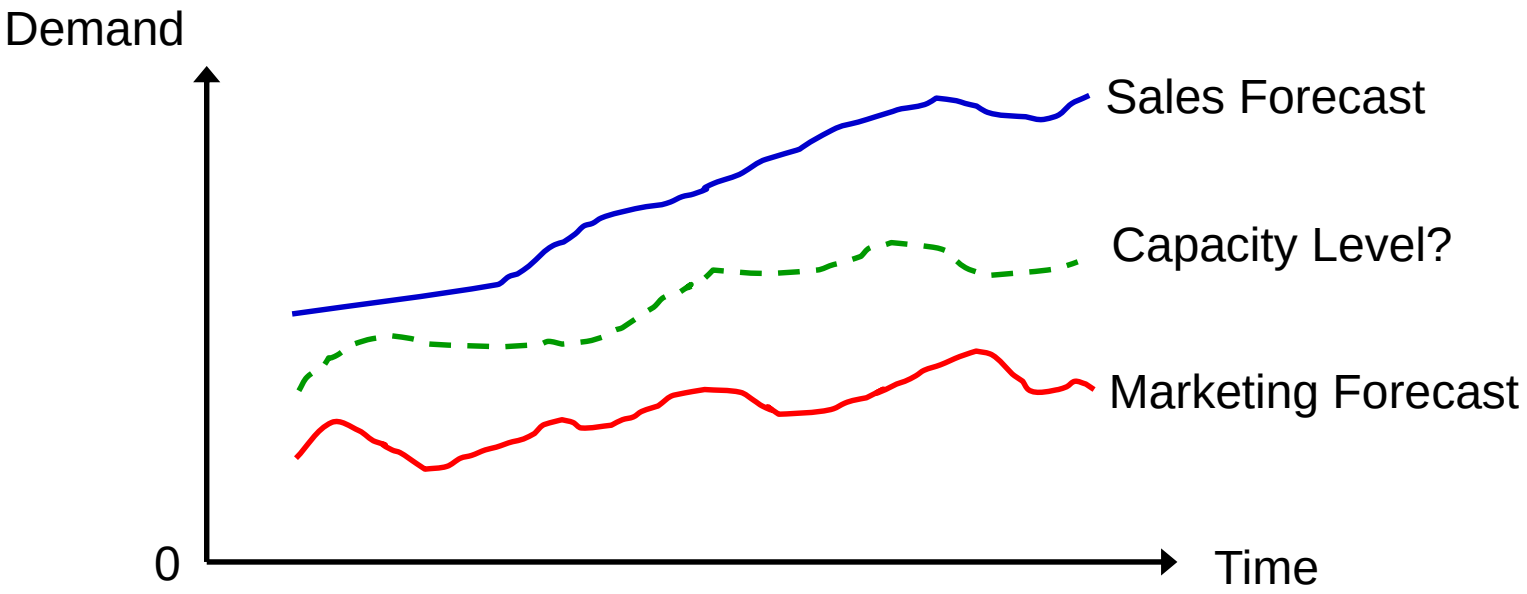
追高殺低!!??

大試身手...

- Newsboy problem 報童問題 (典型的作業研究OR問題)
  - 每天一大早出門到批發商訂報紙，送報賺錢
  - 當日買報紙的需求是不確定的
  - 報紙若當天沒賣出去，則殘值為0 (由於時效性，隔天就不能賣了)
  - 決策議題: 要訂多少報紙呢?

大試身手…

- Capacity Planning Problem (more demand scenarios)
  - How about more than two demand scenarios?
  - Two demand forecasts: Marketing vs. Sales
    - Should capacity level follow marketing, or sales, or …?



  - Scenario Simulator
    - Generate capacity plans (>10 versions) manually…
    - KPIs: CapEX per k, ROIC, payback…

Empirical Study (Lee and Chiang, 2016)

- Empirical Study- Taiwan TFT-LCD Manufacturer
  - We introduce a two-phase framework to decide the best capacity level reducing the losses (i.e., risks) of capacity surplus and capacity shortage.

- 1st stage: Demand Forecast (預測模型)
  - Linear Regression
  - Autoregression
  - Neural Network

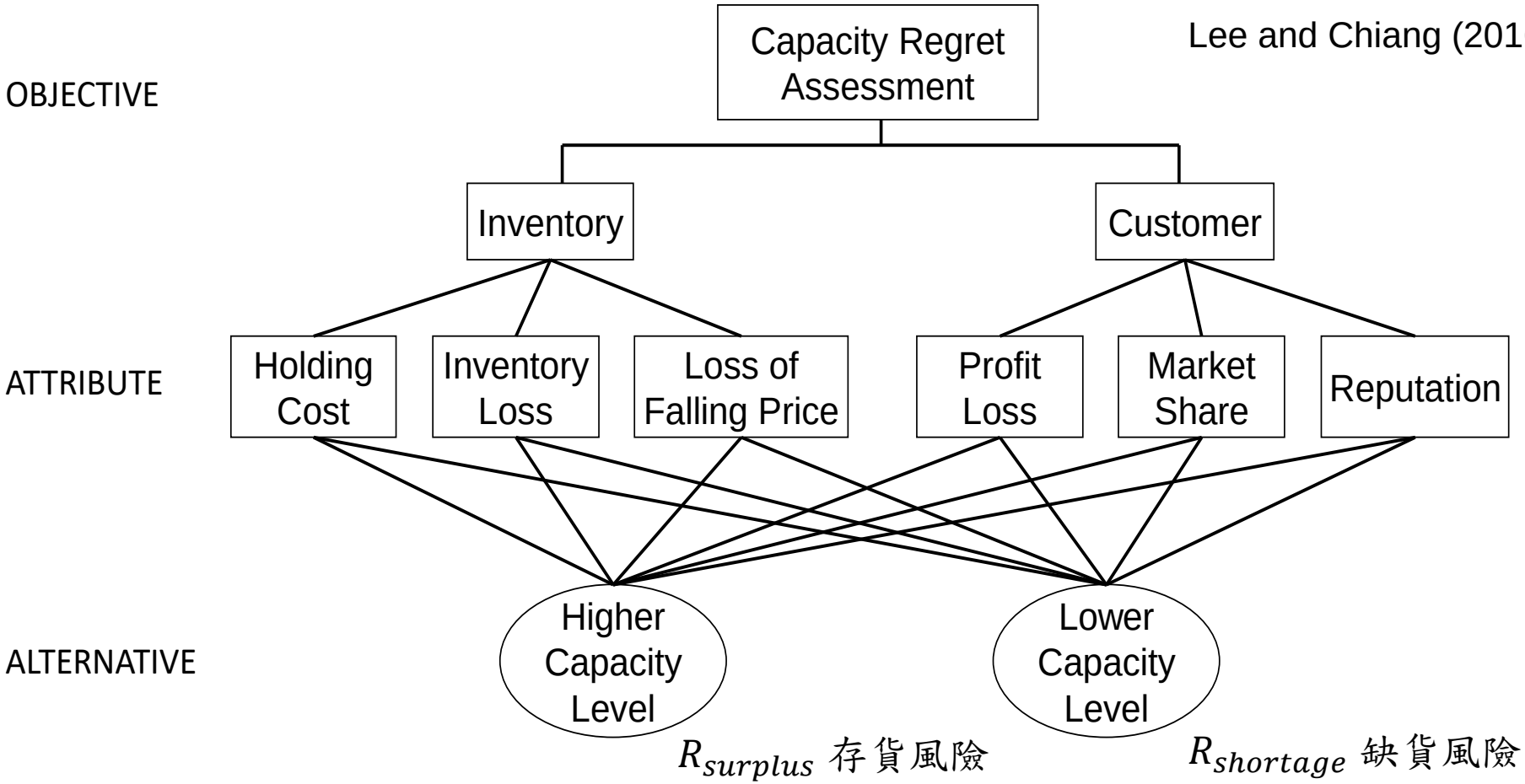
- 2nd stage: Capacity Decision (最佳化模型)
  - Expected Value (EV, 期望值)
  - Minimax Regret (MMR, 薩維基準則)
  - Stochastic Programming (SP, 隨機規劃)

Empirical Study

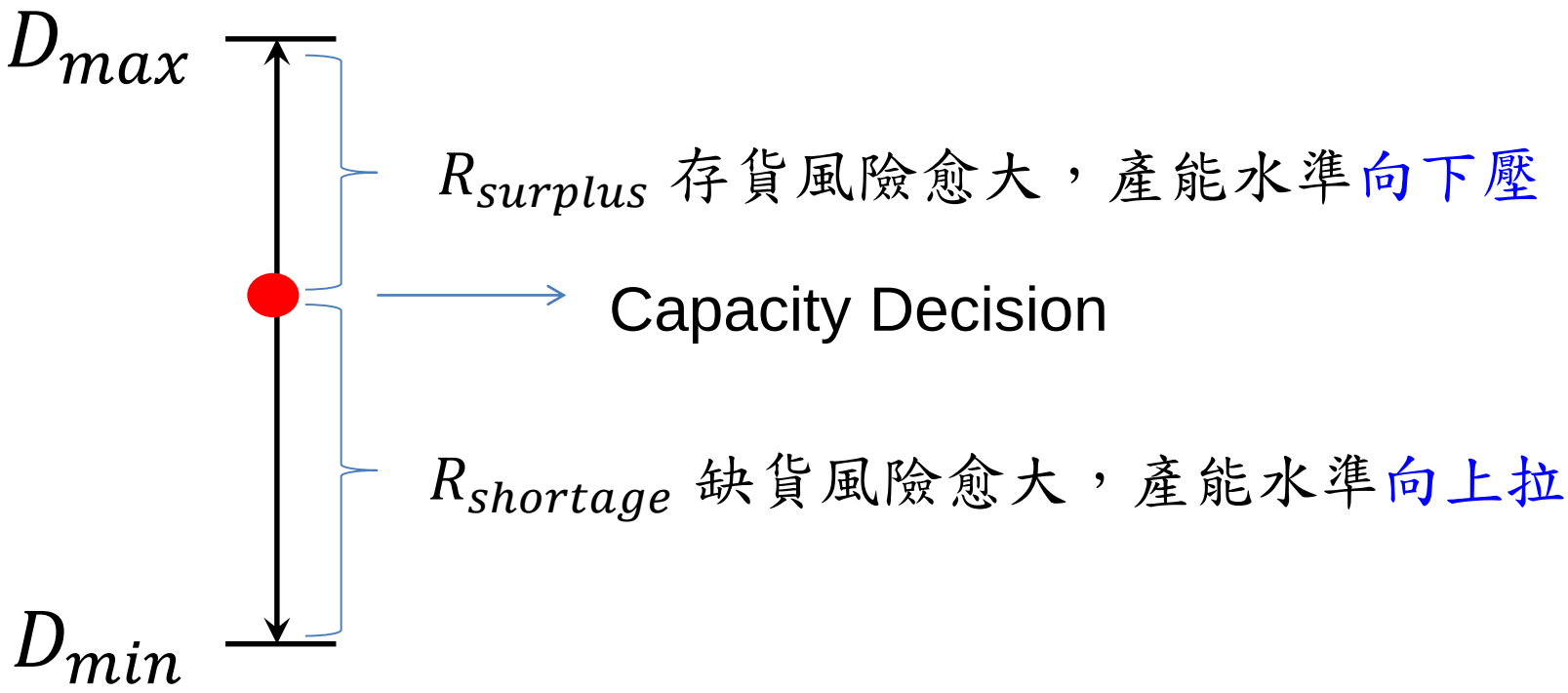
Capacity Regret Assessment

- 透過問卷調查以系統化的方法來收集決策者的風險偏好
- Analytic Hierarchical Process (分析層級程序法, AHP) (Satty, 1980)

Lee and Chiang (2016)



