PREDICTIVE ANALYTICS IN INDUSTRIAL IOT, DATA, AND SYSTEMS

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The Era of Big Data

http://blog.adtailor.com/index.php/2016/04/15/the-present-and-future-of-content-marketing-big-data/

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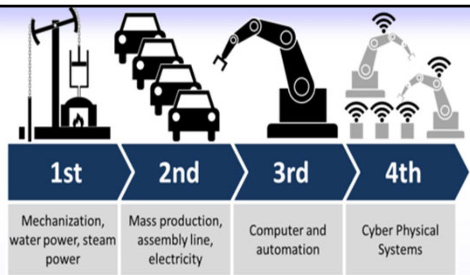
Real Examples of Big Data Applications

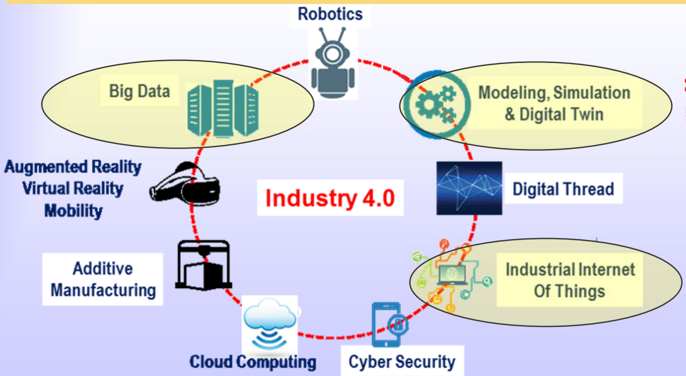
- Amazon Book Recommendation
  - Replaced professional book reviewers
- Netflix: 98% data are missing
  - 100,480,507 ratings: 480,189 users x 17,770 movies
- Google Translator (2006)
- Google's Flu Prediction (2009)
  - 45 features out of 150 millions 'models'
  - >90% accuracy predicting CDC data
  - Later improved by time series models (AR)

Moving towards Industry 4.0

- To propel breakthrough improvements in safety, reliability, and productivity
- To derive intelligent decision-making using data analytics and AI



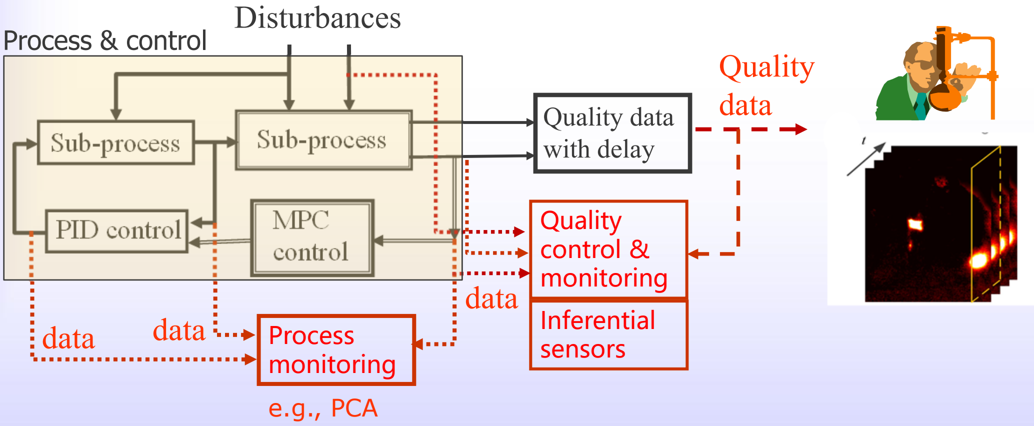
http://www.allaboutlean.com AllAboutLean.com



Source Adapted from: http://www.aethon.com/industry-4-0-means-manufacturers/ and Boston Consulting Group

S. Joe Qin and Leo H. Chiang (2019). Advances and Opportunities in Machine Learning for Process Data Analytics. Computers and Chemical Engineering, 126, Pages 465 – 473.

Data Analytics for Smart Manufacturing



Unsupervised Monitoring **Supervised Monitoring**

Smart Manufacturing – Extracting Actionable Knowledge from Real-time Data

Data Science Sees the Dark Side - Uncertainty

- Engineering principles understand the **white side**
- Industrial IoT's provide more data on both sides
- The challenge is to learn the **dark side** from data
  - The right machine learning leads to intelligence

Message #1

Operator/
Controller

Ambience/
Disturbance

https://www.scmp.com

Data Analytics vs. System Identification

Message #2

System Data Analytics

- ❑ Operation, multisource data
- ❑ Highly collinear data
- ❑ Partial dynamic data
- ❑ Aiming to extract features in the data, to be used for
  - Monitoring, inference
  - Fault diagnosis
  - Interpretation
  - Prediction

System Identification

- ❑ Designed experimental data
- ❑ Full excited data
- ❑ Fully dynamic data
- ❑ Aiming to identify the 'true' system model as accurately as possible; its use for control is implied

System theory and data analytics should be integrated

TIME-DEPENDENT DATA SERIES EXTRACTION

- ❑ Application: Economic time series (Tsay, 2015)

