Process systems engineering for the food, energy and water (FEW) nexus

Brent Young & Bing Li

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Agenda

- Food Energy Water (FEW) nexus
- The Southern Hemisphere "Down Under" (actually NZ) perspective
- Big data and PSE
- Challenges from dairy processing
- Resource recovery from wastewater for food production

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FEW nexus

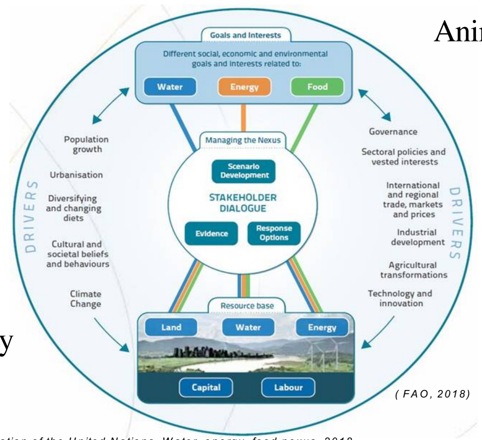
"is about understanding and managing often-competing interests while ensuring the integrity of ecosystems"*

Water use

Chemical use

Sustainability

Water quality



(FAO, 2018)

Animal welfare

Nutrition

Food safety

Future foods

Food security

Provenance

* Food and Agriculture organization of the United Nations, Water–energy–food nexus, 2018.

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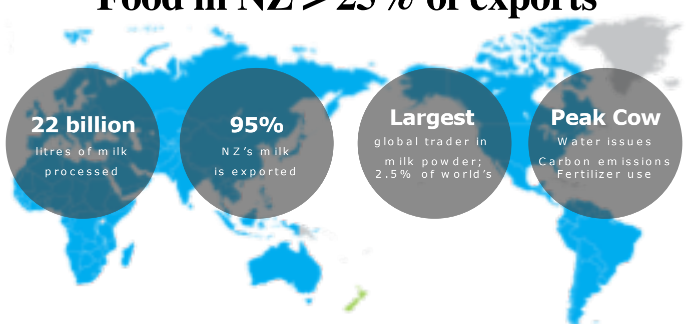
Food in NZ > 25% of exports



22 billion
litres of milk processed

95%
NZ's milk is exported

Largest
global trader in milk powder; 2.5% of world's

Peak Cow
Water issues
Carbon emissions
Fertilizer use

Food in Australia

Previously
Minerals Boom Economy

Moving to
Agriculture Bloom Economy

Water
Very dry continent
Very low water use

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Big Data and PSE

The End of Theory:
The data deluge makes the scientific method obsolete.

Wired Magazine, 2008

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Big Data and PSE

"The largest wave amplitude of 35-40cm was recorded at the Chatham Islands.
9th Sept 2017

- Digital Tsunami, disruption, exponential complexity
- But hopefully provides better business & operational insight
- What is big data? (large data volumes; shapes, sizes, colour)
  - It is not a thing, it is a journey
  - Problems too big to fit on you desktop, using your familiar tools
- Requires skills in:
  - Signal processing, optimisation, image processing
  - Analytics, statistical learning, machine learning, database design

Sounds a bit like PSE!

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Some assumptions - about us, or at least our U/Gs!

- Probably a ‘traditional’ modelling & stats background
- Probably more comfortable with:
  - *Physical-chemical based models, fine-tuned with regressed (x,y) data (i.e. curve fitting)*
  - *Models used for prediction/simulation (but not wider uses)*
  - *Probably a little sloppy on model validation (cross-validation, updating, etc.)*
- Probably watching applications in Natural language processing, image recognition, automated solving of ill-posed problems and think:
  - *Is this relevant to us?*
  - *Tools for classification (categorical/nominal)?*
  - *An augment to ‘traditional’ tools?*