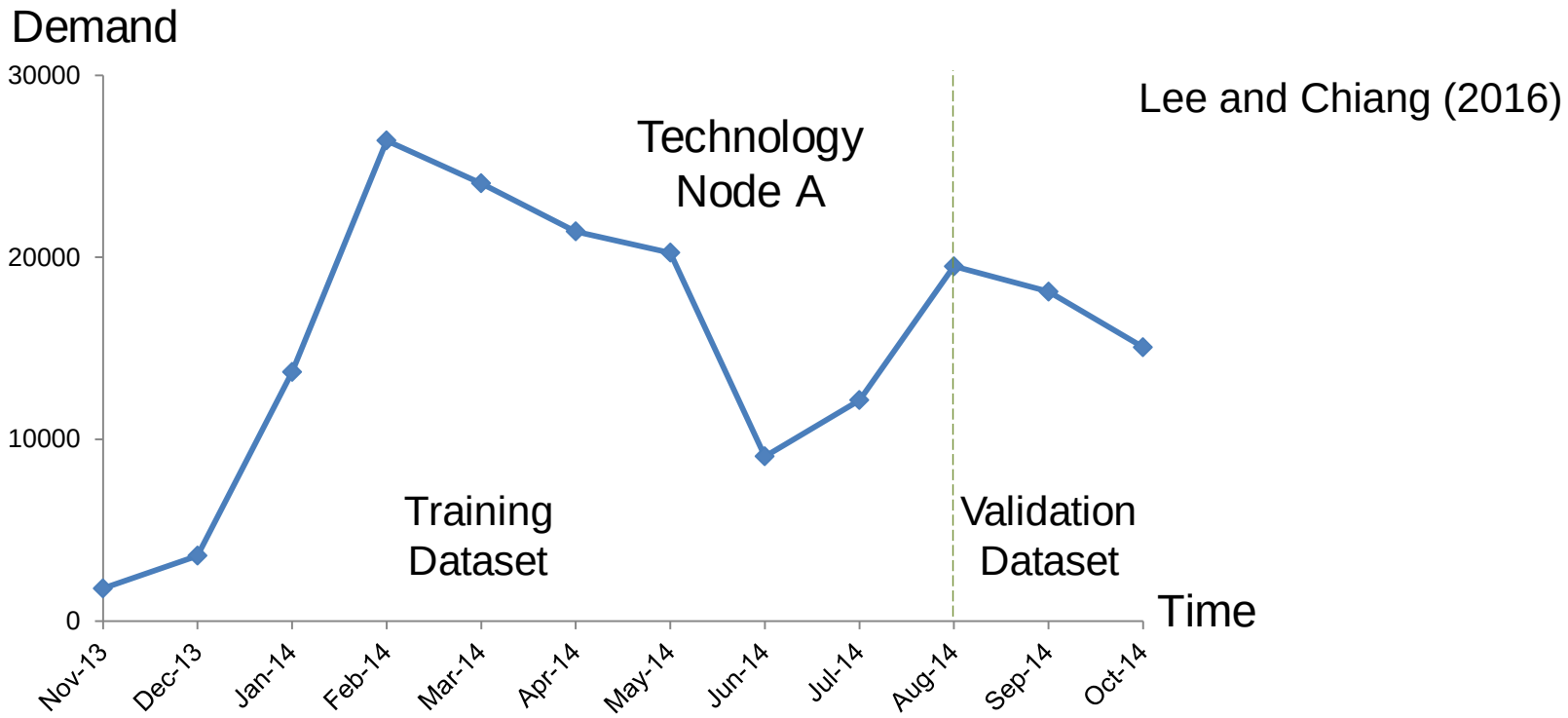
- A Tradeoff Between Two Risks



Empirical Study

Data Source

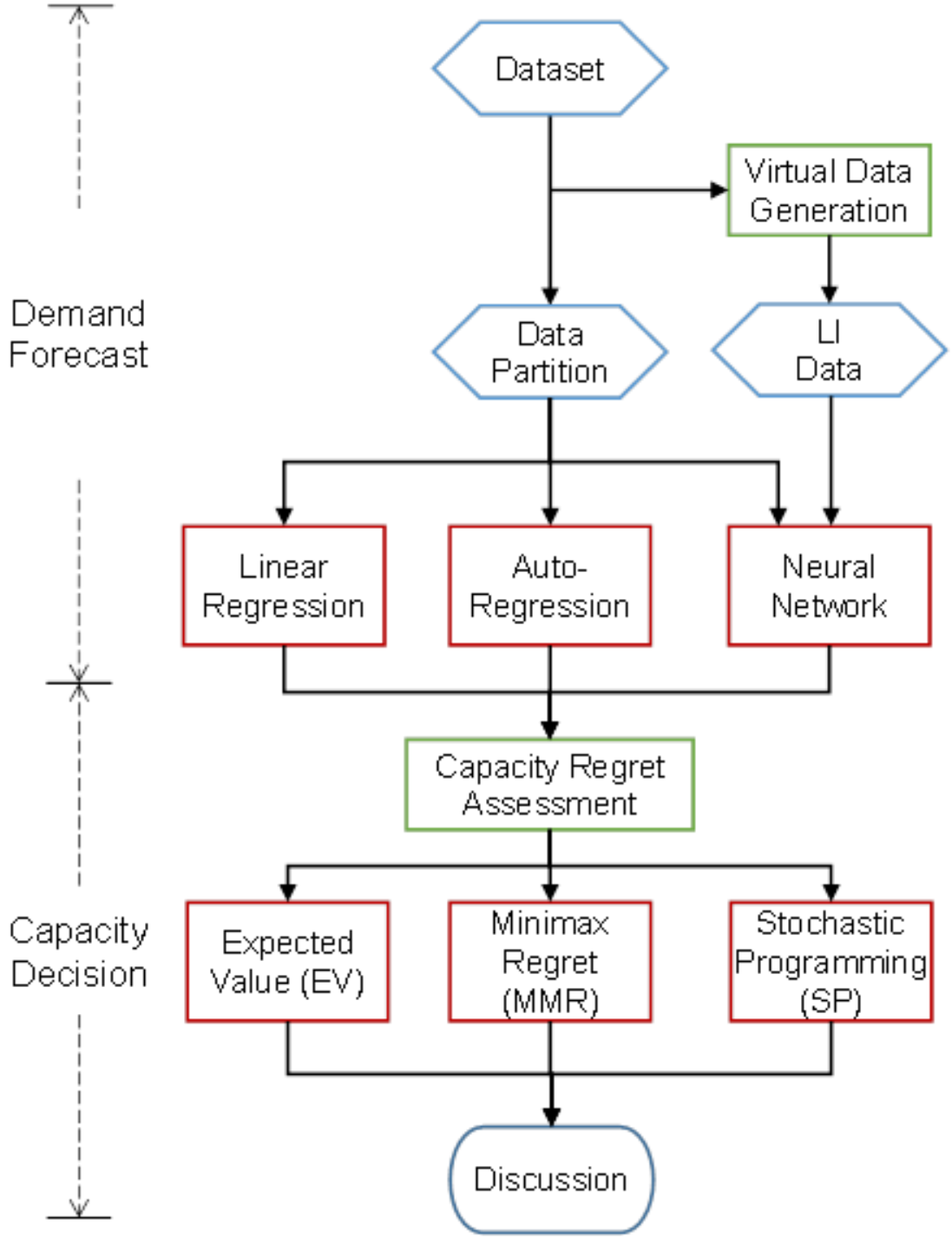
- Nov. 2013 to Oct. 2014
- Aggregate demand for a specific technology node
- Dataset: training data (9 months) and validation data (3 months)
- Objective: determine the capacity level for the future 3 months (Aug. 2014 to Oct. 2014) based on historical demand until July 2014.



Empirical Study

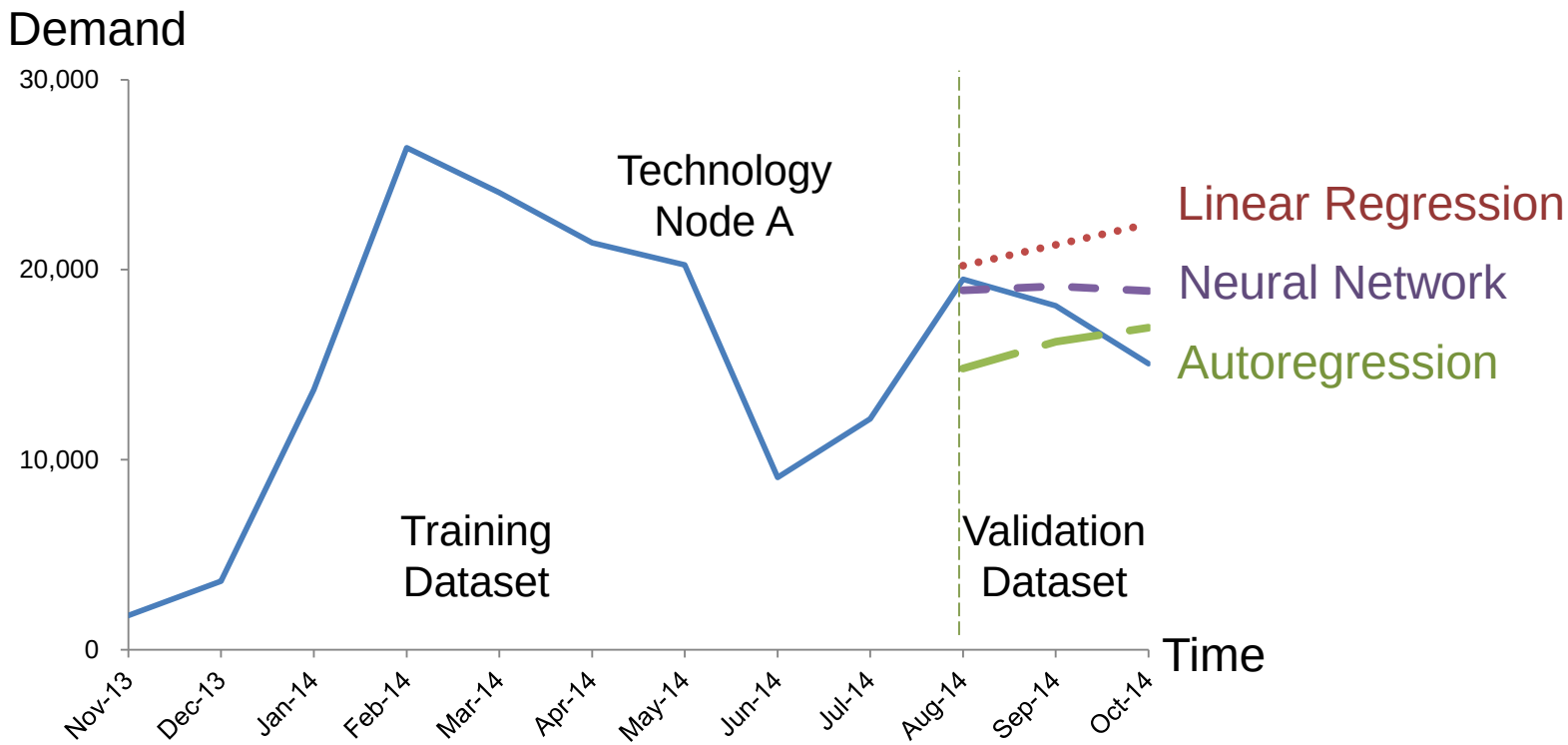
- 2-stage approach
  - Demand Forecast
  - Capacity Decision
- VDGP
  - LI: latent information (Chang et al., 2014)

Lee and Chiang (2016)



Empirical Study

- 1st phase: Demand Forecast
  - linear regression (OLS), autoregression (AR), neural network (NN)
  - Criterion: Mean Squared Error (MSE): NN < AR < OLS



Empirical Study

2nd phase: Capacity Decision

- AHP gives pair-wise comparisons of the capacity surplus and shortage, and calculate the eigenvector (特徵向量) as weights of two risks.
- 31 individuals with TFT-LCD industrial backgrounds
  - 2 for 0-2 yrs, 9 for 2-5 yrs, 13 for 6-9 yrs, 7 for more than 10 yrs of service
  - one third have undergraduate degrees and the others for graduate degrees
- $R_{shortage} = 0.521$ and $R_{surplus} = 0.479$.