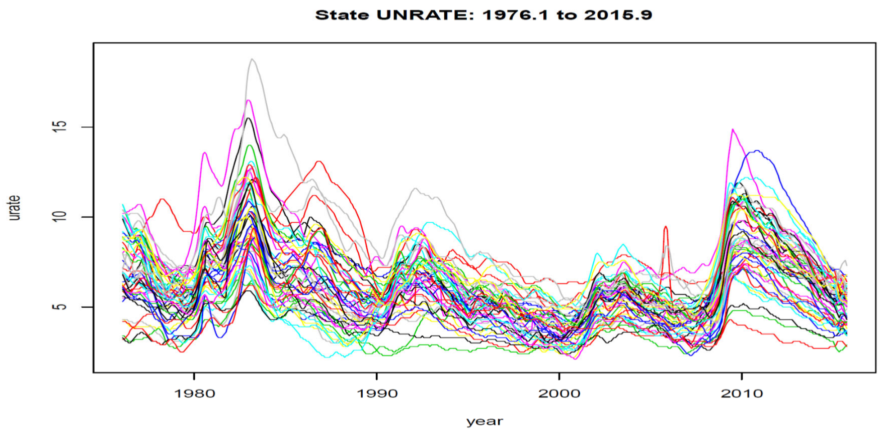
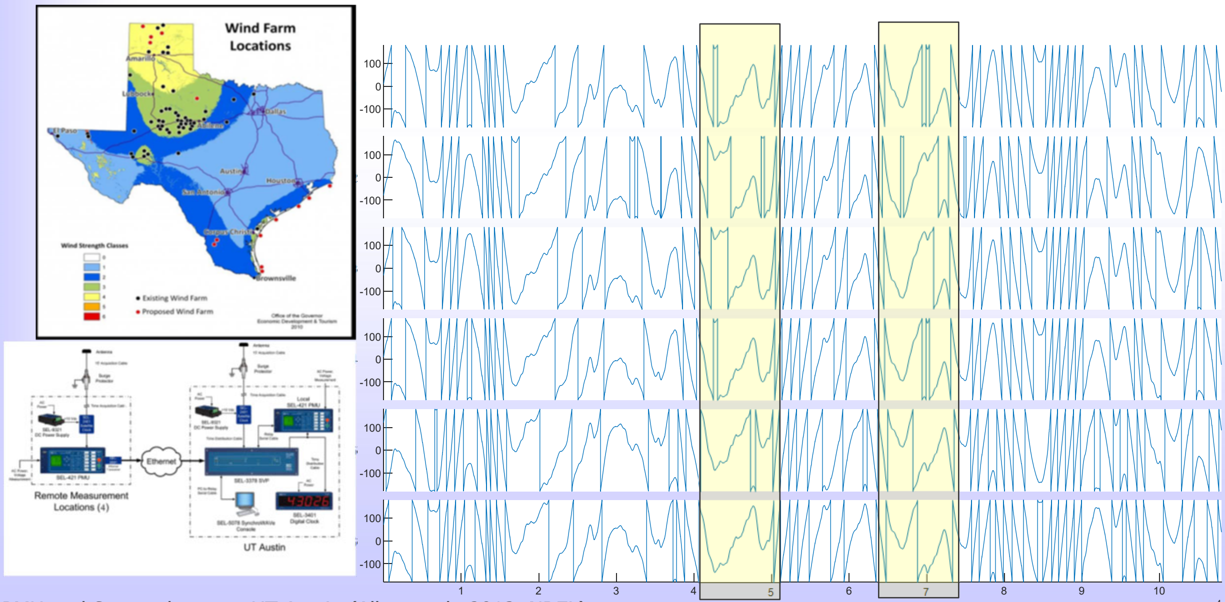


Figure: Time plots of monthly unemployment rates of the 50 States in the U.S. from January 1976 to September 2015. The data are seasonally adjusted.

Application: Power Grid Stability



PMU and Syncrophasor at UT Austin (Allen et al., 2013, NREL)

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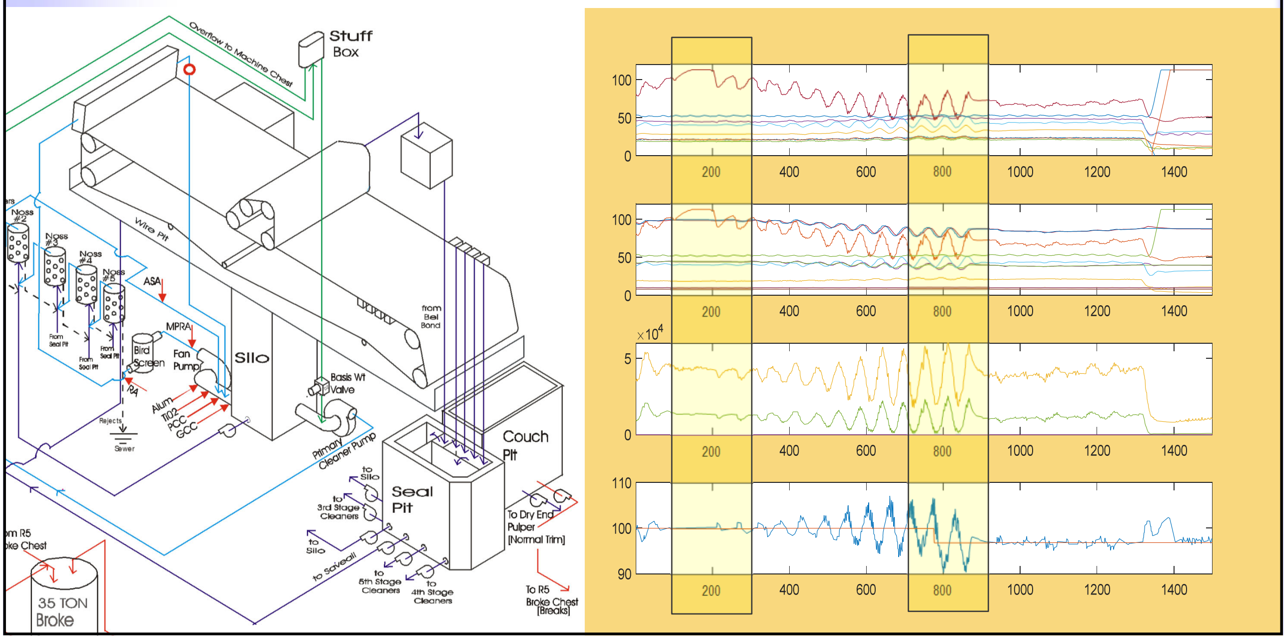
Paper Machine Prognostics: sheet-break dynamics



