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Machine learning in mineral processing

Lidia Auret

Process Engineering

23 March 2018 – Maties Machine Learning

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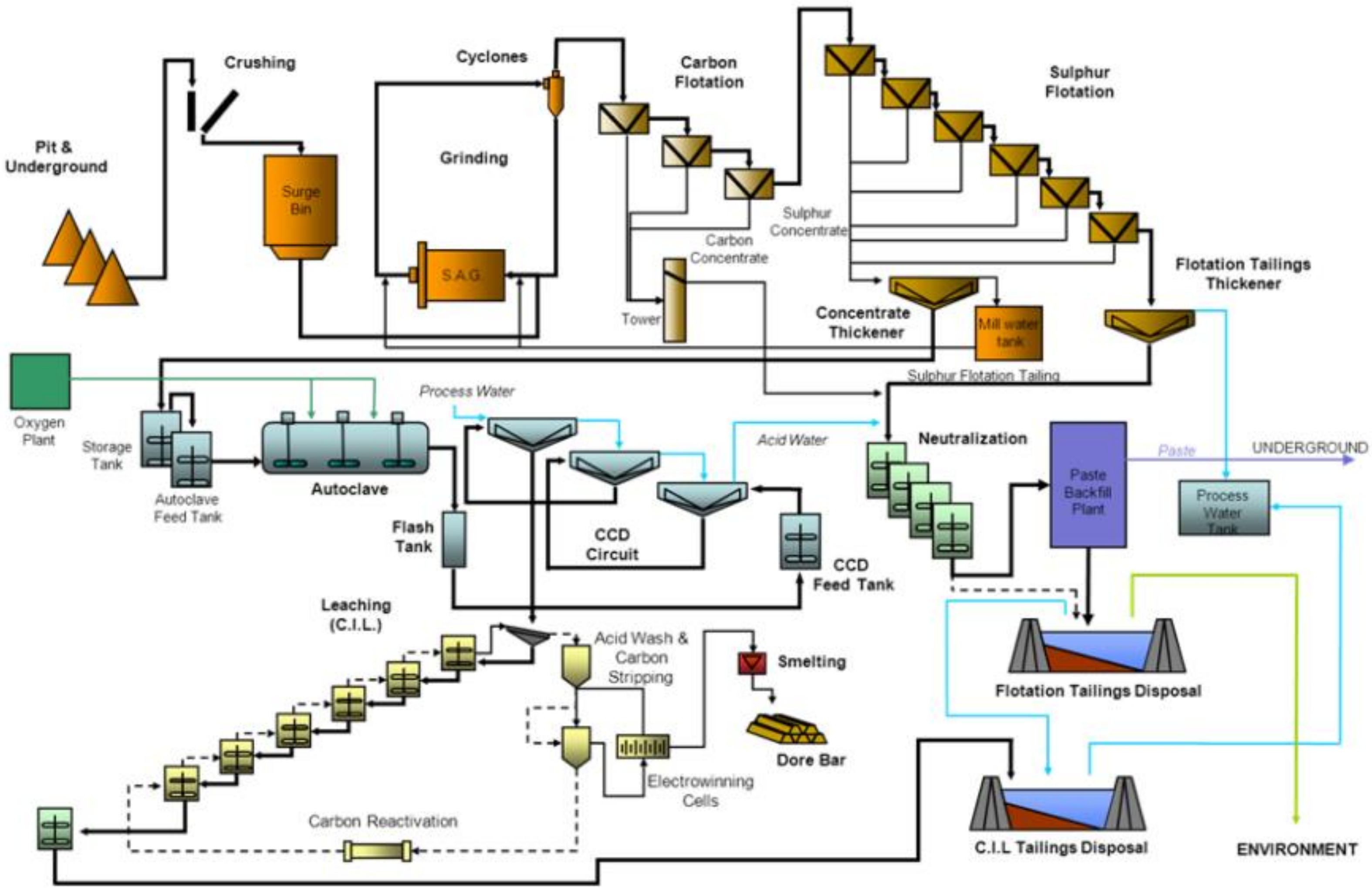
Mineral processing



Continuous, connected, controlled, circulating, complex, changing

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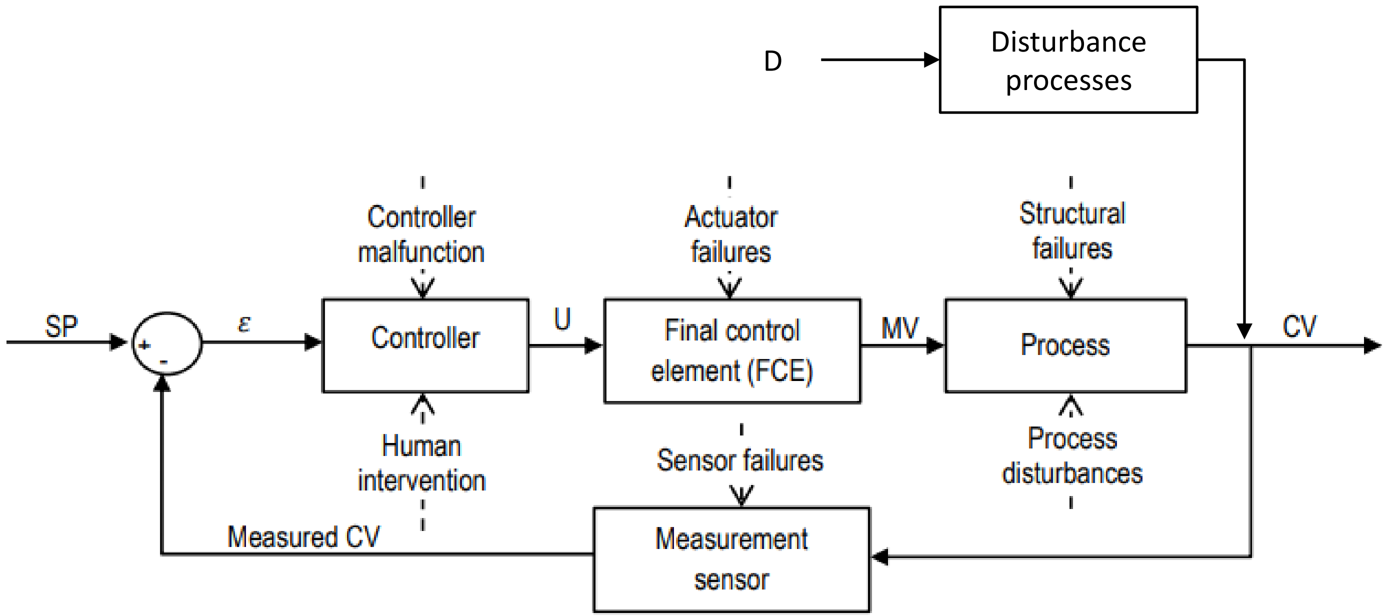
Industrial data