Month	Actual Demand	Capacity Decision			
		Current Policy	EV	MMR	SP
Aug. 2014	19499	20207	16941	17157	18922
Sep. 2014	18110	21305	17921	18306	19135
Oct. 2014	15059	22404	18536	19291	18885
Standard Deviation	2271.3	1098.2	804.7	1068.1	**134.8**
Average Regret	-	1796.0	1032.2	1113.8	874.8

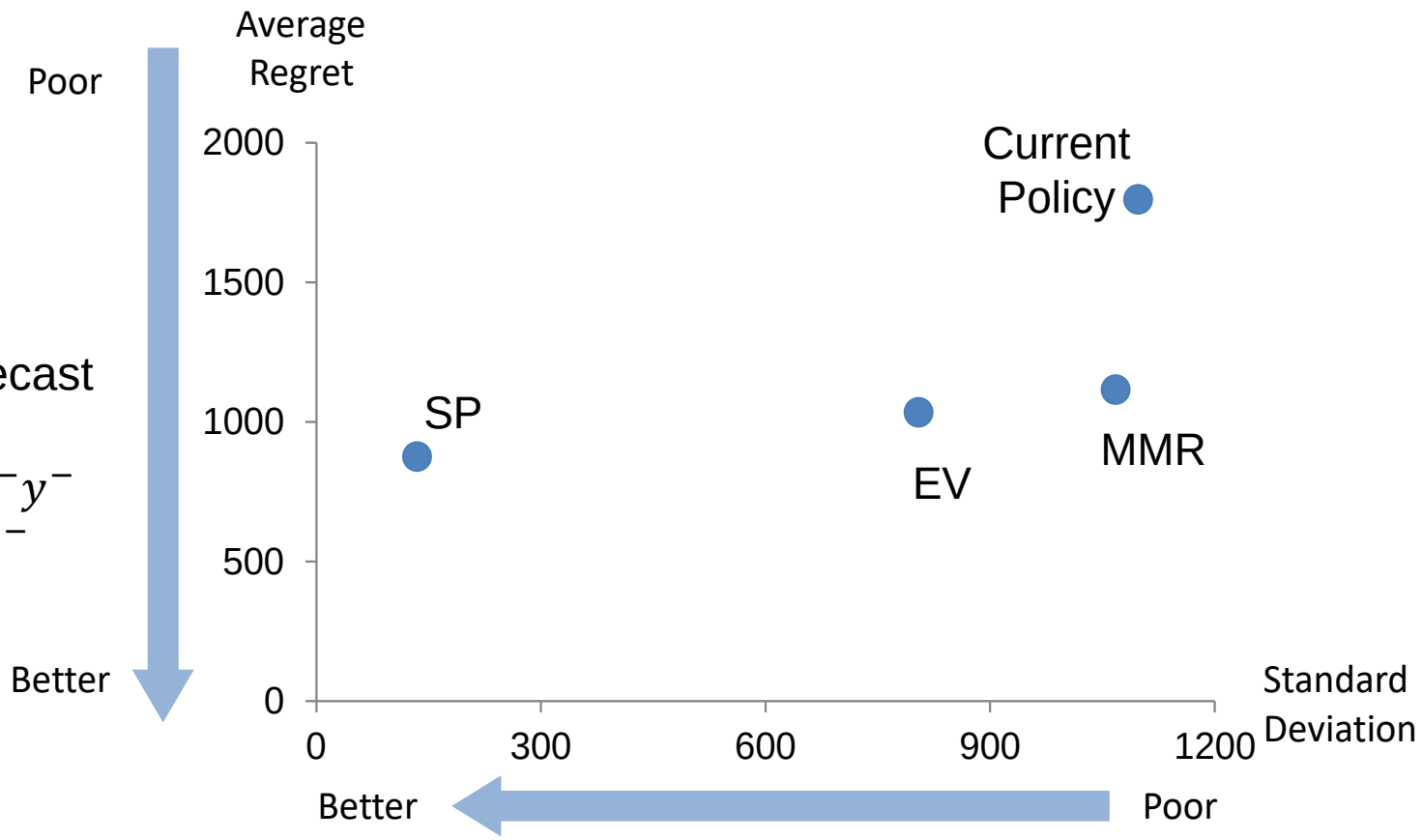
*Current policy builds up the capacity level based on the maximal forecast demand.
**Avg. Reg.: the weighted sum of squared error (WSSE) over the number of validation periods

Empirical Study

- 隨機規劃(stochastic programming, SP)提供一穩健決策 (robust decision)

數學規劃目標與限制

Min $Cx + E[f(x, \tilde{D})]$
s.t. $x \geq 0$
where for a demand forecast $d \in \tilde{D}$
$f(x,d) = \text{Min } P^+y^+ + P^-y^-$
s.t. $d - x = y^+ - y^-$
$y^+, y^- \geq 0$



Lee, Chia-Yen a& Ming-Chien Chiang (2016). Aggregate Demand Forecast with Small Data and Robust Capacity Decision in TFT-LCD Manufacturing. Computers & Industrial Engineering, 99, 415-422.

衡量風險與不確定性

- 我們可以透過模型來預測或模擬許多情境(scenarios)
  - BPNN, SVM, CART, Boosting, PLS, ….
- Then…Which one is correct? What is the next step
- 預測…既然不可能100%準，那決策上的損失風險，就應該納入考量
- 讓我們想個簡單例子：
  - 模型A準確度95%，但不準時的決策會造成"龐大損失"
  - 模型B準確度90%，但不準時的決策只會造成"些許損失"
  - 我們要選模型 A還是模型B呢?
- 預測性的思維 → 處方性的決策

- 精度/良率預測
  - Classification → 探討Confusion Matrix中的trade-off → Cost-sensitive
  - 權衡誤放(type-I)與誤宰(type II)風險的成本 → 處方性分析

Model A		預測	
		FAIL	PASS
實際	FAIL	61	7
	PASS	29	31

Model B		預測	
		FAIL	PASS
實際	FAIL	47	21
	PASS	7	53

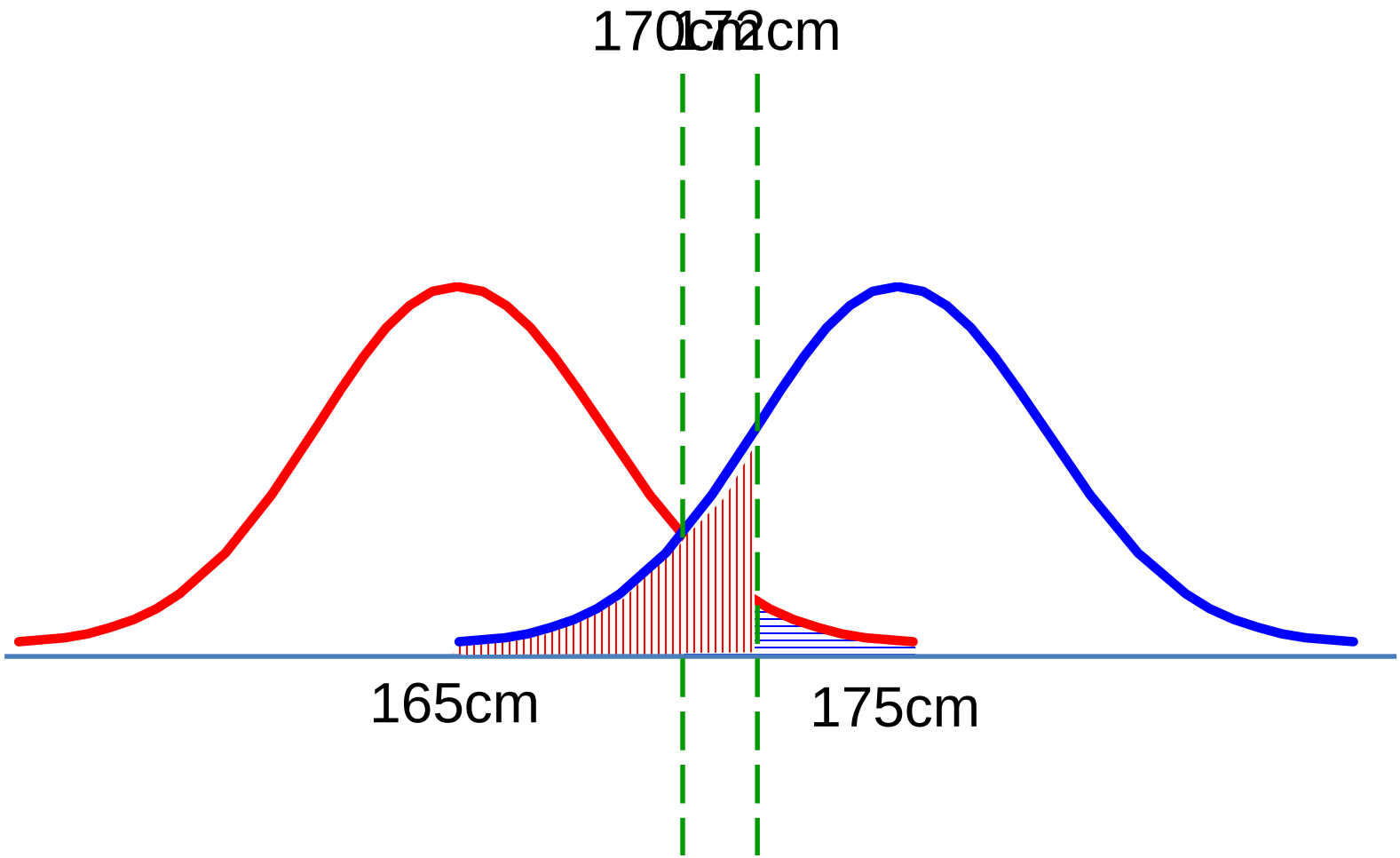
	Testing	
	Accuracy	AUC
Model A	71.9%	70.2%
Model B	78.1%	78.9%

AUC: Area under the Curve of ROC

Lee, C.-Y., and Chien, C.-F., 2022. Pitfalls and protocols of data science in manufacturing practice. Journal of Intelligent Manufacturing, 33, 1189–1207.

可能同時降低型一與型二誤差?

迷思



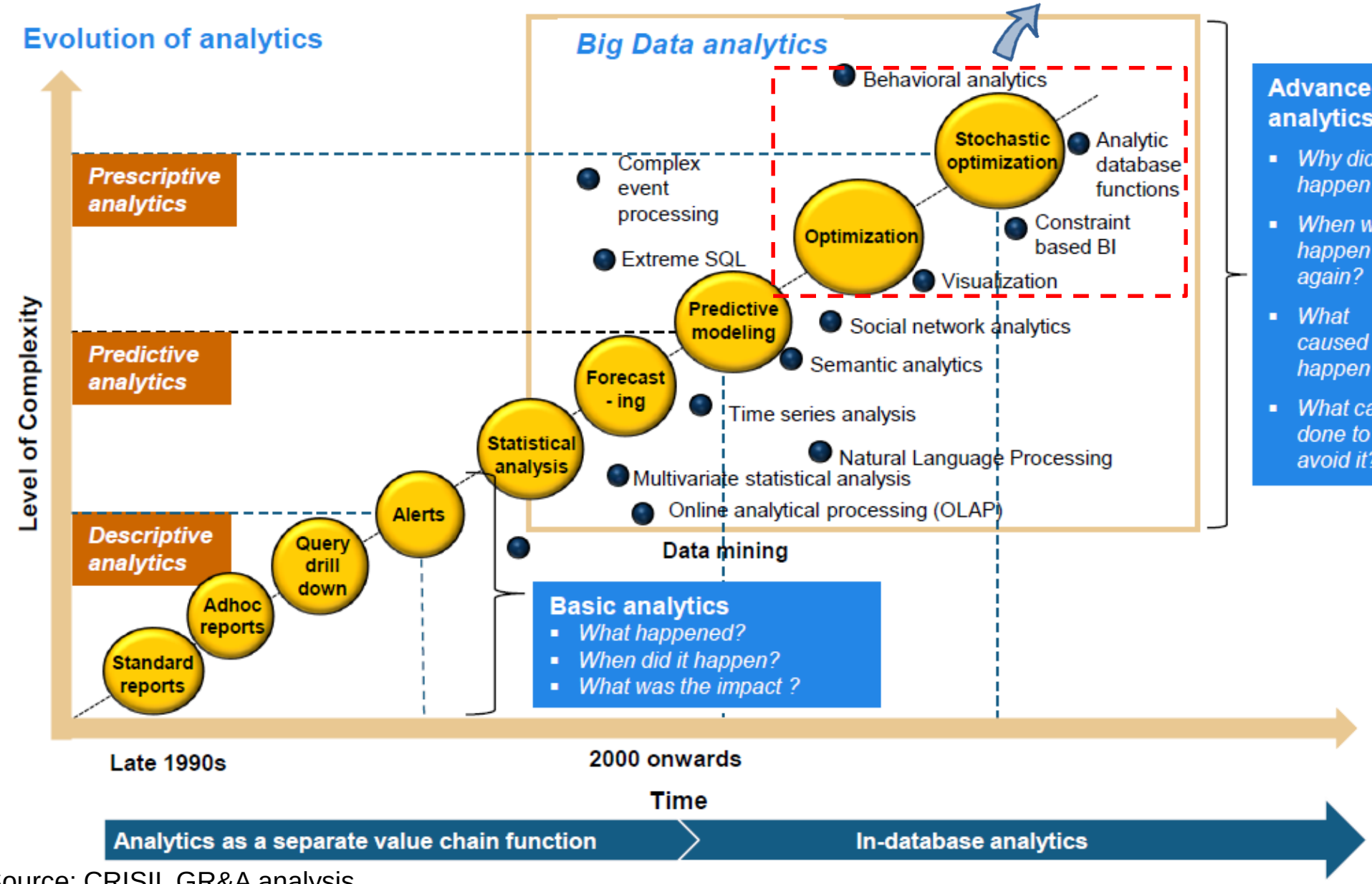
當預測思維搭配上處方決策時...(極重要! 三顆星!!)