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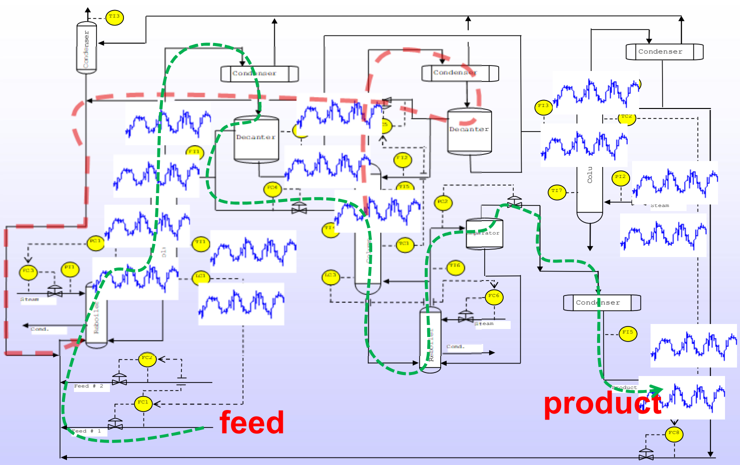
Chemical Processing: improving throughput

Recycle loops make ‘snowballing’



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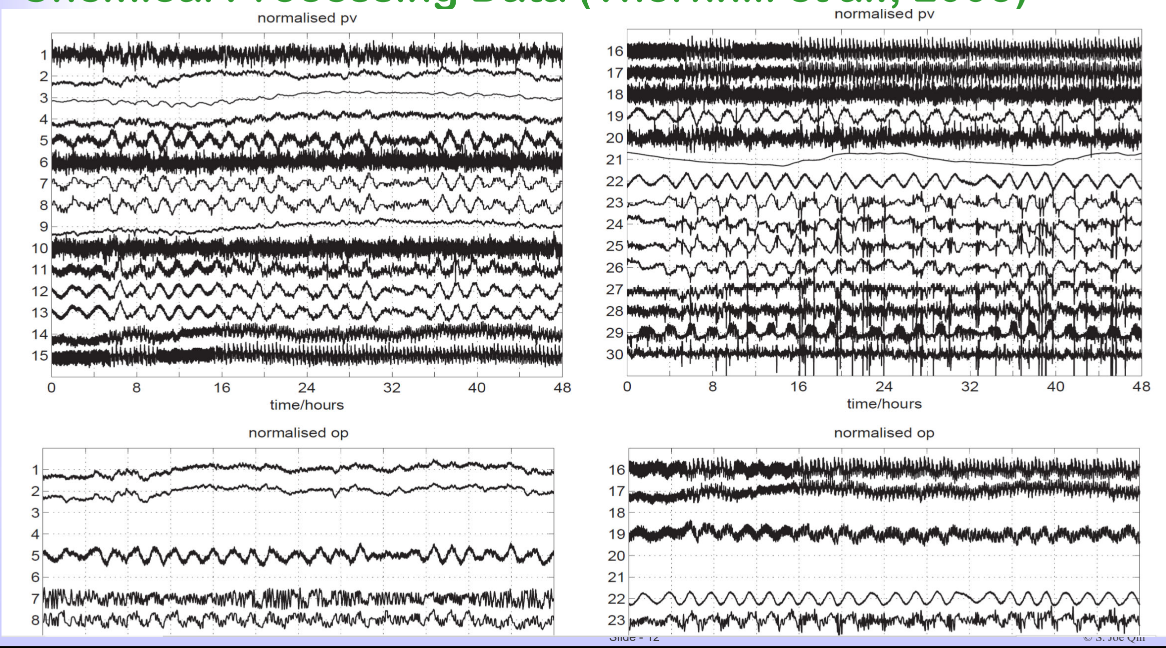
Chemical Processing Data (Thornhill et al., 2003)