- Online physical property sensor data
  - E.g. mass flow rate, density, temperature, pressure
  - ~ seconds
- Online image data
  - E.g. rocks on conveyor belts, flotation froth (mud and bubbles)
  - ~ minutes
- Offline laboratory data
  - E.g. metal content, particle size distribution
  - ~ hours
- Offline image data
  - E.g. microscopic grain shape and colour
  - ~ days

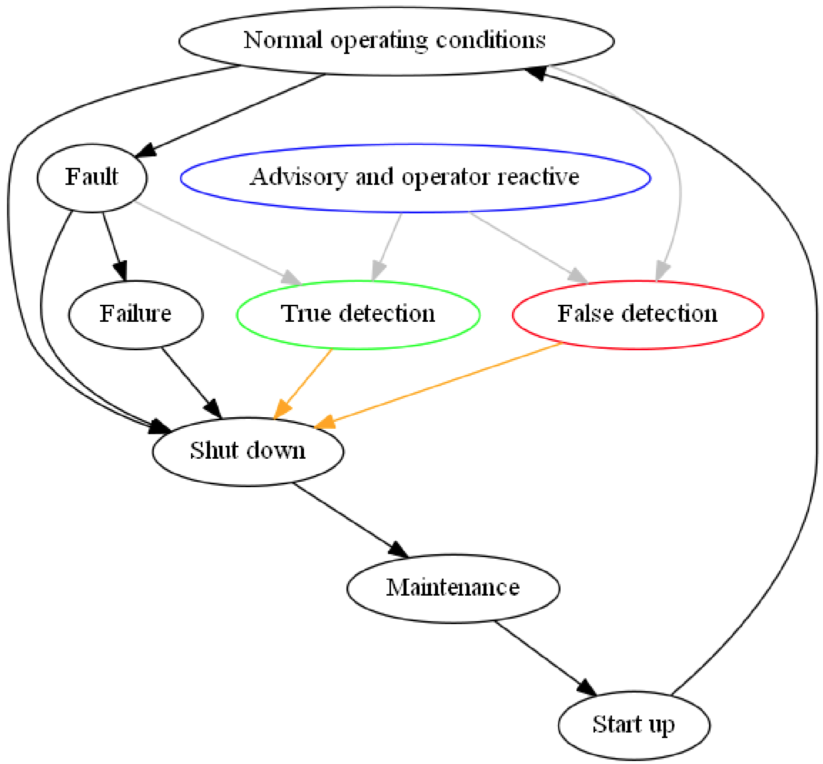
Abnormal event detection

- Many faults and failures can occur in complex processes
- Large variation in normal operating conditions due to range of allowable disturbances



Abnormal event detection

- Missed detections can lead to suboptimal performance, equipment failure, safety and environmental violations
- False alarms can lead to unnecessary downtime and loss of trust in alarm systems



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Abnormal event detection

- Unsupervised learning problem
  - Abundance of one class of data: Normal operating conditions
- Fault detection
  - Feature extraction
  - Data description / support estimation
- Fault identification
  - Topology extraction
  - Supervised learning model inspection:
    - Variable importance
    - Partial dependence

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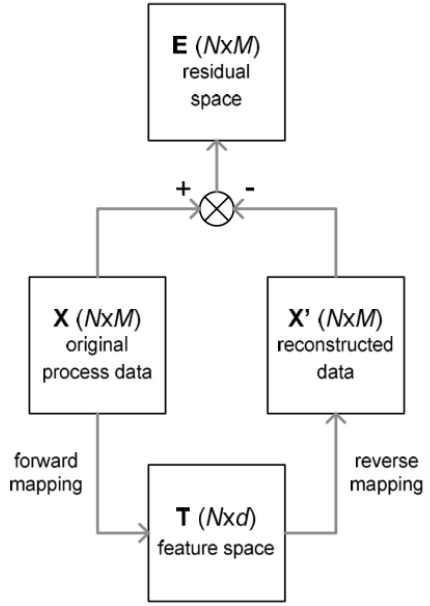
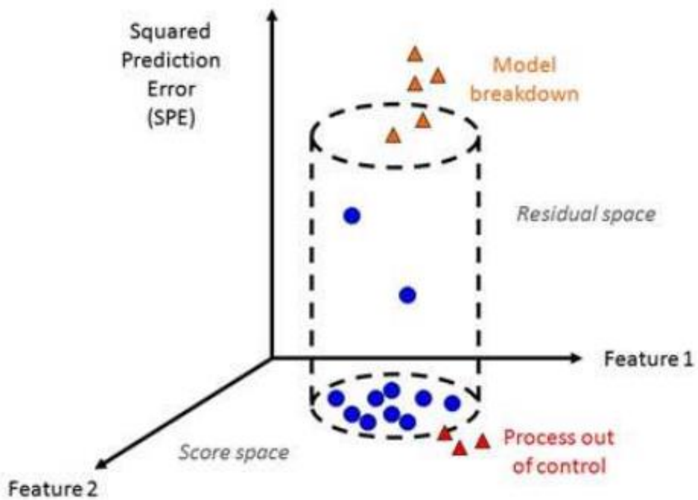
Abnormal event detection