- 為了降低對未來的不確定性 (建構關鍵因子推論的預測模型)
  - 資料科學並非用很複雜的數學模型~ (即使有時候讓我們方便許多)
  - 記得 Manufacturing → “Hand Make” → 黑手~
  - 站起來，走到現場去。透過觀察與討論，找出「推論用的關鍵因子」
  - 切記，一旦收集到「數據」，便已成歷史
  - 如何透過歷史來探索未來 (鑑往知來)，數據科學扮演關鍵角色。

- 為了提升決策品質(建構風險權衡最佳化的決策模型)
  - 由於預測不一定準，且常有多個預測情境(scenarios)
  - 決策風險的量測是必要的
  - 站起來，走到現場去。透過觀察與討論，找出「權衡用的風險因子」
  - 切記，「魚與熊掌不可兼得」，因此需要權衡得失 (風險)
  - 如何透過有限資源來規劃未來 (見識謀斷)，作業研究扮演關鍵角色

方法複雜度與附加價值

Operations Research 作業研究
(多角化、投資組合、排程、產能規劃、製程監控)



Source: CRISIL GR&A analysis

什麼是分析(Analytics)?

- Hillier and Lieberman (2010)
  - “Analytics is the scientific process of transforming data into insight for making better decisions”
- Descriptive analytics (敘述性分析)
  - Using innovative techniques to locate the relevant data and identify the interesting patterns in order to better describe and understand what is going on now.
- Predictive analytics (預測性分析)
  - Using the data to predict what will happen in the future.
- Prescriptive analytics (處方性分析)
  - Using the data to prescribe what should be done in the future. The powerful optimization techniques of operations research are what are used here.

什麼是處方性分析?

- The Wyndor Glass Co. products high-quality glass products, including windows and glass doors. (Hillier and Lieberman, 2010)

- It has three plants.
  - Plant 1 makes aluminum frames and hardware
  - Plant 2 makes wood frames
  - Plant 3 produces the glass and assembles the products
- Top management has decided to revamp the product line.
- Production capacity are released to launch two new products having large sales potential:
  - Product 1: An 8-foot glass door with aluminum framing
  - Product 2: A 4×6 foot double-hung wood-framed window

http://img.archiexpo.com/images_ae/photo-g/55456-4334799.jpg
https://www.andersenwindows.com/

什麼是處方性分析?

- This problem can be recognized as LP problem of the classic product mix (產品組合) type.

- Linear Programming (線性規劃, LP)

- Formulation as a Linear Programming Problem
  - x_1: number of batches of product 1 produced per week
  - x_2: number of batches of product 2 produced per week
  - Z: total profit per week from producing these two products

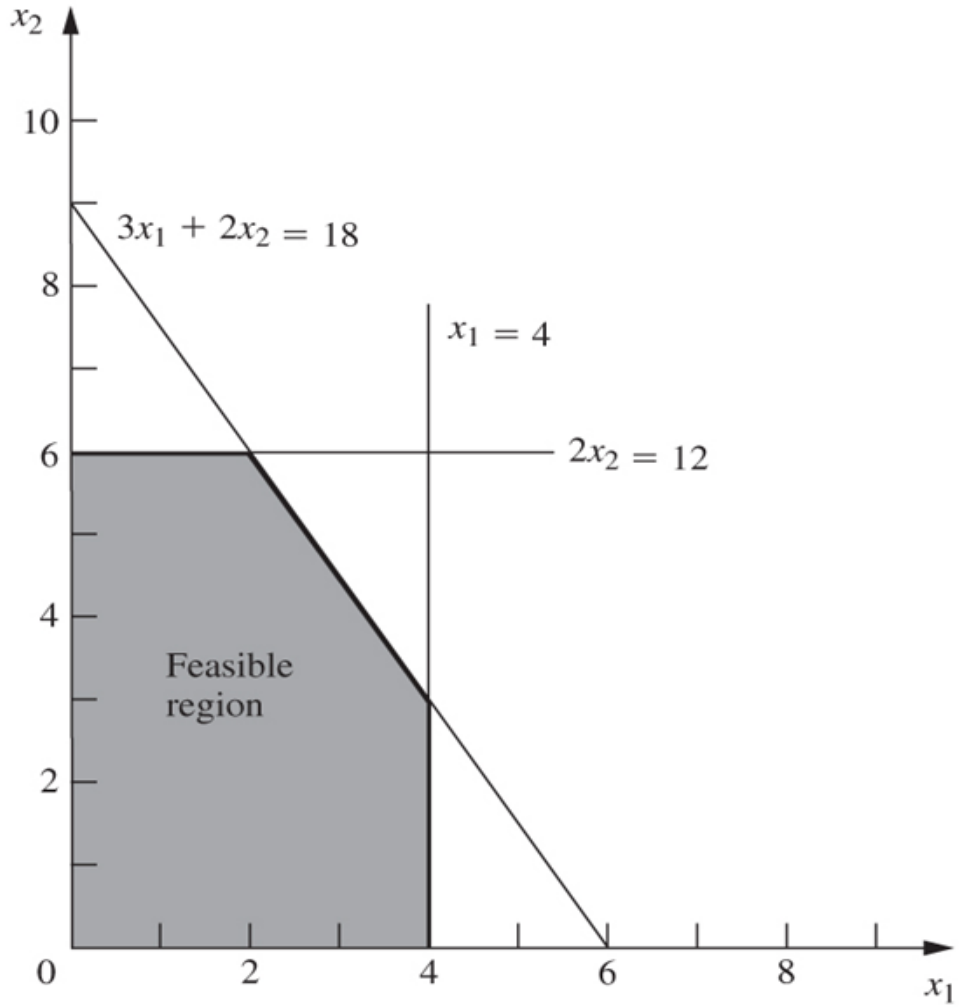
	Production Time		Available Time
Plant	Product 1	Product 2	
1	1	0	4
2	0	2	12
3	3	2	18
Profit ($1,000)	$3	$5	

$$
\begin{aligned}
Z &= 3x_1 + 5x_2 \\
\text{s.t.} \quad x_1 &\le 4 \\
2x_2 &\le 12 \\
3x_1 + 2x_2 &\le 18 \\
x_1, x_2 &\ge 0
\end{aligned}
$$

什麼是處方性分析?

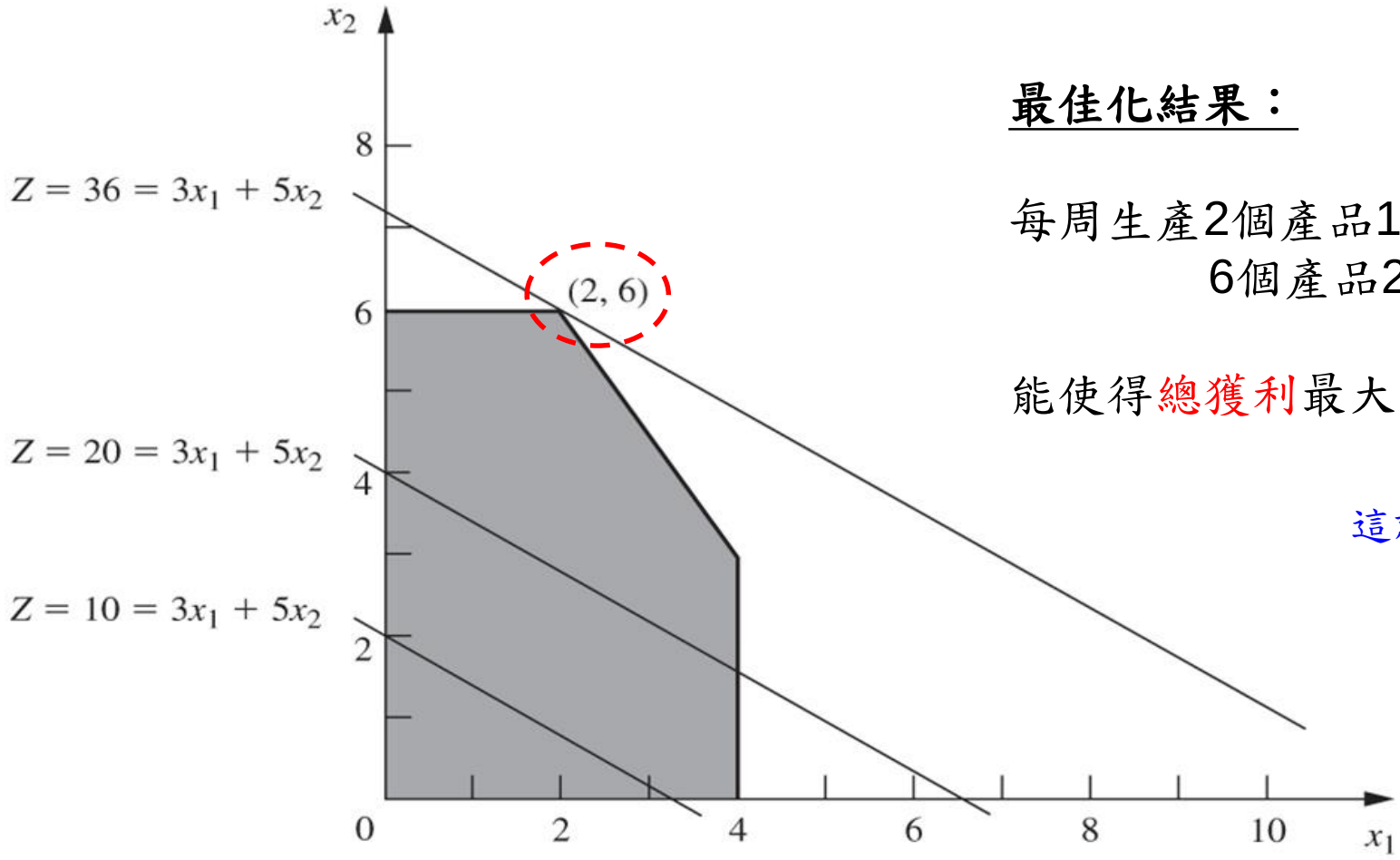
- Graphical Solution
- The resulting region of permissible values of (x_1, x_2), called the feasible region.

$$
\begin{aligned}
Z &= 3x_1 + 5x_2 \\
\text{s.t.} \quad x_1 &\le 4 \\
2x_2 &\le 12 \\
3x_1 + 2x_2 &\le 18 \\
x_1, x_2 &\ge 0
\end{aligned}
$$



什麼是處方性分析?

- Graphical Solution
- Move the objective function with fixed slope through the feasible region in the direction of improving Z.



最佳化結果：

每周生產2個產品1 (x_1)
6個產品2 (x_2)

能使得總獲利最大!

這就是處方~

什麼是處方性分析?