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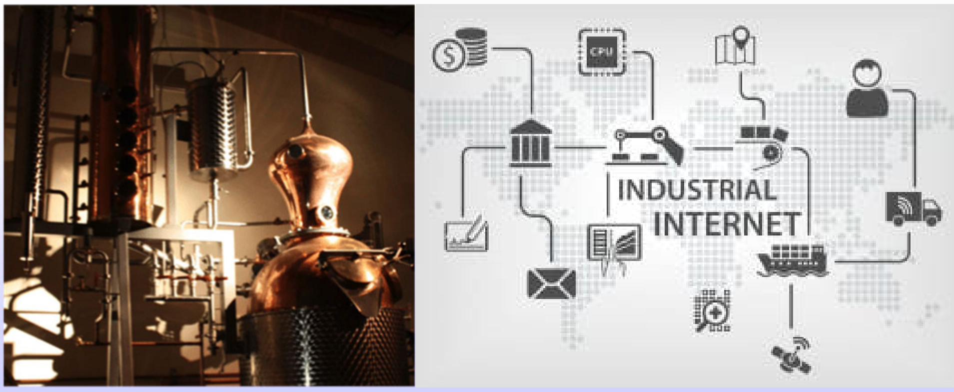
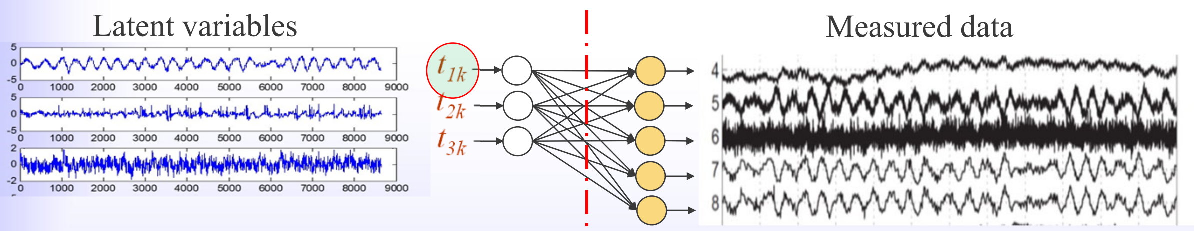
Industrial IoT Sensors vs. **Dynamic Dimension**

More sensors are installed, but the dimension of the dynamics does not increase!



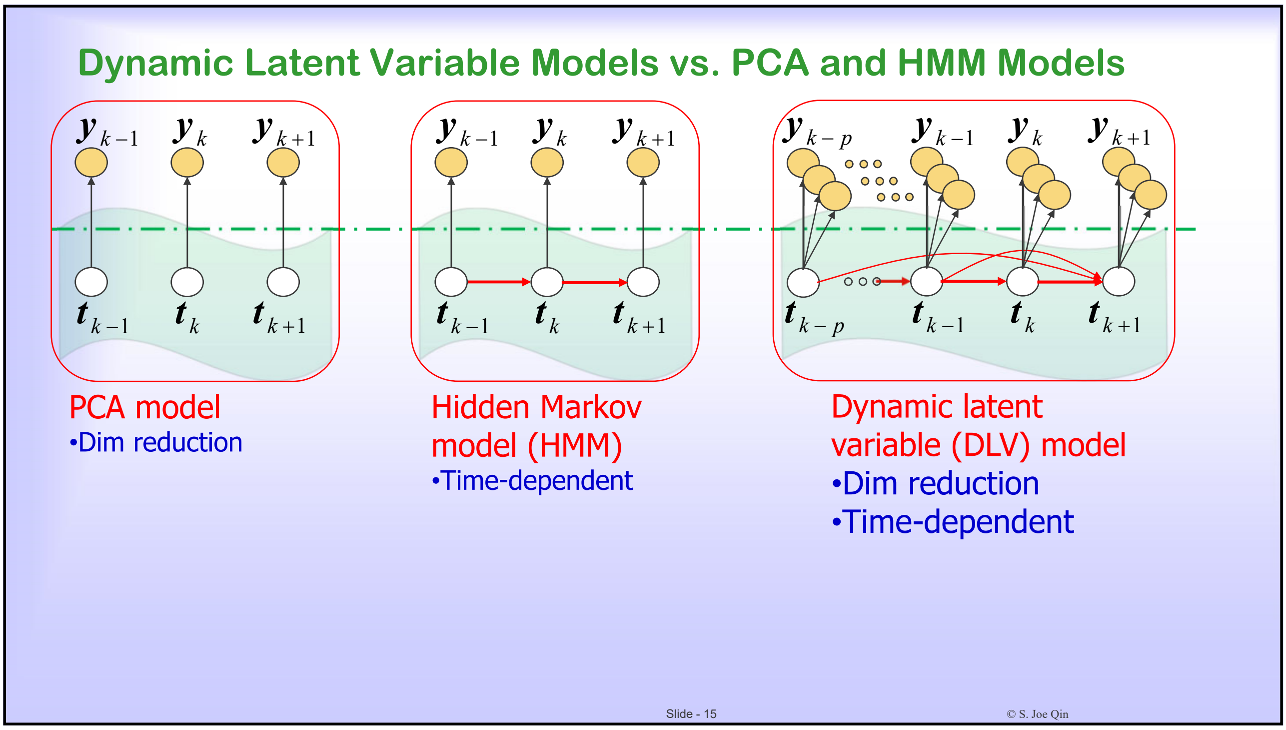
https://www.sparklinglogic.com/prescriptive-analytics-industrial-iot/

Example: three latent variables, but only one is time dependent.
Question: how to extract the time-dependent feature?