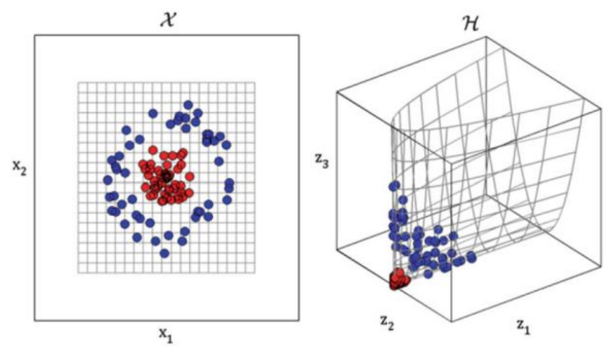
- Feature extraction
  - Sensor data **correlated** (through mass and energy balances, control instructions)
  - Sensor data **noisy**
  - **Feature space** represents lower dimensional, noise-free information
  - **Residual space** represents feature extraction model validity

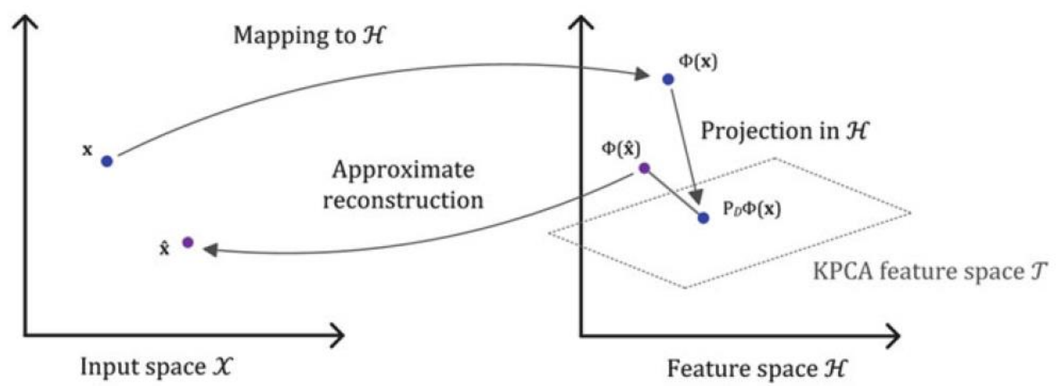




Abnormal event detection

- Feature extraction
  - Principal component analysis
    - $\boldsymbol{T}^* = \boldsymbol{X}\boldsymbol{P}^*; \widehat{\boldsymbol{X}} = \boldsymbol{T}^*(\boldsymbol{P}^*)^{\boldsymbol{T}}$
  - Kernel principal component analysis





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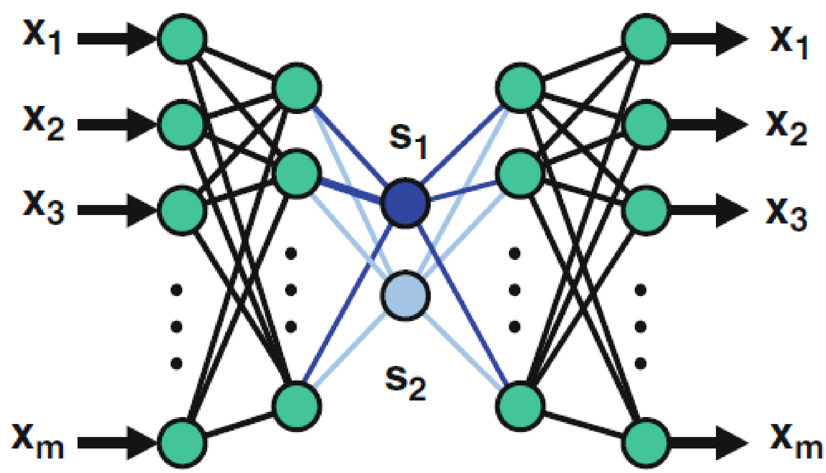
Abnormal event detection

- Feature extraction
  - Autoassociative neural networks (NLPCA)