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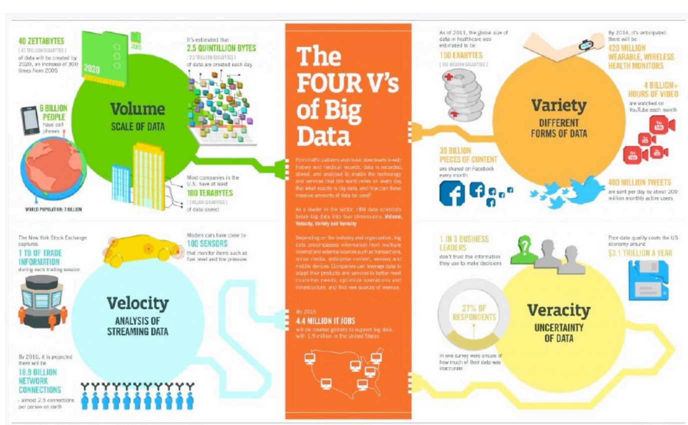
The 4 Dimensions of Big Data



Ref: IBM Infographics

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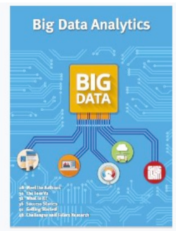
Big Data and PSE

- 4Vs: are these all relevant?
- What vs Why?
  - Many businesses not interested in the "Why"
  - The "Why" oft ignored or irrelevant
  - Not the case in the processing industries
- Recent CEP Big Data Analytics Survey…

6. In the food industry, diverse data sources are incorporated in modeling tastes, nutritional content, and recipe formulation for food products. The industry is shifting toward using multivariate methods to identify correlations from bigger data sets. In food manufacturing, spectrum analyzers and imaging sensors are used to detect product quality issues. Lastly, model-based control and optimization enable safer and more efficient processes.

Big Data Analytics in Chemical Engineering, Feb 2017, Lu & Castillo (Dow)



Chemical Engineering Progress 2016

Actually we've done this for some time!

PSE Challenges from diary processing quality prediction research

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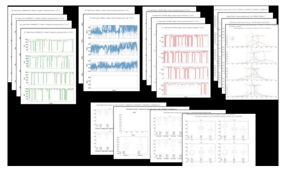
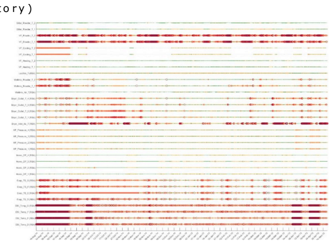
1st step: Look at the data (often underestimated)



Sheer volume of plots

- Huge amounts of data & plots
  - Too many to sensibly read & compare?
  - At what frequency?
- What are our intentions for the plots?
  - How to exploit Human's unique ability to instantly spot trends/patterns?
  - Don't bias results (poor chart design, graphical lies)
  - Paper vs screen (static vs animation, exploratory)
- How to be selective with the data?



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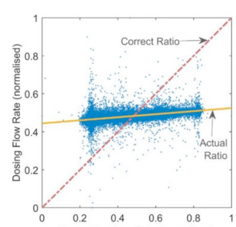
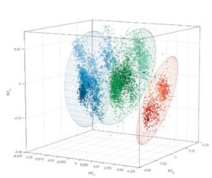
"Simple" things: plotting/visualisation

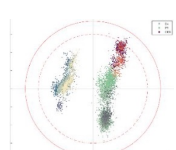
Do simple things first
- Easy to spot mistakes if you plot the right things



- Exploit humans
  - How to exploit the unique Human abilities to instantly spot trends/patterns?

  - Paper vs screen (static vs animation, exploratory)





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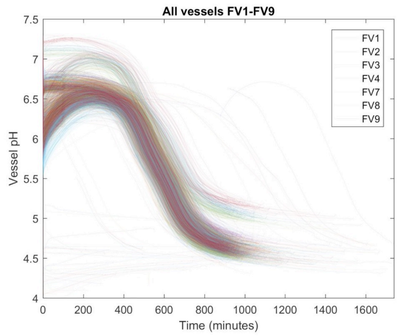
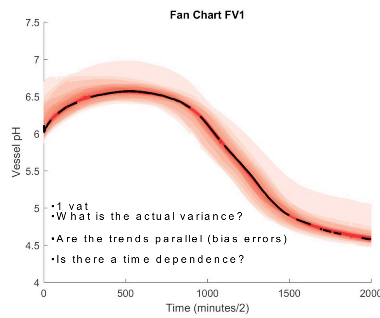
Variation/Uncertainty



3000 pH trends for cream cheese fermentation (1 year, all vats)

- 1/2 day data prep
- 1 day plotting



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What statistics apply?