Unknown latent sources to be extracted: the dark side

Known data


Dynamic Latent Variable Models vs. PCA and HMM Models
y_{k-1} y_k y_{k+1}
t_{k-1} t_k t_{k+1}
PCA model
•Dim reduction
y_{k-1} y_k y_{k+1}
t_{k-1} t_k t_{k+1}
Hidden Markov model (HMM)
•Time-dependent
y_{k-p} y_{k-1} y_k y_{k+1}
t_{k-p} t_{k-1} t_k t_{k+1}
Dynamic latent variable (DLV) model
•Dim reduction
•Time-dependent
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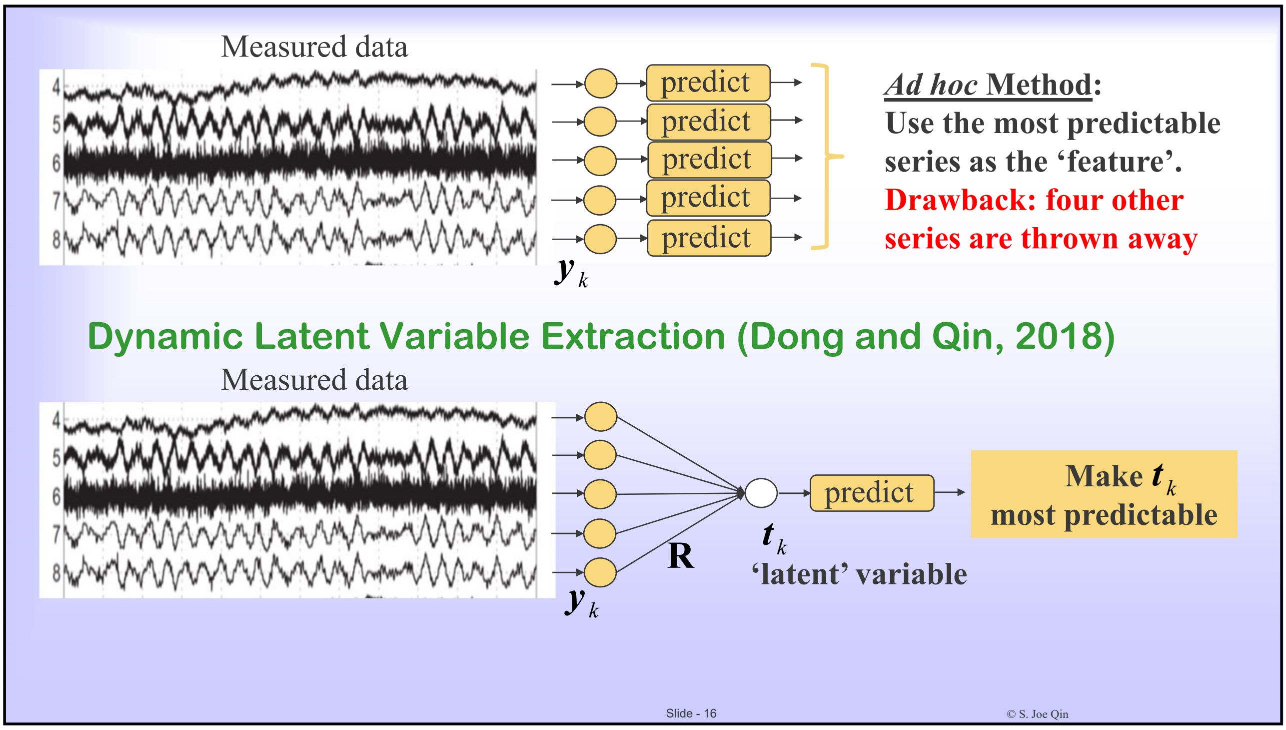
Measured data
predict
predict
predict
predict
predict
y_k
Ad hoc Method:
Use the most predictable series as the 'feature'.
Drawback: four other series are thrown away
Dynamic Latent Variable Extraction (Dong and Qin, 2018)
Measured data
R
y_k
predict
t_k
'latent' variable
Make t_k most predictable
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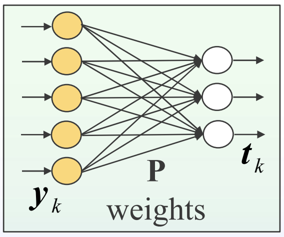
Dynamic Latent Variables (DiPCA, DiCCA)

- **Principal Component Analysis**

$$\min_{\mathbf{P}} \sum_k \left\| \boldsymbol{y}_k - \mathbf{P}\boldsymbol{t}_k \right\|^2$$

$$\text{s.t. } \boldsymbol{t}_k = \mathbf{P}^T \boldsymbol{y}_k;\ \ \mathbf{P}^T\mathbf{P} = \mathbf{I}$$



PCA modeling

- **DiPCA**

$$\min_{\mathbf{R},\{\boldsymbol{\beta}_j\}} \sum_k \left\| \boldsymbol{t}_k - \hat{\boldsymbol{t}}_k \right\|^2$$

$$\text{s.t. } \boldsymbol{t}_k = \mathbf{R}^T \boldsymbol{y}_k;\ \ \hat{\boldsymbol{t}}_k = \sum_{j=1}^{p} \boldsymbol{\beta}_j \boldsymbol{t}_{k-j}$$

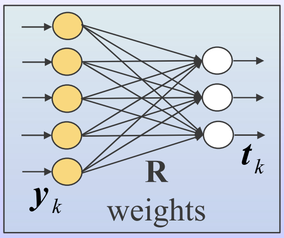
and constraining the norm of $\mathbf{R}$

- **DiCCA**

$$\min_{\mathbf{R},\{\boldsymbol{\beta}_j\}} \sum_k \left\| \boldsymbol{t}_k - \hat{\boldsymbol{t}}_k \right\|^2$$

$$\text{s.t. } \boldsymbol{t}_k = \mathbf{R}^T \boldsymbol{y}_k;\ \ \hat{\boldsymbol{t}}_k = \sum_{j=1}^{p} \boldsymbol{\beta}_j \boldsymbol{t}_{k-j}$$

and constraining the norm of $\{\boldsymbol{t}_k\}$



DLV modeling

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DiPCA, DiCCA references

DiPCA

Dong, Yining, and S. Joe Qin (2018). A Novel Dynamic PCA Algorithm for Dynamic Data Modeling and Process Monitoring. *Journal of Process Control*, 67, Pages 1-11.