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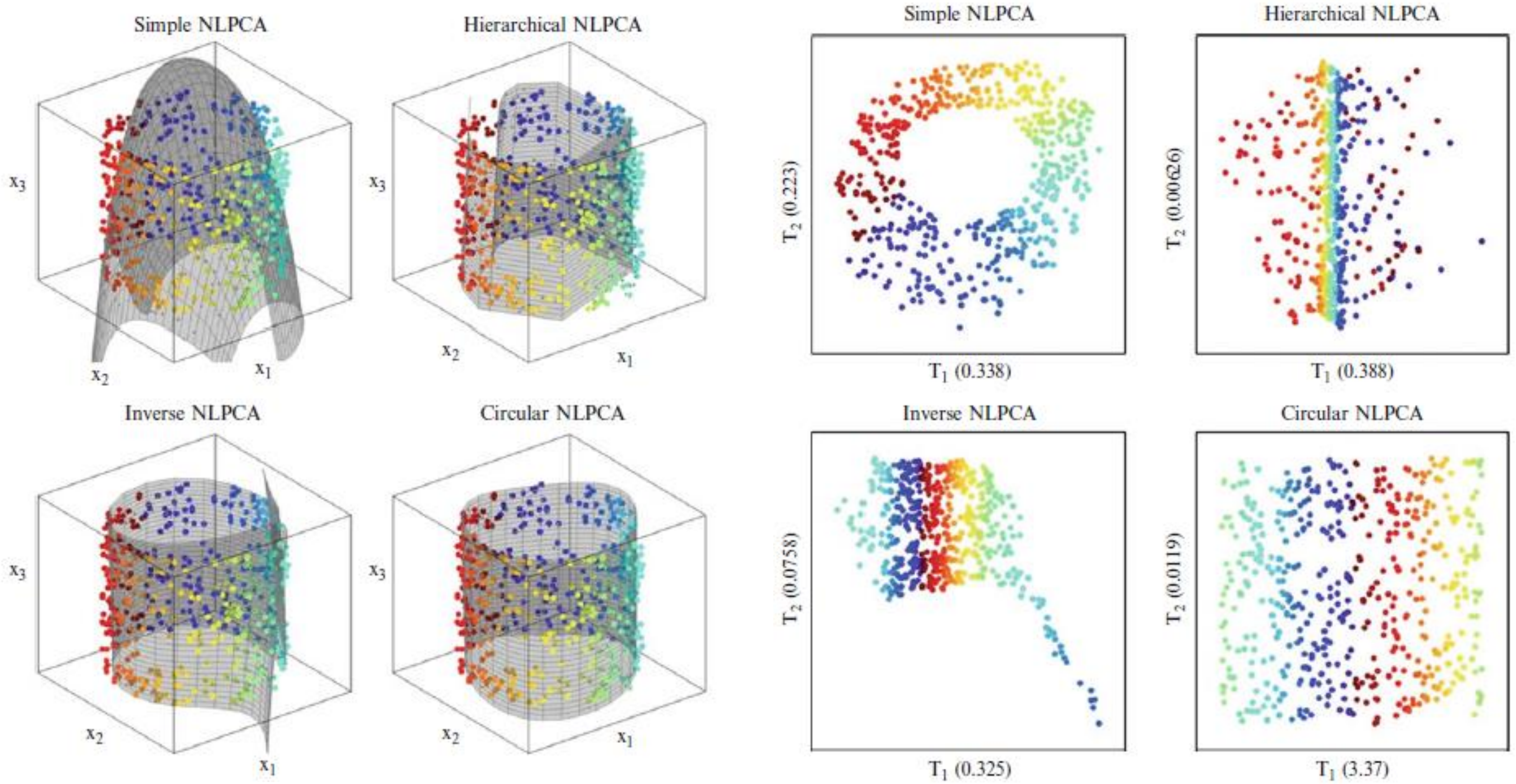
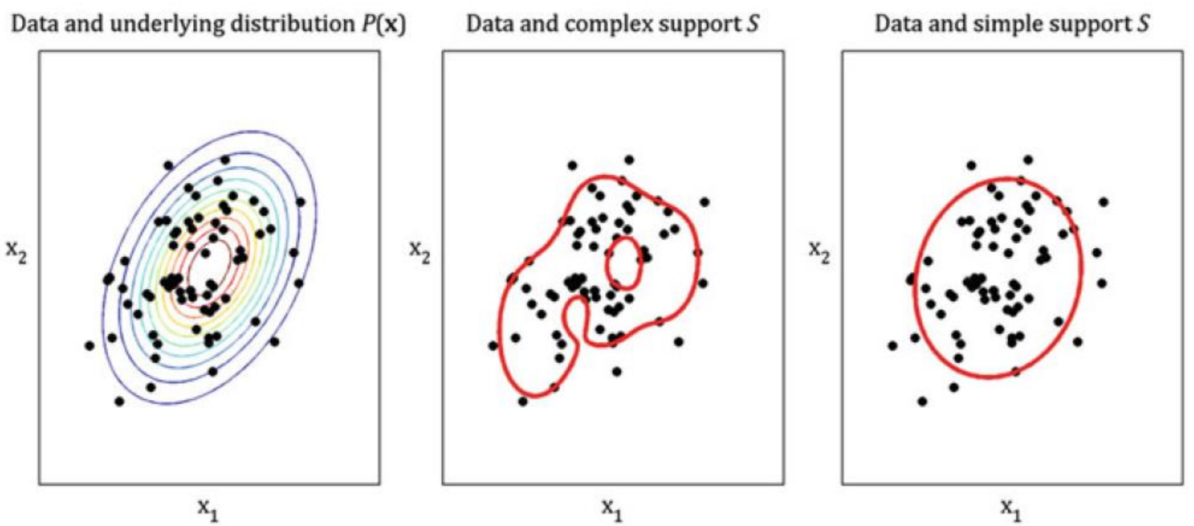


Abnormal event detection

- Data description / support estimation
  - Kernel density estimation
  - One-class support vector machines



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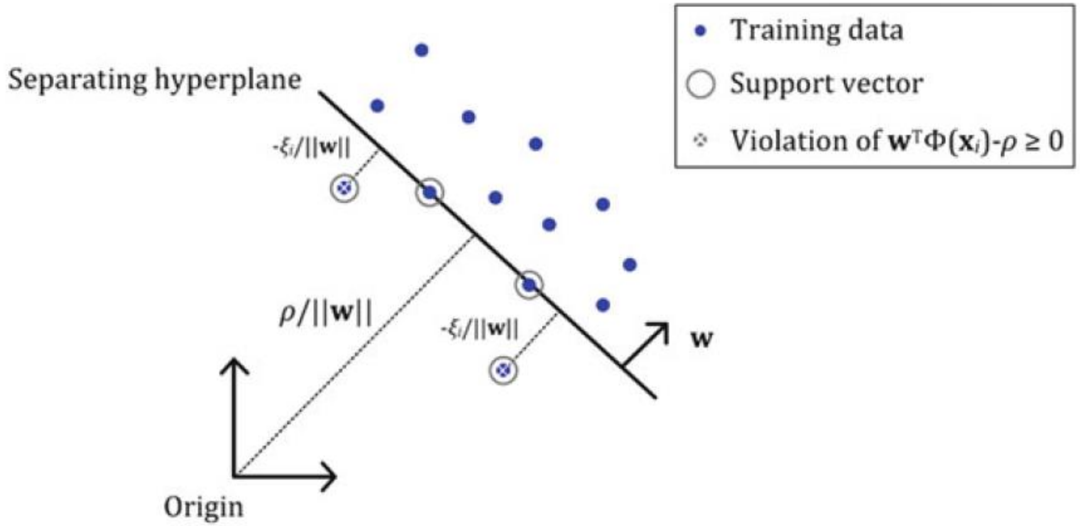

$$\min_{\mathbf{w},\rho,\xi}\left(\frac{1}{2}\|\mathbf{w}\|^2+\frac{1}{\nu N}\sum_{i=1}^{N}\xi_i-\rho\right)$$