遇到問題

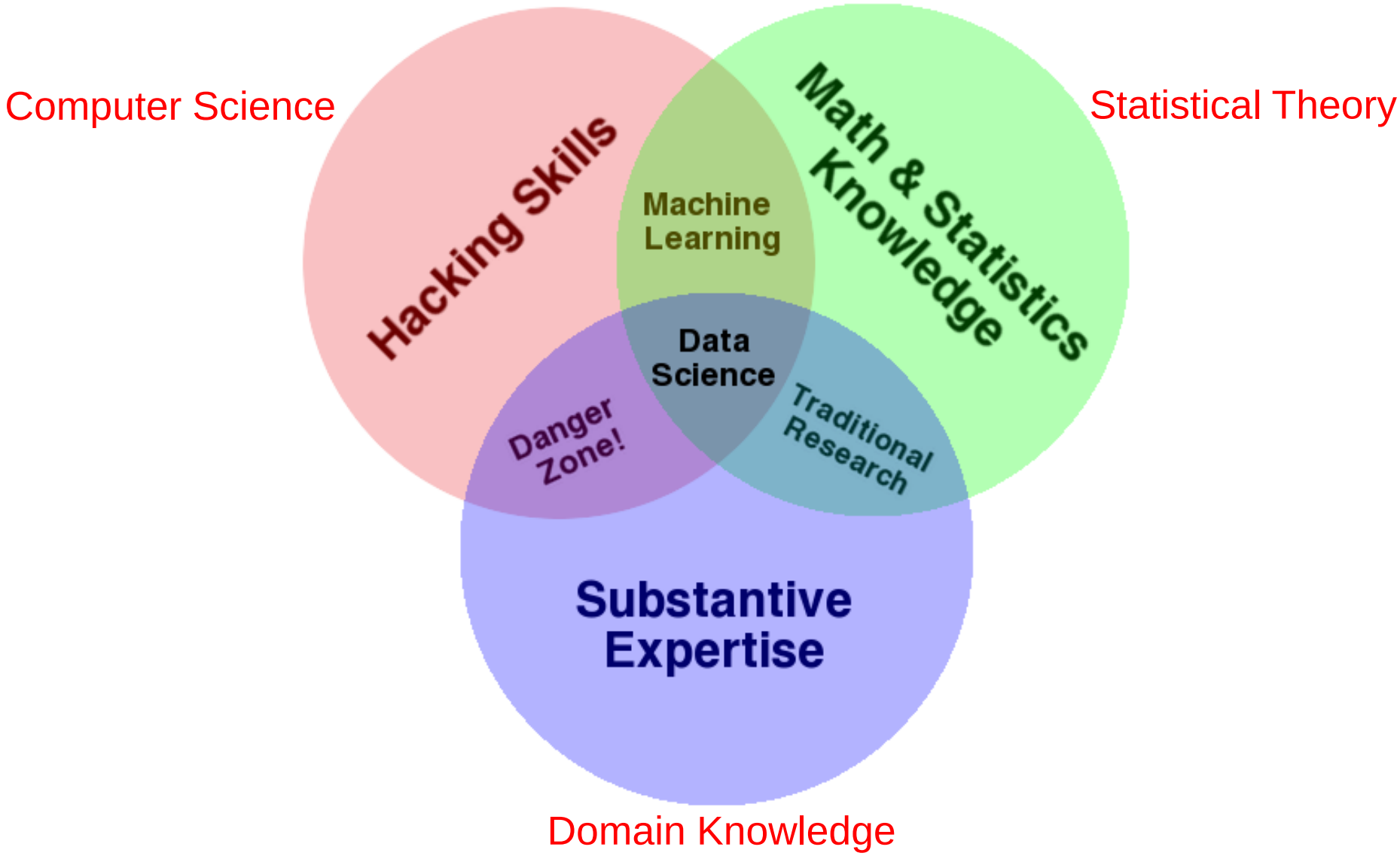
給定資源限制條件 (限制式)

給定期望改善的KPI (目標函數)

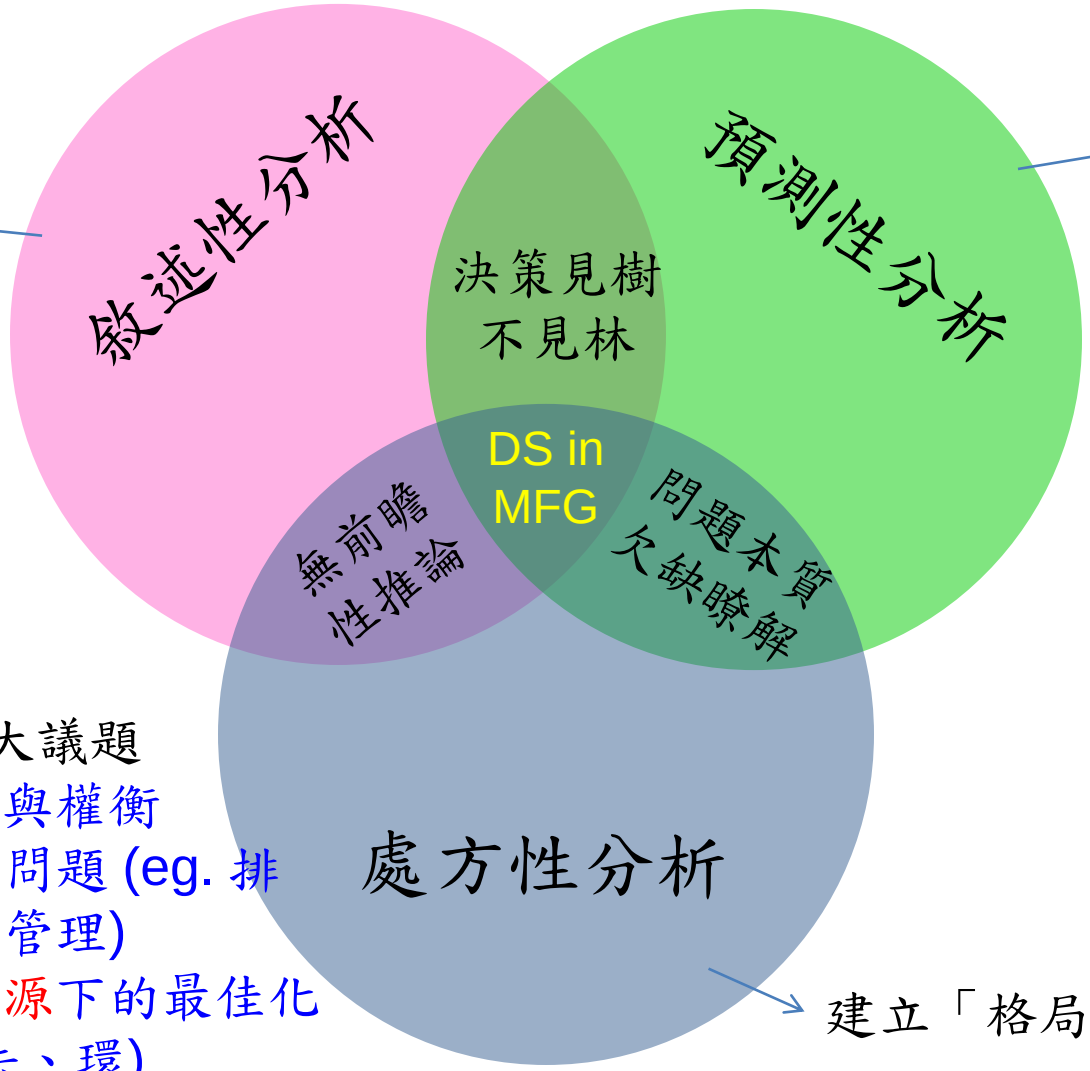
提供solution

這就是一種處方

Data Scientist: nerd or geek !?



事實上，製造資料科學是...



釐清「定位」

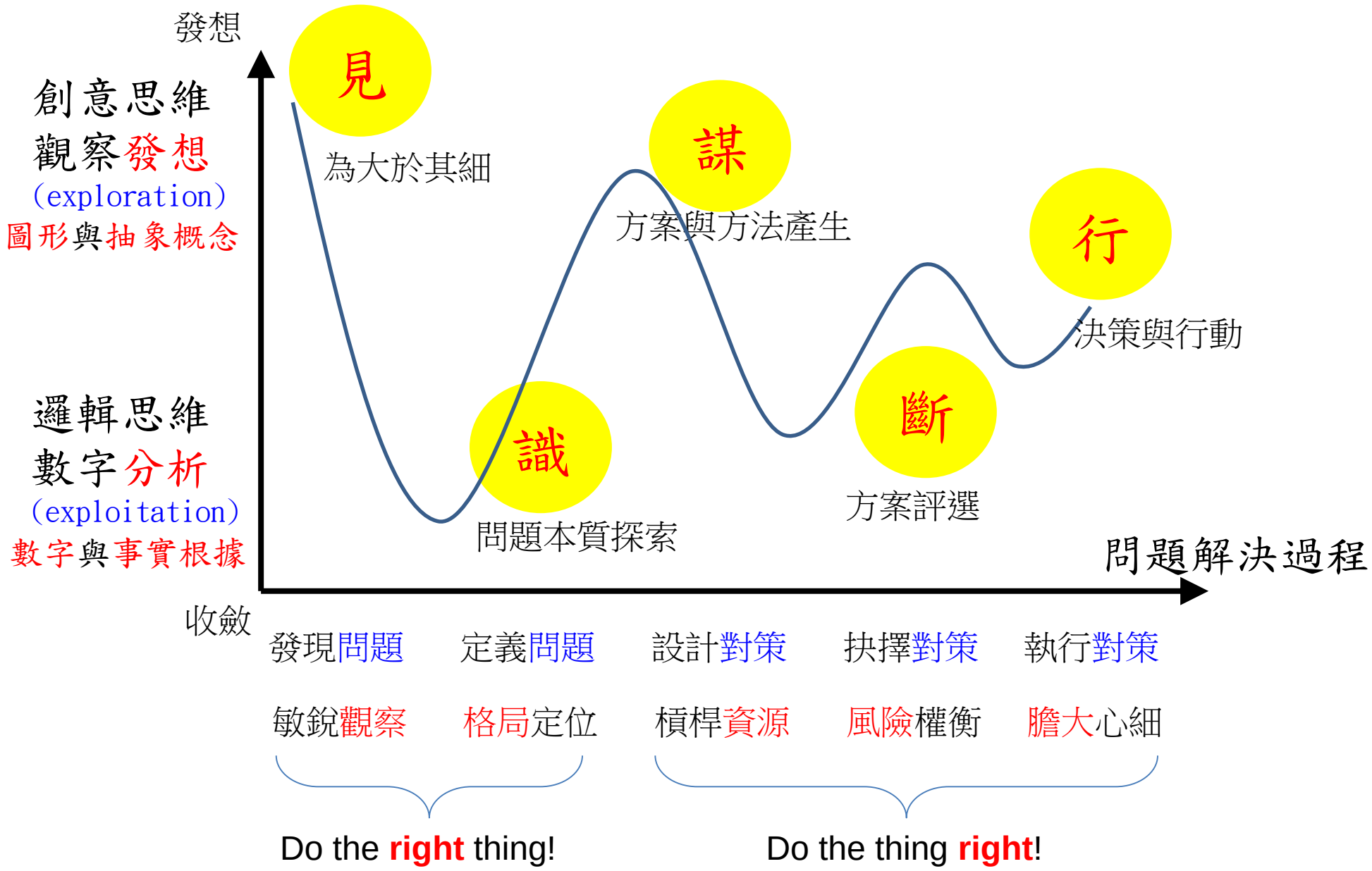
掌握「趨勢」

建立「格局」(因為牽涉到資源)

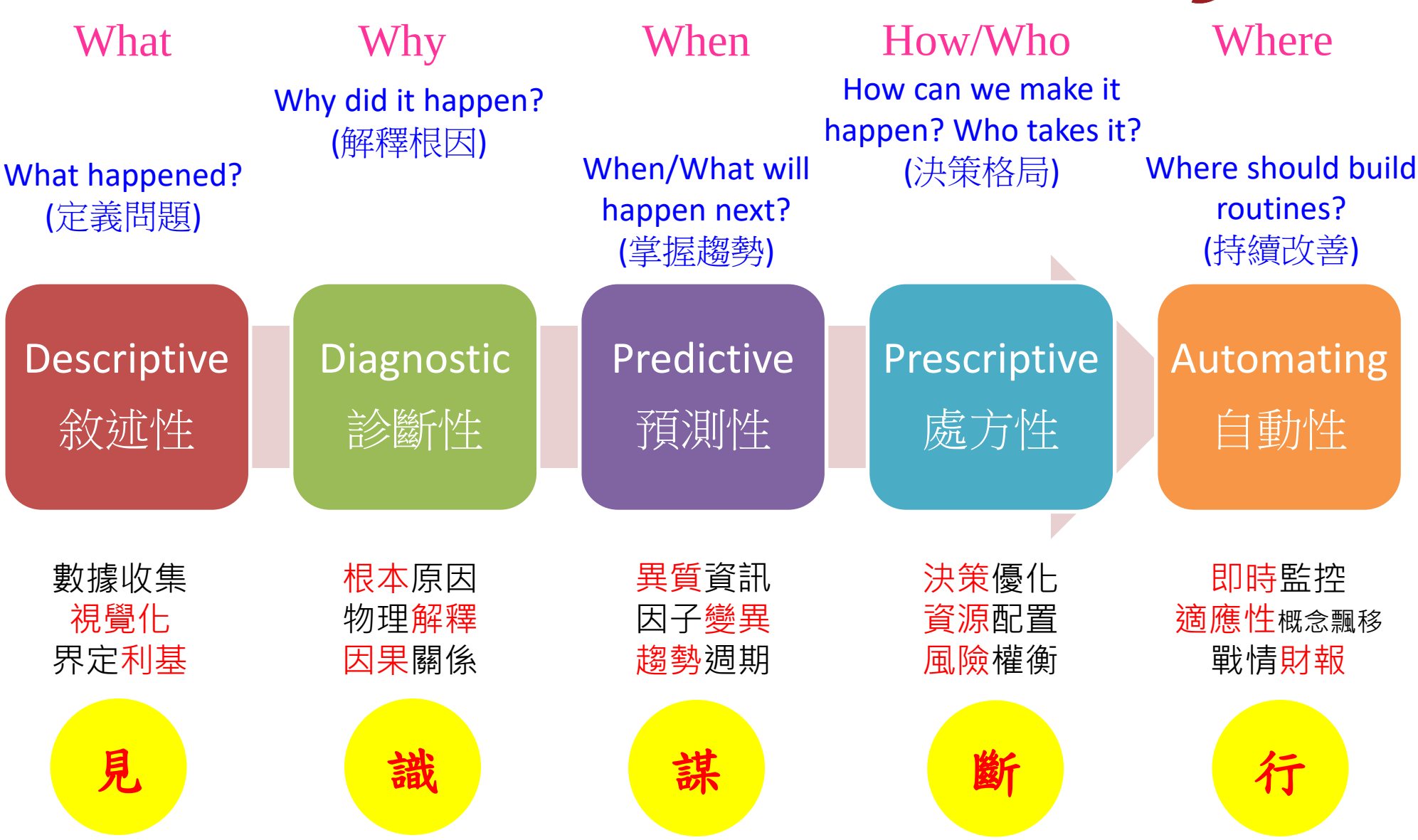
處方性分析補足了
製造資料科學的三大議題

1. 決策風險的測量與權衡
2. 一部份未解決的問題 (eg. 排程、庫存、專案管理)
3. 「槓桿」有限資源下的最佳化 (人、機、料、法、環)

問題解決過程(Problem Solving)



構析(Analytics)五階段



結語

Conclusion

Big Data資料量愈多愈好?
找到的Pattern也是愈多愈好?