DiCCA

Dong, Yining, and S. Joe Qin (2018). Dynamic Latent Variable Analytics for Process Operations and Control. *Computers and Chemical Engineering*, 114, Pages 69-80.

DiCCA SVD implementation

Dong, Yining, Y. Liu, and Qin, S. Joe (2020). Efficient Dynamic Latent Variable Analysis for High Dimensional Time Series Data, *IEEE Transactions on Industrial Informatics.* 16(6), 4068-4076.

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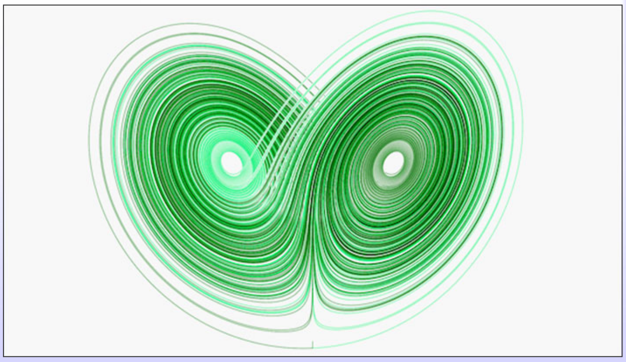
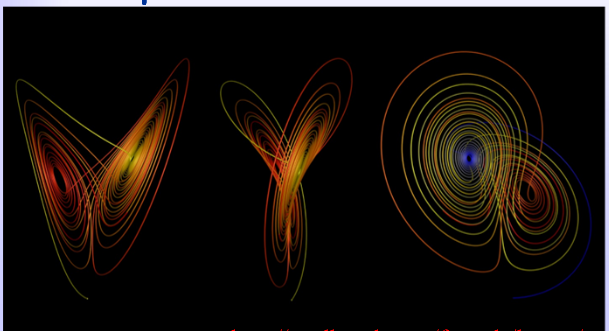
Example: Lorenz Attractor

$$\begin{cases} \dfrac{dx}{dt} = -\sigma x + \sigma y \\ \dfrac{dy}{dt} = -xz + rx - y \\ \dfrac{dz}{dt} = xy - bz \end{cases}$$

- Emulate the earth's atmosphere
  - Explain the 'butterfly effect'
  - What is the best 2D view of the most dynamic features?
- Project to 2D and make them most predictive



https://commons.wikimedia.org/wiki/File:Lorenz_apparition_small.gif



http://paulbourke.net/fractals/lorenz/

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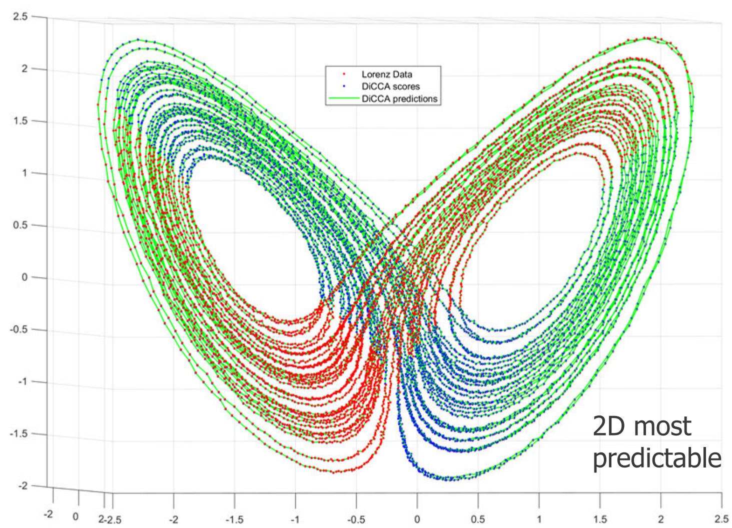
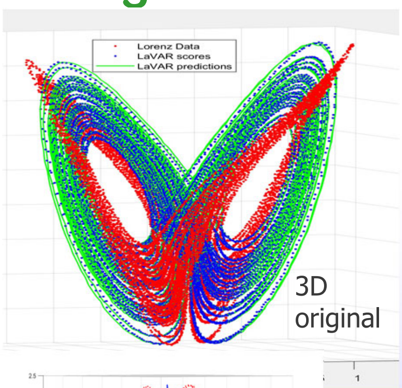
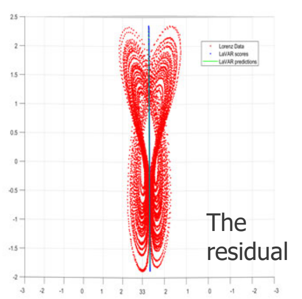
Latent Vector Autoregressive Modeling – Most Predictable 2D View