subject to $\mathbf{w}^T\Phi(\mathbf{x}_i)-\rho+\xi_i \geq 0;\quad i=1,\ldots,N$

and $\xi_i \geq 0;\quad i=1,\ldots,N$

and $\rho \geq 0.$

Abnormal event detection

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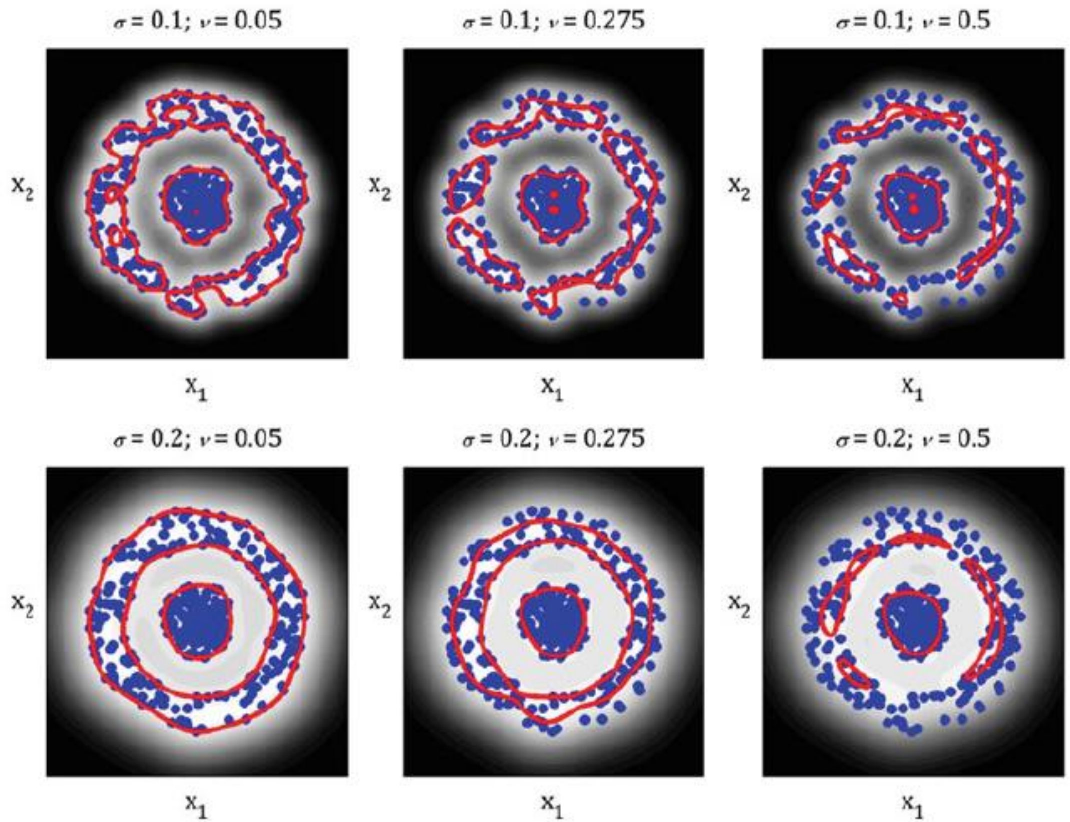

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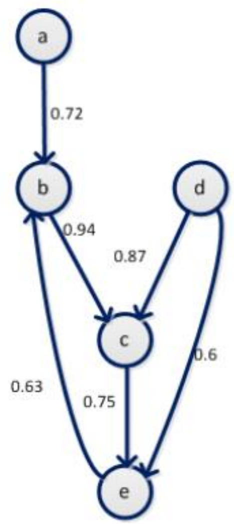
Abnormal event detection

- Topology extraction
  - Identification of propagation path of fault
  - Transfer entropy / lagged cross-correlation used to determine direction and strength of connections between variables



$$CM = \begin{array}{c} \\ a \\ b \\ c \\ d \\ e \end{array} \begin{array}{c} \begin{array}{ccccc} a & b & c & d & e \end{array} \\ \begin{bmatrix} 0 & 0.72 & 0 & 0 & 0 \\ 0 & 0 & 0.94 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 \\ 0 & 0 & 0.87 & 0 & 0.6 \\ 0 & 0.63 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

$$t(\mathbf{x}|\mathbf{y}) = \sum p(\mathbf{x}_{i+h}, \mathbf{x}_i, \mathbf{y}_i) \log\left(\frac{p(\mathbf{x}_{i+h}|\mathbf{x}_i, \mathbf{y}_i)}{p(\mathbf{x}_{i+h}|\mathbf{x}_i)}\right)$$

$$\rho_k^{LC} = \frac{1}{N-k} \sum_{i=1}^{N-k} \frac{(x_i - \mu_x)(y_{i+k} - \mu_y)}{\sigma_x \sigma_y}$$

Abnormal event detection

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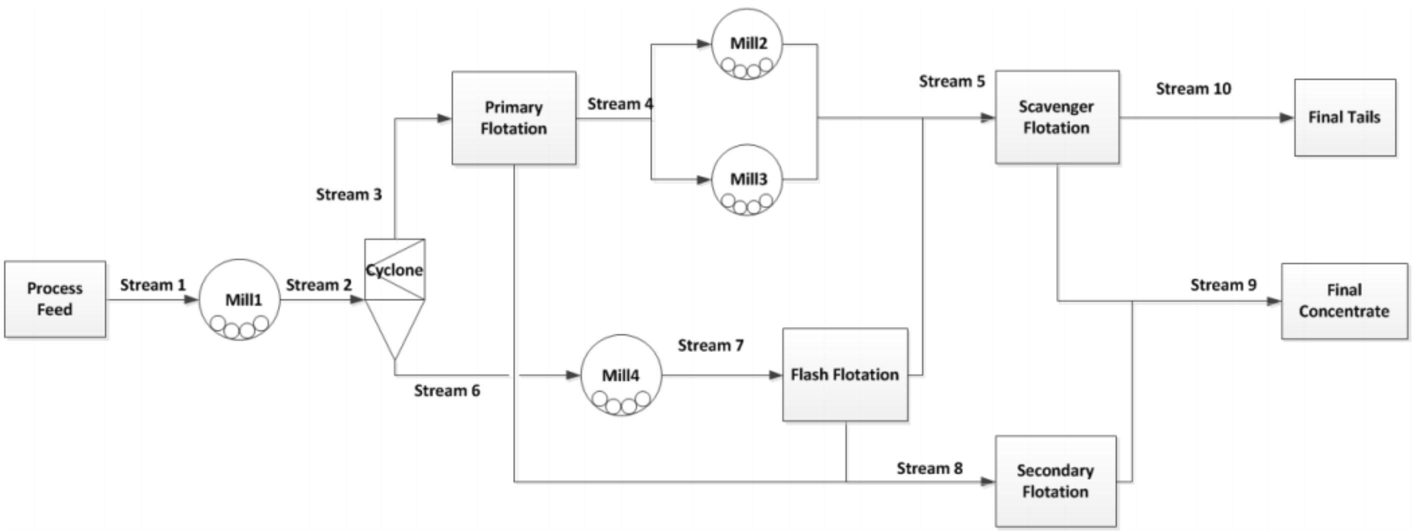