迷思

- 對，但也不完全對
  - 統計是以樣本推論母體，因此樣本愈多，對母體推論愈精確
  - 「證據愈多，說話愈大聲」：但並非單純資料量的多寡 → **異質性**
    - 找一些想法或背景不一樣的「**人**」加入團隊
    - Sensor不是裝在自家，而是競爭者、客戶、甚至End User身上
- 數位神經系統(Bill Gates, 1999)
  - 即時監控
    - 透過sensor與IoT快速感知**內外部變化**
    - 預測與決策：快速反應緊急狀況，避免最大損失
  - 資訊快速存取(streamline big data)
    - 資訊的**異質性(Heterogeneity) ：猶太人的第十人理論**
  - 問題偵測與定位，如何精準問題？
    - 內部**老司機**
    - 外部顧問
    - 從財務**成本結構**下手
    - 尋找第二專長的商業機會點(跨領域)
    - 參與**產業技術**研習會、聽頂尖專家演講(走在技術趨勢上)

AI is black box? Explainable AI (XAI)?

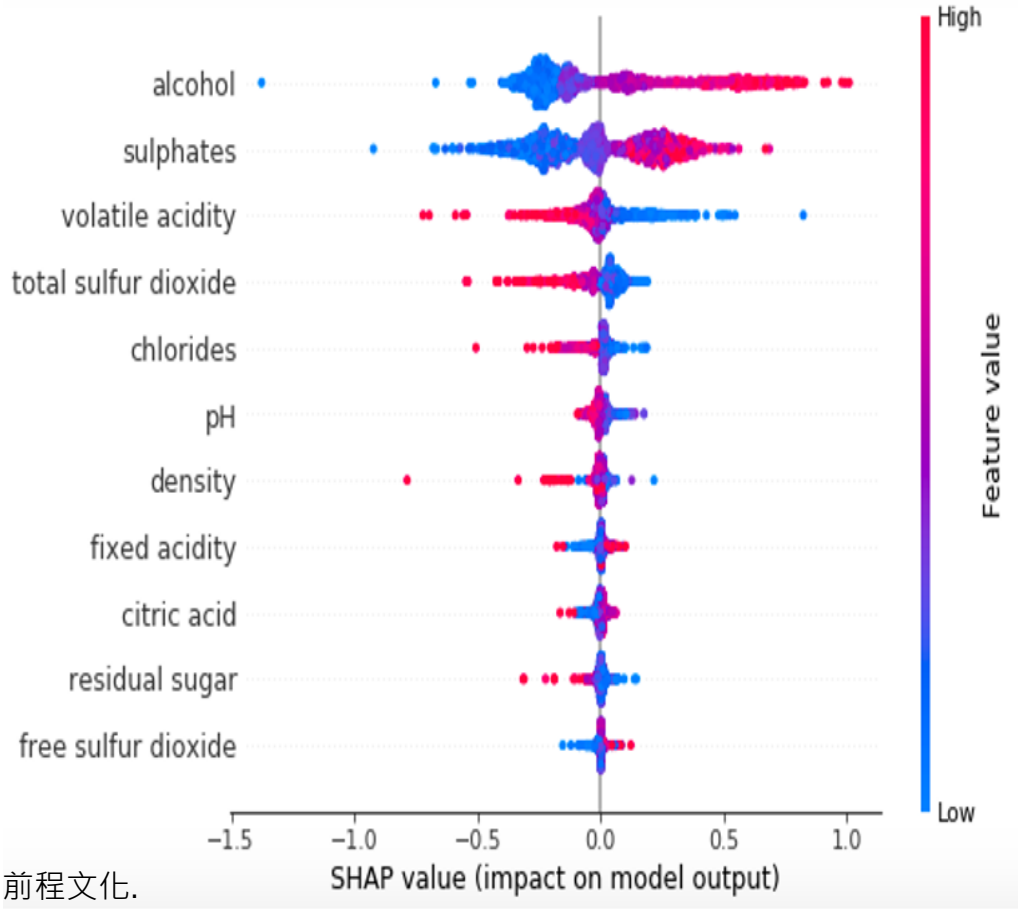
Explainable AI (XAI)- 夏普利迴歸值

- 線性迴歸中，估計迴歸係數亦即找出各特徵對模型的貢獻。然而線性迴歸可能受到多元共線性影響或存在交互作用 ，因此有時不易找出每個特徵貢獻。
- 夏普利值將**平均邊際貢獻**引入線性迴歸中，視某一特徵為一名玩家，該特徵對於預測值的貢獻則相當於該玩家的收益，告訴我們如何在特徵之間公平地分配重要性亦即各別的貢獻。

SHAP value

- 夏普值是一個整合衡量特徵重要性的方法，同時滿足**區域準確度**、**遺漏性**及**一致性**的特性，並符合**加性特徵貢獻法**。
- 夏普值摘要圖 (UCI紅酒品質數據)
  - 特徵重要性：酒精度、硫酸鹽、揮發酸
  - 特徵相關性(與目標值)

「當某特徵的夏普值越大（x 軸右側）且特徵值也越大（偏紅），則表示目標值與該特徵呈現正相關（例如酒精度），而當某特徵的夏普值越大（x 軸右側）且特徵值也越小（偏藍），則表示目標值與該特徵呈現負相關（例如揮發酸）。」



李家岩、洪佑鑫(2022)，製造數據科學：邁向智慧製造與數位決策。前程文化.

Retraining and Transfer (1→N)

- Concept Drift
  - Concept drift detection (何時模型不準了需要retraining)
    - Hypothesis test and control chart
  - Concept drift understanding (釐清模型不準的根本原因)
    - Time of concept drift occurs (When)
    - The severity of concept drift (How)
    - The drift regions of concept drift (Where)
  - Drift adaptation (如何retrain模型)
    - Training new models for global drift
    - Model ensemble for recurring drift
    - Adjusting existing models for regional drift
- Transfer Learning & Domain Adaptation
    - Instance based transfer learning
    - Feature based transfer learning
    - Parameter based transfer learning
    - Relational knowledge-based transfer learning

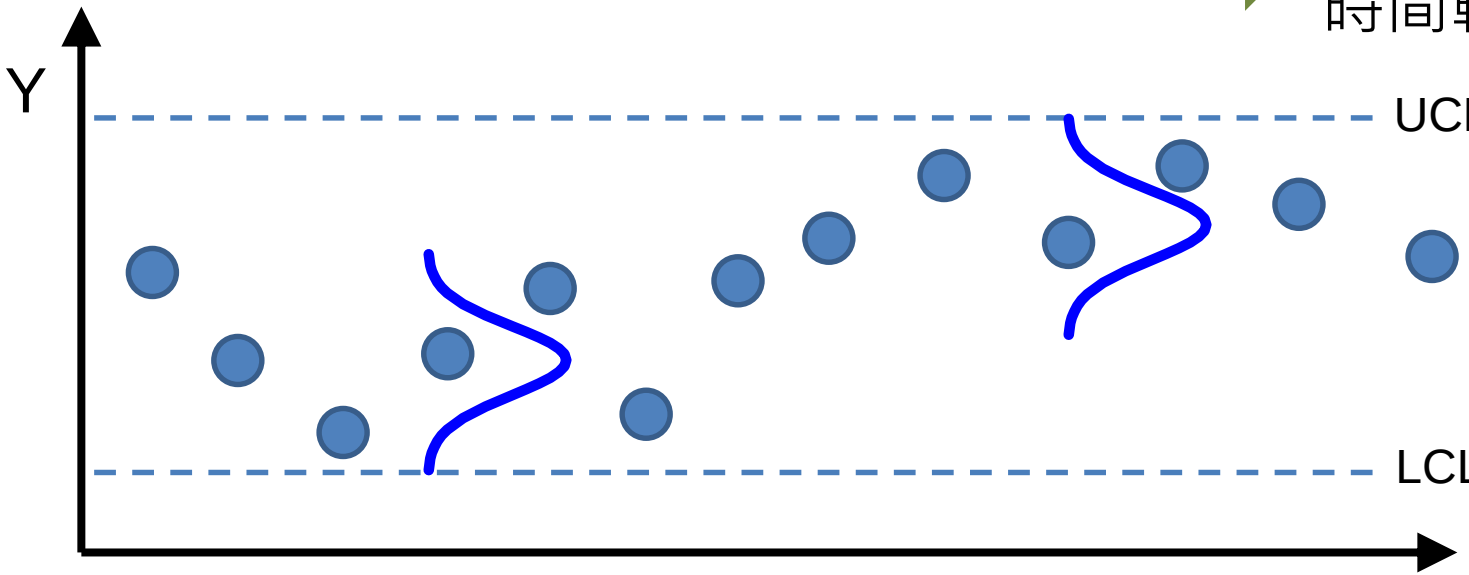
Lu et al. (2020). Learning under concept drift: a review. https://arxiv.org/abs/2004.05785v1
Ran, et al. (2019). A survey of predictive maintenance: systems, pruposes and approaches. IEEE Communications Surveys & Tutorials.

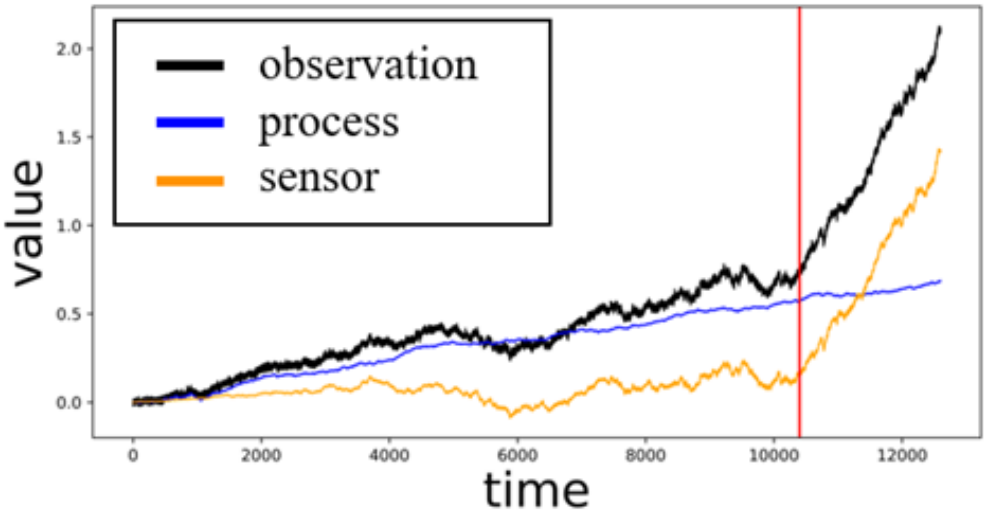
時空展開Spatio-Temporal Fan-Out

資料飄移/概念漂移(concept drift)