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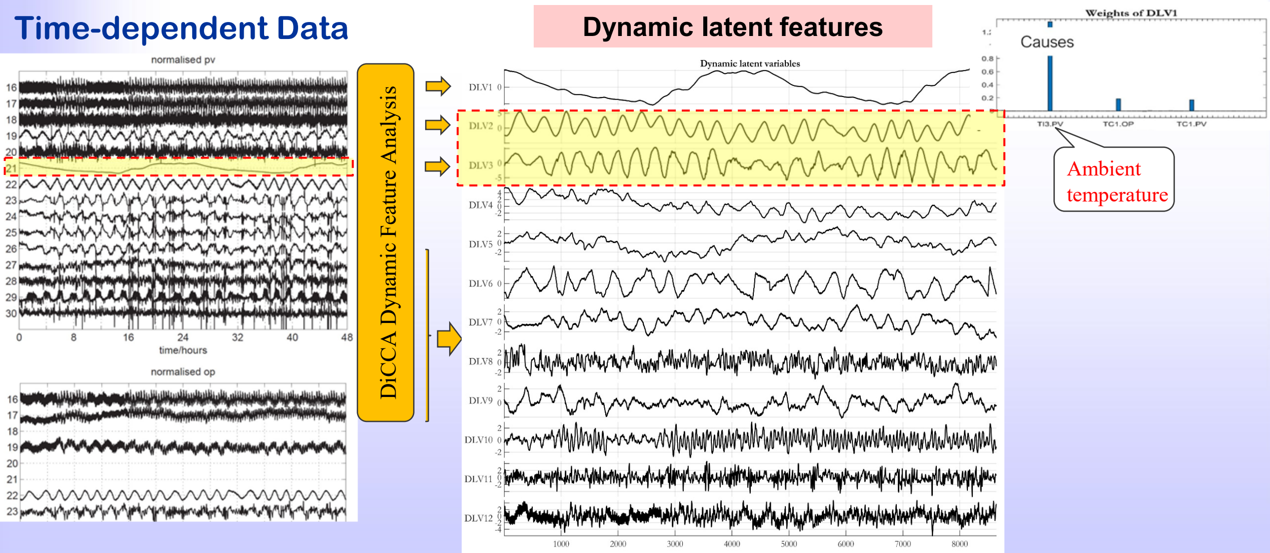
Chemical Plant Dynamic Feature Extraction



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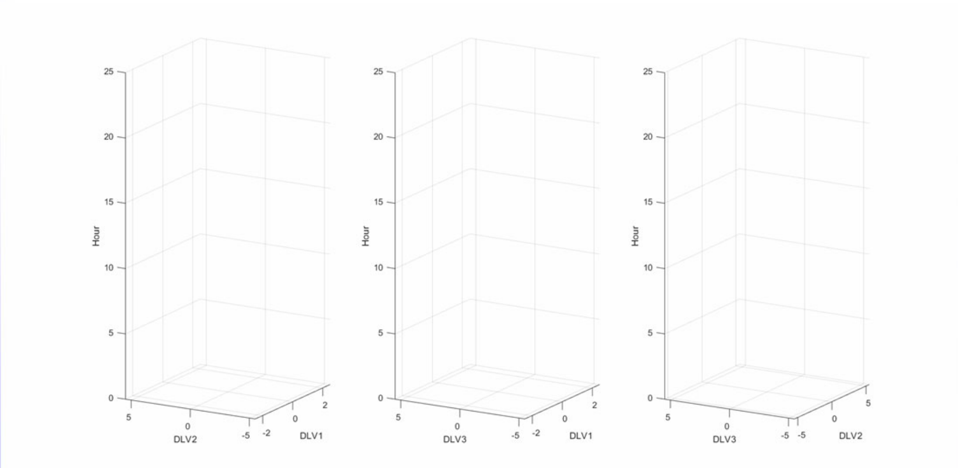

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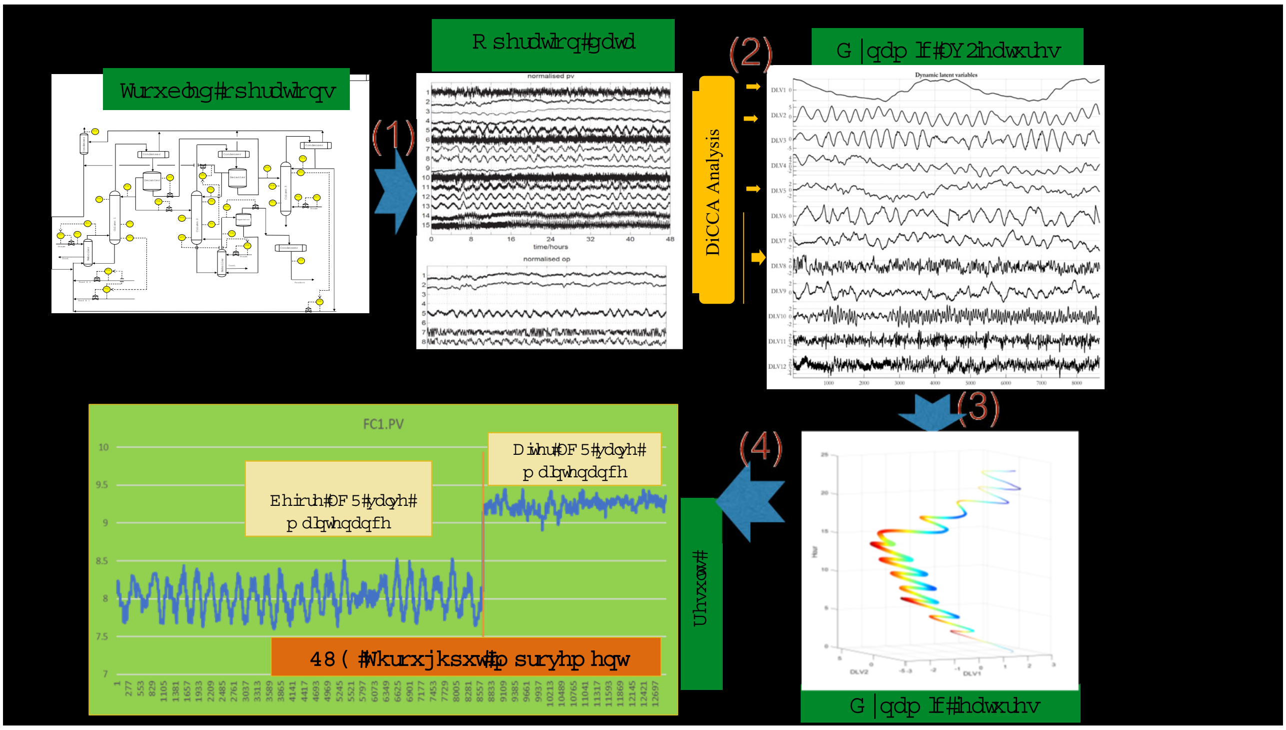