Abnormal event detection

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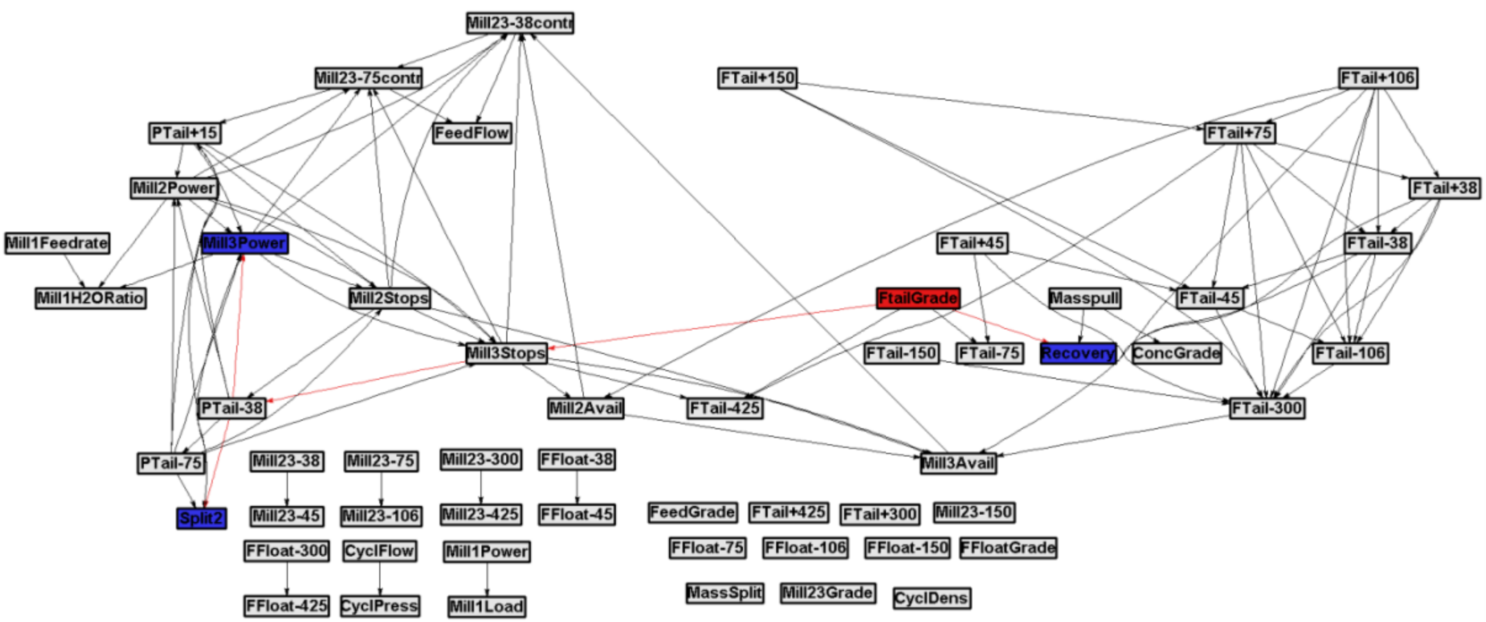

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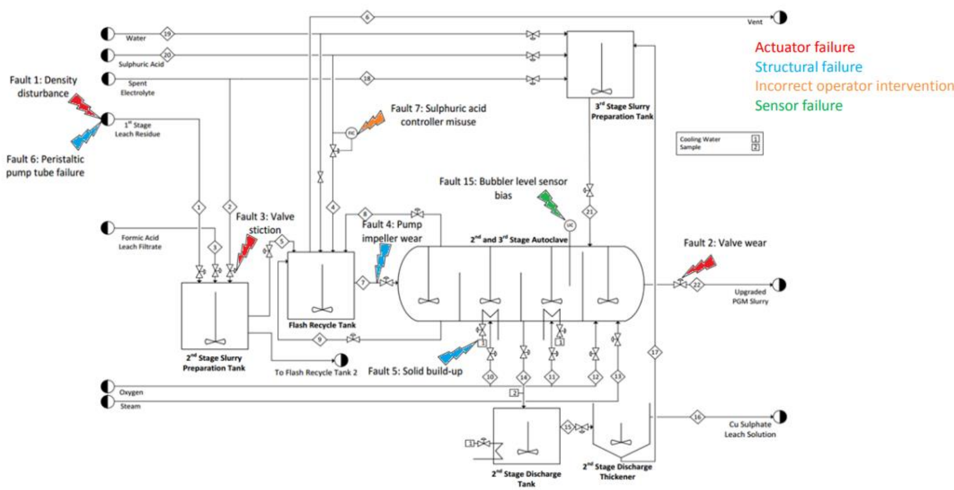
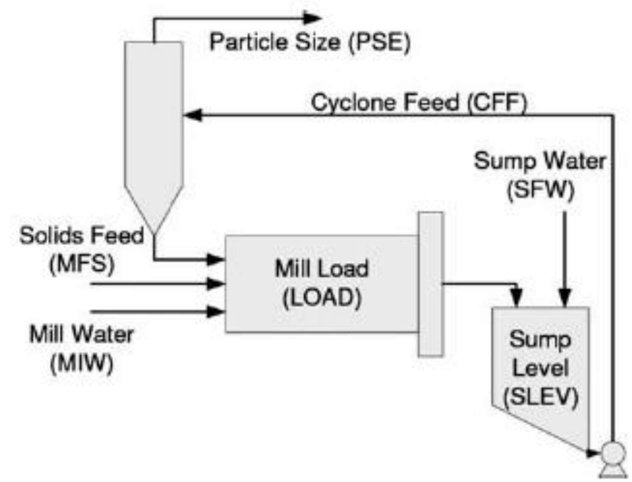
Abnormal event detection