時間軸

空間軸

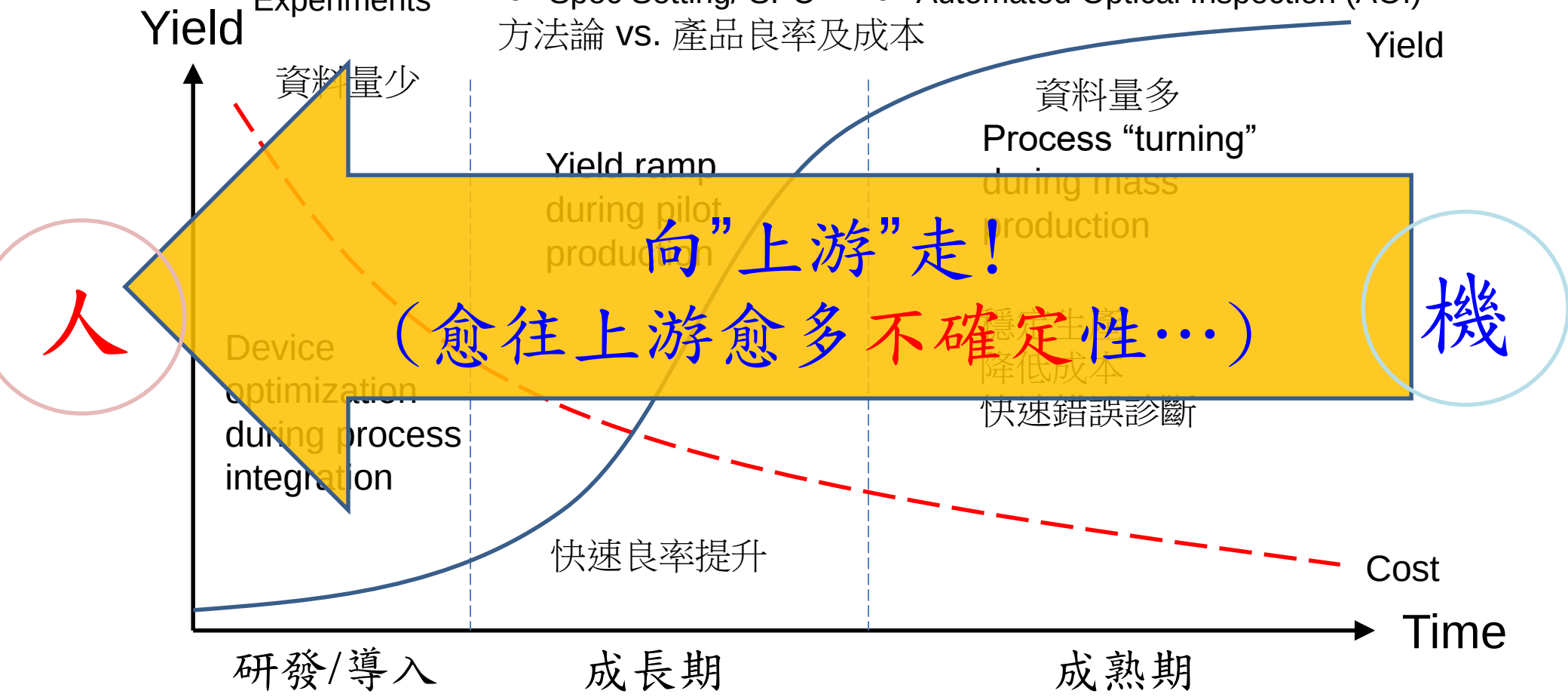




遞移學習(transfer learning)

跨越問題與方法的鴻溝

- Engineering Parameter Optimization
- Design of Experiments
- Tool Matching
- Benchmarking
- Troubleshooting
- Scheduling
- Spec Setting/ SPC
- Prognostics & Health Management (PHM)
- Virtual Metrology/ In-line Predictive Monitoring
- Run-to-Run (R2R) Control/ FDC
- Preventive/Predictive Maintenance(PM/PdM)
- Automated Optical Inspection (AOI)



Lee and Chien (2022)

In the R&D product development or the fab ramp-up phase, the small data issue is common.

智慧製造與工業3.5

"「工業3.5」是工業3.0和工業4.0之間的混合策略...當務之急，先發展能讓智慧製造系統發揮效能的大數據分析和彈性決策能力..."

簡禎富 (2017, 哈佛商業評論)

德國工業4.0的願景

- 物聯網蒐集和分析所有生產過程相關的大數據
- 虛實整合系統以整合價值鏈的所有生產區塊
- 「大規模個人化生產」(mass personalization)
  - 延遲差異化/模組化

工業3.0

- 有限的數據和資訊來預測產品的需求
- 建置產能，然後想方法銷售
- 提升產能利用率和規模報酬
- 但由於生產數據與終端市場並沒有全面連結，最後一定會因為供需落差，而出現存貨和缺貨同時存在的現象。

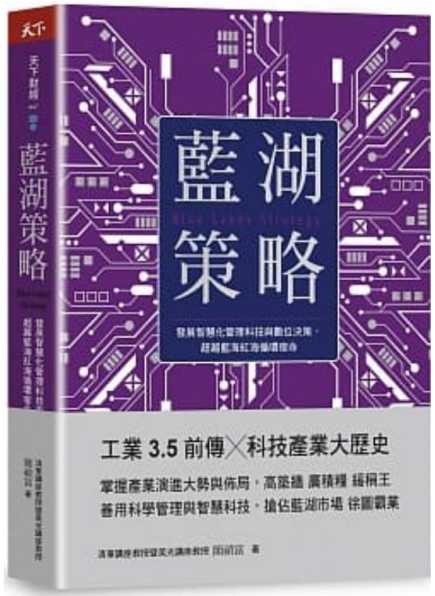
工業4.0

- 大量個人化、彈性決策、聰明生產
- 有需求才生產、少量多樣高附加價值
- 結合終端使用者的物聯網與虛實整合，使各環節上的浪費得以消除
- 人體神經系統，偵測變化和即時決策
- 平台化，提升對供應鏈上下游廠商的資訊穿透和掌控能力，建置專屬製造平台，透過網路定期更新收費服務。

智慧製造與工業3.5 (簡禎富, 2017, 哈佛商業評論)

四大策略關鍵

- 策略關鍵1：現有製造優勢與管理經驗系統化與數位化
  - 不只是靠低成本競爭，在競爭紅海中存活，是賺「管理財」
  - 很大比率早年技職體系培養，年齡通常在50到65歲之間...
- 策略關鍵2：產品生命週期與營收管理
  - 讓製造系統兼顧前台客製化和後台規模化的效能，需要串連設計、製造、銷售、物流、服務與保固的管理流程和大數據，縮短市場端到製造端的落差
  - 台廠高度分工，個別企業難以掌握整個供應鏈的供需數據和產品生命週期各個階段的需求，...有些公司內部甚至不同資訊系統各自為政沒有整合...
- 策略關鍵3：軟硬體設備和分析能力垂直整合
  - 台灣製造業大多中小規模，專業分工，受限於企業資源和決策者視野的局限，以致重視硬體甚於軟體，不重視數據分析和決策的軟實力，和人才培養。
- 策略關鍵4：永續發展和綠色供應鏈
  - 歐盟國家未來更可以此做為防守其他國家製造業的戰略武器
  - 特別是台灣在資源回收和循環經濟也有隱形冠軍...整合到廠務與綠色供應鏈，促進產業共生和資源循環利用



馬雲 (2017/04)

- 第一次技術革命的能源是煤，第二次技術革命的能源是石油，第三次技術革命的能源主要是數據。所以社會的變革會越來越大，每一次技術的變革都是就業的變革…
- 一切業務不是基於數據的，忘掉，別做了，所有數據必須業務化，一切數據必須業務化，只有這樣才能迎接這個時代，
- 我們要讓機器做人做不好的事情，人創造不了的事情，這是我認為在Machine intelligence 上面…人類有責任和擔當讓機器成為人的合夥人，成為人的合作夥伴，而不是讓機器來取代，這是我們這一代的人。
- 未來三十年已經不是力量的競爭、肌肉的競爭，甚至不是知識的競爭，而是服務別人能力的競爭，而是體驗的競爭，所以女人在未來的三十年將會蓬勃起來。
- 我們不能一方面說轉型升級，一方面還要對落後產業進行保護，這是不靠譜的。
- 小型企業創新是靠產品，中型企業創新靠技術，大型企業創新靠制度
- 智慧的競爭，我們一定要想明白讓孩子們必須去學習音樂、體育、運動、美術。音樂讓人有智慧通靈，體育運動讓人懂得團隊精神，我們讓孩子學會畫畫，有想像力，我們讓孩子懂得很多知識以外的事情。

結語

- The source of complexity in manufacturing is "variability (變異)".
  - Automation (自動化) is a powerful way to reduce variability.
  - Data Science facilitates automation and real-time decision.

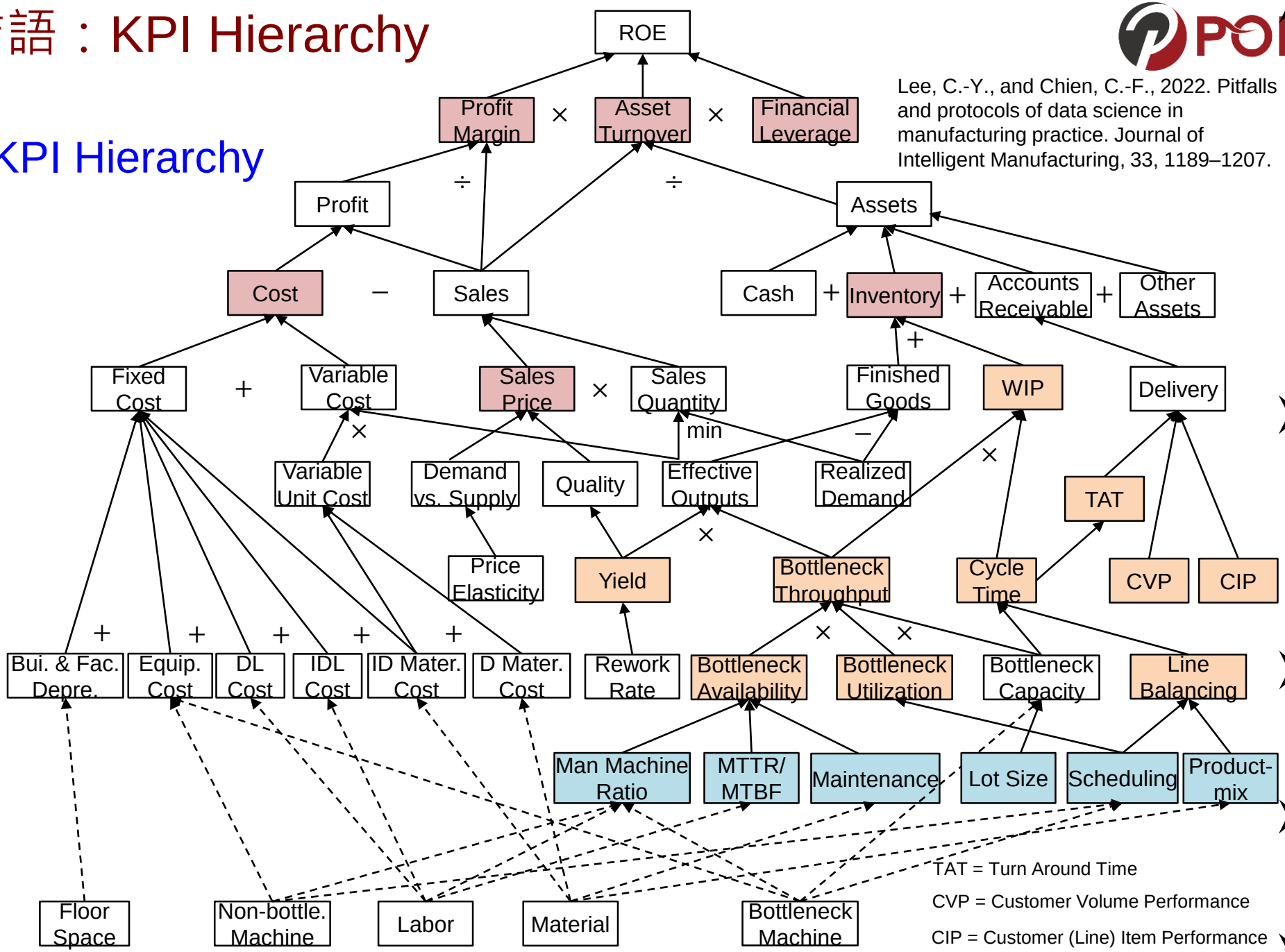
- However …
  - 1. 資料科學是為了「**追求真理/槓桿資源**」，非單純的「**IT**」
  - 2. 資料科學的最終目的在於「**決策**」，而「**預測**」只是過程
  - 3. 如果真的要以data分析，務必收集**第一手**資料 (田野調查訪談)
  - 4. 跟「**變異**」一起共處吧~
  - 5. 事實上 …凡是能"量化"的可都已經不有趣了 …