Traditional Stats	Computational Stats
• Small to medium problem sizes	• Very large problem sizes
• Independent, identically distributed data sets	• Non-homogeneous data sets
• Manually computable & tractable: Closed form algorithms	• Computationally intensive; Numerically tractable (iteration)
• Strong unverifiable assumptions (linearity, normality)	• Weak or no assumptions
• Statistical inference	• Structural inference
• Statistical optimality	• Statistical robustness

Ref: Wegman, 1988 (Matrinez, p3)

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What is an appropriate model?

Linear regression
- Easy to fit, easy to interpret,
- Too large, marginal results, global models too ambitious ?

Latent variables (PCR)
- Smaller models, (but use all variables)
- How to interpret?

Build small & sparse models
- Lasso
  - Great at bias, good for relative importance
- Regression trees
  - Easy to explain, unwieldy to use, grow large & need pruning – how?
- Black box models
  - Why drop known phenomena?

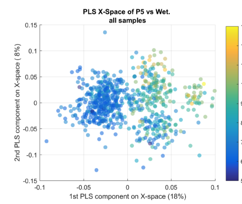
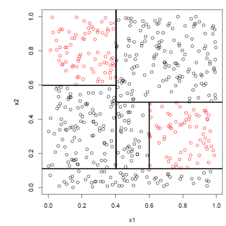


Figure 16: Wettability PLS model scores - All Data



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Issues/Challenges

Meaningful data
- Most data is happenstance collected passively
- Data is often information poor (despite big). Not enough "bad batches", hard to spot, care with cleaning
  - Up and down re-sampling
- Limited value for predictive activity

Multiple data structures
- P, F, T is scalar, NIR is a vector, HSI is a matrix cube
- Fuse & align this data
- Data with high time resolution leads to over-parameterized models
  - Data "wrangling" to tidy and align data takes 50-80% of analysis time

A-priori knowledge
- Usually available; don't throw it away. Also capture uncertainty.
- Big data methods are black-box.

Ref: *Big Data: Challenges & Future research Directions*
Reis, Braatz & Chiang, 2016

Resource recovery from wastewater for food production

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Future wastewater treatment

- Industry 4.0 based
  - Cyber—Physical System
  - Information optimized
- Energy neutral
  - Anaerobic digestion
  - Solar/H2/Biodiesel
- Resource oriented
  - Carbon source/Nutrients
  - Precious metal/heavy metal
  - Water: Cascade utilization/effluent reuse
- Location matters

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Opportunities

- Novel Concepts/Plants/Processes
  (e.g. P recovery via struvite precipitation)
  - Technology readiness level?
  - Optimization and control opportunities?

Challenges

- Multi-scale, multi-process, multi-objective
  - Social, environmental, economical objectives
  - optimization and control
  - uncertainty matters

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Resource recovery for food production

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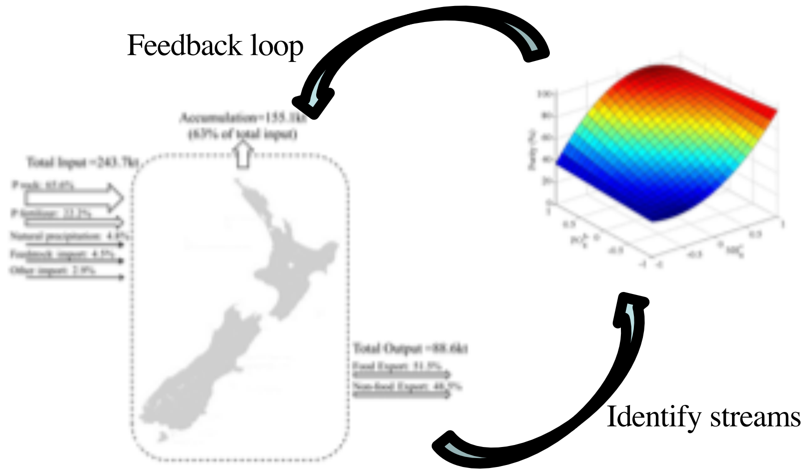
Resource recovery for food production



Iterative process

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