- Research approach
  - Scarcity of industrial data with faults detected and identified
  - Simulation of complex, dynamic processes with known faults
  - Repository with dynamic models and simulated data





github.com/ProcessMonitoringStellenboschUniversity

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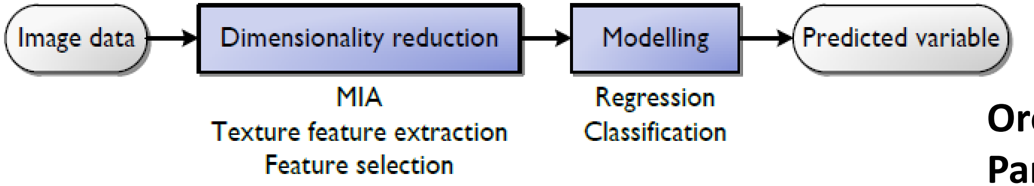
Soft sensors

- Ore characteristics
  - Metal content, particle size → correlated to process performance
  - Captured by image data
- Soft sensor
  - Trained model for prediction of process performance from measured process data



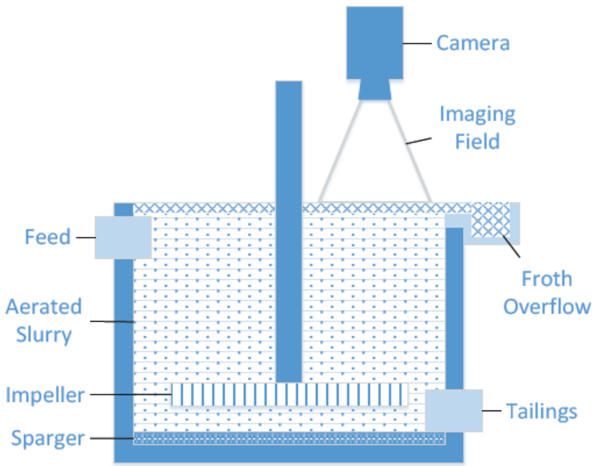
Ore grade
Particle size
Process state

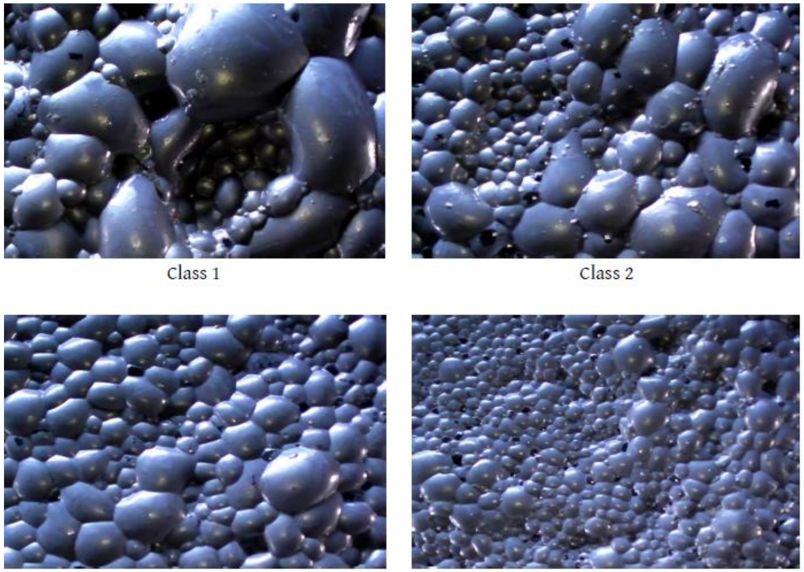
GLCM
Wavelet
Textons
Steerable pyramids
Etc.

k-NN
LDA

Soft sensors

- Flotation grade prediction with convolutional neural networks texture features and classification





Class 1 Class 2

Class 3 Class 4

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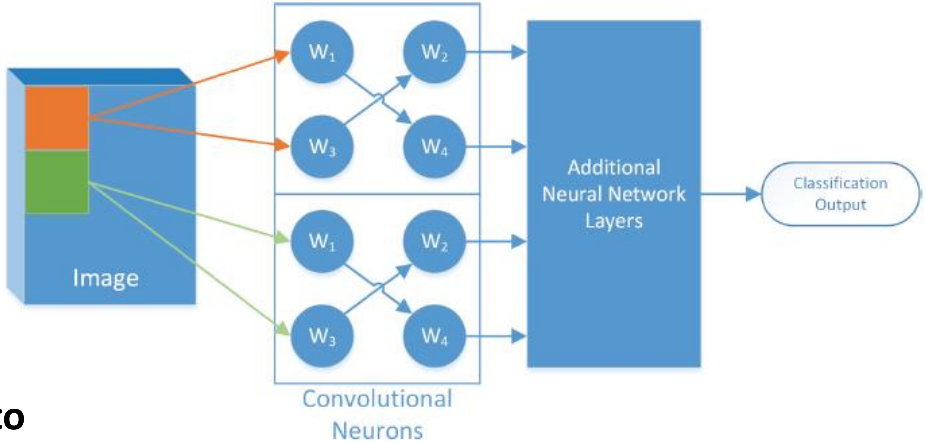
Soft sensors

- Flotation grade prediction with convolutional neural networks texture features and classification