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Related Latent Dynamic Modeling Methods

❑ Qin et al. 2020 provides a unified review

- S. Joe Qin, Yining Dong, Qinqin Zhu, Jin Wang, Qiang Liu (2020), Bridging systems theory and data science: A unifying review of dynamic latent variable analytics and process monitoring, Annual Reviews in Control, 50, 29–48.

Contents lists available at ScienceDirect

Annual Reviews in Control

journal homepage: www.elsevier.com/locate/arcontrol

ELSEVIER

Review article

Bridging systems theory and data science: A unifying review of dynamic latent variable analytics and process monitoring

S. Joe Qin [a,*], Yining Dong [b], Qinqin Zhu [c], Jin Wang [d], Qiang Liu [e]

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Related Latent Dynamic Methods: Statistics

- Box, G. E. P., & Tiao, G. C. (1977). A canonical analysis of multiple time series. *Biometrika, 64*, 355–365.
  - Frist to realize dynamics in reduced dimensions
- Brillinger, D. R. (1981). *Time series: Data analysis and theory. Expanded Edition*. Holden- Day, Inc., San Francisco.
  - Elegant frequency domain formulation, but the corresponding time domain models are non-causal
- Pena, D., Smucler, E., & Yohai, V. J. (2019). Forecasting multiple time series with one-sided dynamic principal components. JASA, 114, 1683–1694.
  - Enforced causal models, but no explicit latent dynamic models
  - The latent prediction is based on past data, not past latent variables

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Related Methods: Dynamic Factors in Econometrics

- Pan, J., & Yao, Q. (2008). Modelling multiple time series via common factors. Biometrika, 95, 365–379.
  - Extracts the white noise latent variables, then builds VARMA models in the reduced dimensions.
  - Enforces latent dynamic models
- Lam, C., Yao, Q., & Bathia, N. (2011). Estimation of latent factors for high-dimensional time series. Biometrika, 98, 901–918.
  - Extracts all DLVs with one eigen-decomposition or an equivalent SVD.

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Related Methods: Subspace Identification

- Akaike, H. (1975). Markovian representation of stochastic processes by canonical variables. SIAM Journal on Control, 13, 162–173.
  - First to represent time series in state space
  - No modeling of reduced dimensional latent variables
- Later work extends it to include exogenous variables for system identification (Akaike (1976); Larimore (1990, 1996); Van Overschee and De Moor (1994); Verhaegen (1994)).
  - If reduced dimensional latent variables are modeled as state variables, first-order dynamics is resulted

Related Methods: Linear Gaussian State Space

- Q. Wen, Z. Ge, and Z. Song, "Data-based linear Gaussian state-space model for dynamic process monitoring," AIChE J., vol. 58, no. 12, pp. 3763–3776, 2012
  - represents a reduced dimensional, first-order latent variable model
  - Expectation-maximization (EM) is applied to estimate the latent variables and model parameters
  - The latent variables do not have rank-ordered predictability
- Zhou, L., Li, G., Song, Z., & Qin, S. J. (2017). Autoregressive dynamic latent variable models for process monitoring. IEEE Transactions on Control Systems Technology, 25, 366–373.
  - represents a reduced dimensional, multiple-order latent variable model

Related Methods: Machine Learning

- Wiskott, L., & Sejnowski, T. (2002). Slow feature analysis: Unsupervised learning of invariances. Neural Computation, 14, 715–770.
  - A special case of DiCCA with first-order integrating dynamics
- Richthofer, S., & Wiskott, L. (2015). Predictable feature analysis. 2015 IEEE 14th international conference on machine learning and applications (ICMLA) (pp. 190–196).
  - Predictable feature analysis with multiple-order dynamics
- Goerg, G. (2012). Forecastable component analysis (ForeCA). 30th International Conference on Machine Learning, ICML 2013.
  - Forecastable component analysis

Conclusions

- Data analytics bring knowledge of the dark side – learning the uncertainty
  - Complement the 'white side' – known models

- Analyzing data from dynamic systems requires new methods
  - Data and/or noise are usually time dependent
  - Operation data are often partially excited in dynamics, requiring latent dynamic models
- Latent dynamic models define reduced dynamic dimension, and are statistically parsimonious
  - can be most predictive and infer causality

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  - Prof. Qinqin Zhu (Waterloo)
  - Mr. YX Liu (USC)