- 預測性思維 → 處方性決策

- 製造資料科學要掌握製造現場(過去、現在)並協助企業策略發展(未來).
  - 掌握每個細節，製造現場的決策，如何影響企業的**財務指標**

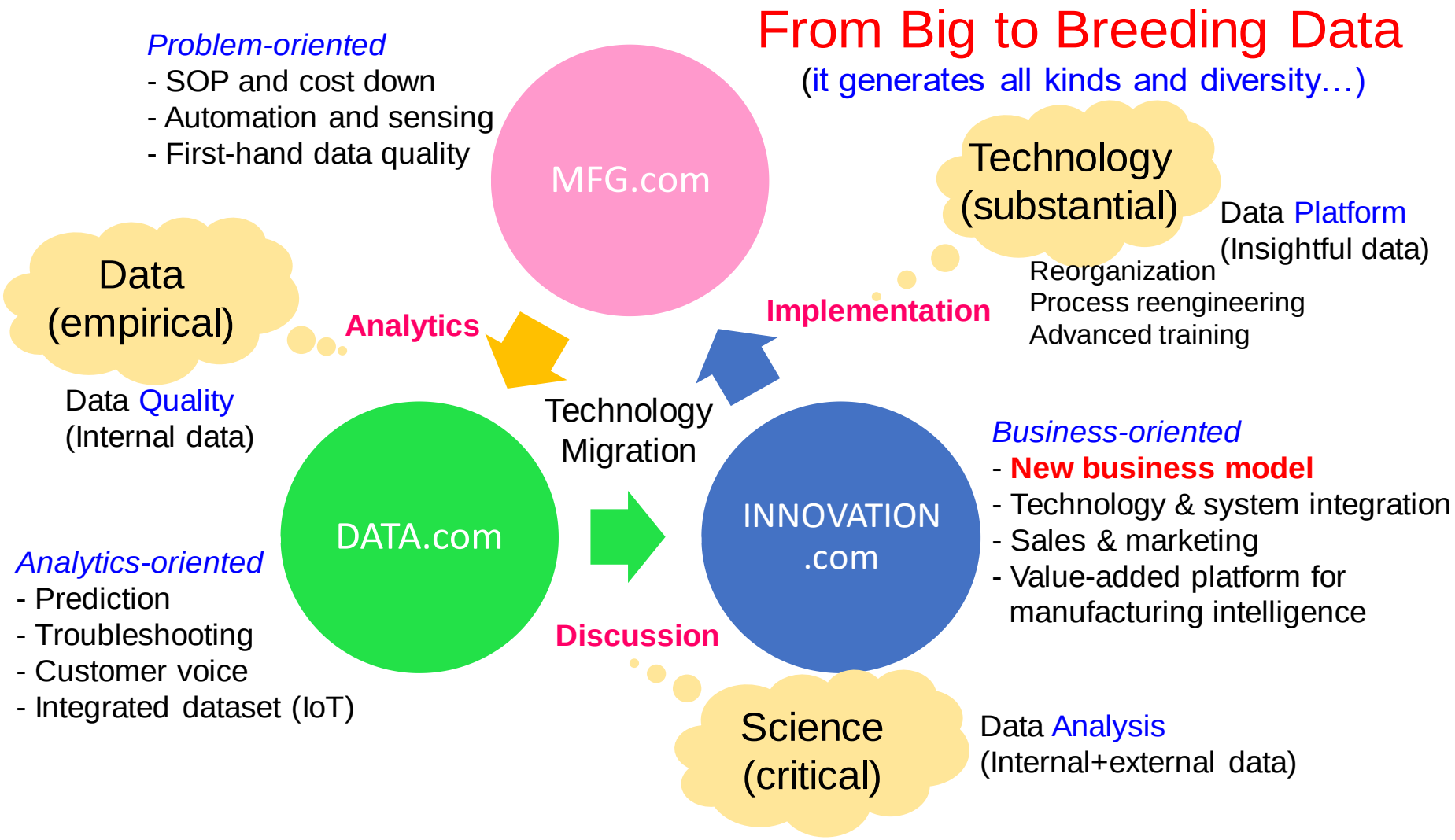
結語：KPI Hierarchy

KPI Hierarchy



Lee, C.-Y., and Chien, C.-F., 2022. Pitfalls and protocols of data science in manufacturing practice. Journal of Intelligent Manufacturing, 33, 1189–1207.

結語：從大數據到「養」數據...



Lee, C.-Y., and Chien, C.-F., 2022. Pitfalls and protocols of data science in manufacturing practice. Journal of Intelligent Manufacturing, 33, 1189–1207.

最後...ChatGPT一下...

在高科技與精密製造業中，人工智能於工廠內的應用愈來愈多，包括需求預測、瑕疵檢測、製程診斷、工程參數優化、設備維修保養、產能規劃等議題。然而由於產品少量多樣與需求變異大，在大環境經濟景氣衰退的情況下，使用人工智能在工廠進行改善專案時應該注意什麼事項？

在經濟景氣衰退的情況下，使用人工智能在工廠進行改善專案時，應注意以下幾點：

1. 注意成本效益：在經濟不景氣的情況下，成本效益變得更加重要。因此，在引入人工智能技術之前，必須評估其成本效益，以確保所投資的資源能夠獲得回報。 → As-Is → To-Be Enhancement
2. 考慮多樣性產品：由於產品少量多樣，因此在使用人工智能技術時必須考慮到產品的多樣性，以確保技術能夠適應不同類型的產品，並且在生產中維持高品質。 → Domain Adaptation
3. 考慮需求波動：在經濟不景氣的時期，需求可能會有波動。因此，使用人工智能技術時應該考慮到需求波動，以確保生產能夠靈活地調整以滿足變化的需求。 → Concept Drift
4. 確保資料的品質：人工智能技術需要可靠的數據支持，因此在開始任何改善專案之前，必須確保所使用的數據是準確且可靠的。同時，需要注意數據的時效性，以確保人工智能模型能夠反映當前的生產狀況。 → Data Quality
5. 關注人員培訓：使用人工智能技術需要有經驗豐富的人員來設計、實施和管理系統。因此，要確保人員具備相應的技能和知識，並定期進行培訓和學習，以確保系統能夠持續運作。 → Staff Training

總之，在經濟不景氣的情況下，使用人工智能技術可以幫助企業提高生產效率和品質，但同時也需要注意上述事項以確保改善專案的成功實施。

放眼世界，我認為「藍海」根本不存在...

王品若能成為市場龍頭，不是因為有什麼了不起的創新，而是所有同仁都老老實實的捲起袖子打拚。

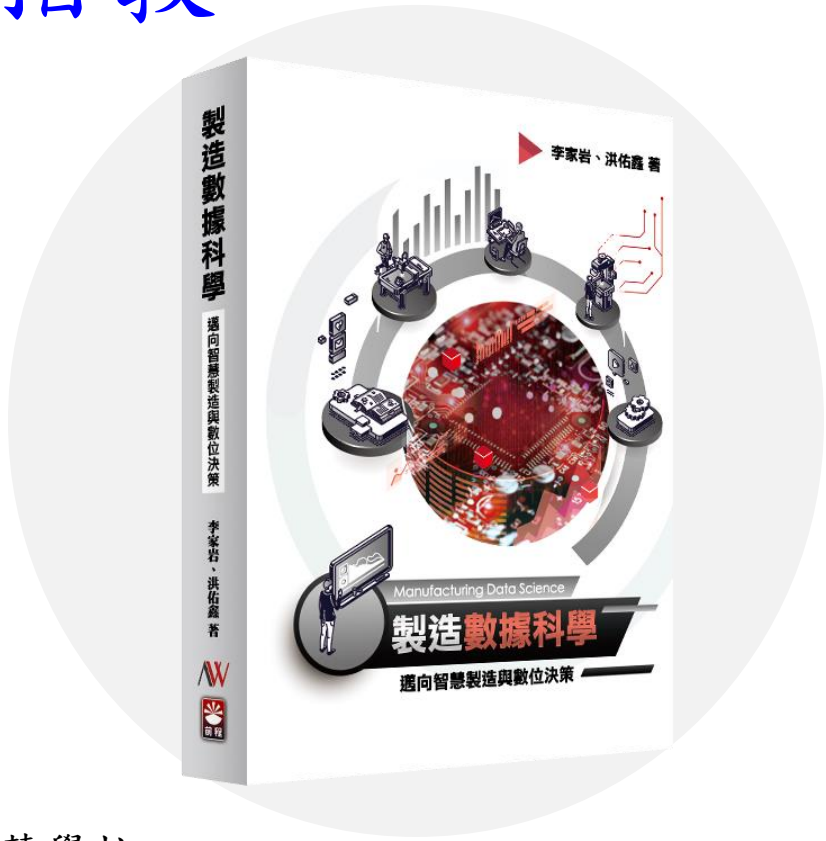
讓企業或個人成功的原因，絕對不是什麼藍海策略，而是那個做到極致、絕不放棄的堅持精神。

戴勝益 (2014)

References

- 李家岩、洪佑鑫，2022，製造數據科學，前程文化。
- 簡禎富、許嘉裕 ，2014，資料挖礦與大數據分析，前程文化。
- Guyon, I. and A. Elisseeff, 2003. An Introduction to Variable and Feature Selection. Journal of Machine Learning Research, 3, 1157–1182.
- Han, J., M. Kamber, and J. Pei, 2011. Data Mining: Concepts and Techniques, 3rd edition, Morgan Kaufmann.
- Hillier, F. S. and G. J. Lieberman, 2010. Introduction to Operations Research, 9th ed., McGraw-Hill, New York.
- Hsu, S. and C. Chien, 2007. Hybrid Data Mining Approach for Pattern Extraction from Wafer Bin Map to Improve Yield in Semiconductor Manufacturing. International Journal of Production Economics, 107, 88–103.
- Hung, S.-Y., Lee, C.-Y., and Lin, Y.-L., 2020. Data science for delamination prognosis and online batch learning in semiconductor assembly process. IEEE Transactions on Components, Packaging and Manufacturing Technology, 10 (2), 314-324.
- Hung, Y.-H., Lee, C.-Y., Tsai, C.-H., and Lu, Y.-M., 2022. Constrained particle swarm optimization for health maintenance in three-mass resonant servo control system with LuGre friction model. Annals of Operations Research, 311, 131–150.
- Lee, C.-Y. and Chiang, M.-C., 2016. Aggregate Demand Forecast with Small Data and Robust Capacity Decision in TFT-LCD Manufacturing. Computers & Industrial Engineering, 99, 415–422.
- Lee, C.-Y., and Chien, C.-F., 2020. Pitfalls and protocols of data science in manufacturing practice. Accepted in Journal of Intelligent Manufacturing.
- Lee, Chia-Yen, Chou, B.-J., and Huang, C.-F. 2022. Data science and reinforcement learning for price forecasting and raw material procurement in petrochemical industry. Advanced Engineering Informatics, 51, 101443.
- Lee, C.-Y., and Dong, Z.-H.. 2019. Hierarchical equipment health index framework. IEEE Transactions on Semiconductor Manufacturing, 32 (3), 267-276.
- Lee, C.-Y. and Johnson, A. L., 2013. "Operational Efficiency", book chapter edited in: Badiru, A. B. (Editor), Handbook of Industrial and Systems Engineering, 2nd Edition, 17-44, CRC Press.
- Lee, C.-Y., and T.-L. Tsai, 2019. Data Science Framework for Variable Selection, Metrology Prediction, and Process Control in TFT-LCD Manufacturing. Robotics and Computer-Integrated Manufacturing, 55, 76-87.
- Lu, H.-W., and Lee, C.-Y., 2022. Kernel-based dynamic ensemble technique for remaining useful life prediction. IEEE Robotics and Automation Letters, 7 (2), 1142-1149.
- Shen, P.-C., and Lee, C.-Y., 2022. Wafer Bin Map Recognition with Autoencoder-based Data Augmentation in Semiconductor Assembly Process. IEEE Transactions on Semiconductor Manufacturing.
- Savage, L. J. 1951. “The theory of statistical decision,” Journal of the American Statistical Association, 46, 55–67
- Wu, M.-Y. and C.-Y. Lee, 2015. Sampling-based NSGA-II for Stochastic Scheduling in Auto Parts Manufacturer. 2015 Chinese Institute of Industrial Engineers (CIIE) Conference & Annual Meeting, Taichung, Taiwan.

感謝大家的支持跟參與
還請多多指教



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