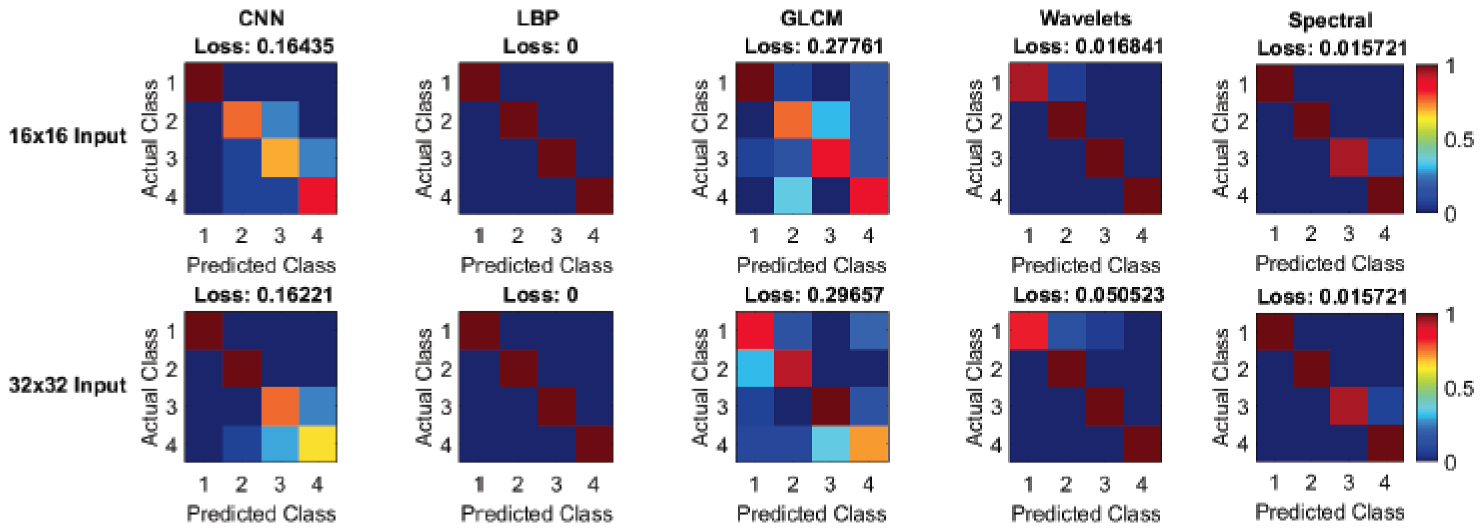
Variants generated to supplement data set

Bottleneck introduced to create lower dimensional feature space

Class labels used for training

Soft sensors

- Flotation grade prediction with convolutional neural networks texture features and classification



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Soft sensors

- Flotation grade prediction with convolutional neural networks texture features and classification

Interpretability important for industrial adoption

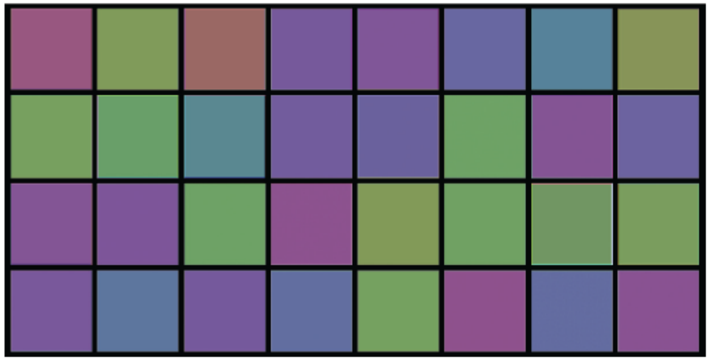

Figure 8-9: Deepdream Optimal Inputs for Filter Activation in First Convolutional Layer

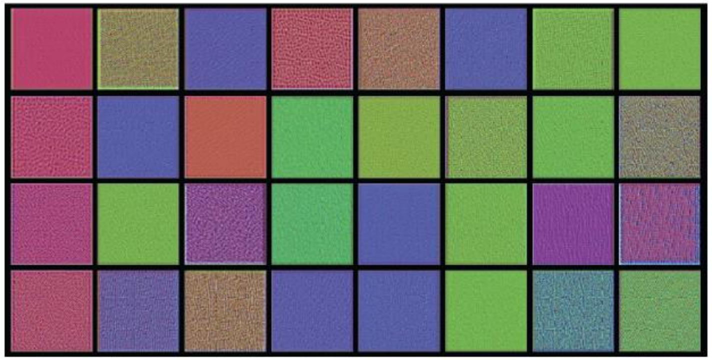

Figure 8-11: Deepdream Optimal Inputs for Filter Activation in Second Convolutional Layer (Contrast was enhanced in this image for visualisation purposes)

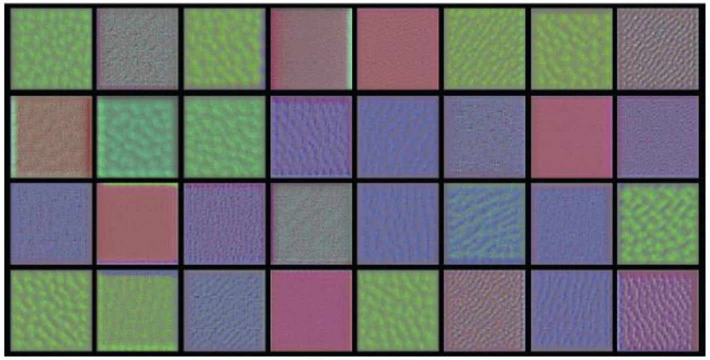

Figure 8-13: Deepdream Optimal Inputs for Filter Activation in Third Convolutional Layer

Challenges and opportunities

- Data size, quality and fusion
  - Potentially massive data sets
  - Shifting process conditions
  - Online process data + offline process data + maintenance records + mine plan + purchase orders + etc.
- Exploiting process knowledge
  - Dynamic Bayesian networks
  - Hybrid modelling
- Process recovery
  - Actionable insights
  - Reinforcement learning

Questions?

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