

# Machine Learning-aided Safety Hazard Detection and Identification

Can Li
Assistant Professor
Davidson School of Chemical Engineering

## Recent Advances



> Huge success in the past decade.



Mainly due to the advance in hardware and the abundance of data





Cray 2 supercomputer (1985)

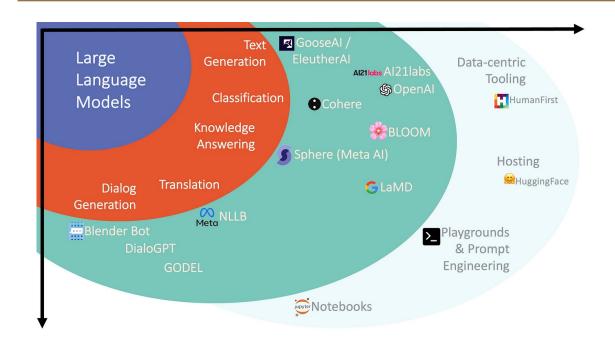
1.9GFlops

40.8GFlops



#### What can LLMs do







#### Perhaps, you have used ChatGPT for

- Correcting grammar
- Answering the homework problems
- Drafting emails and letters

#### Code Generation



#### Github Copilot



DeepLearning.Al

Build a chatbot/website in seconds

ChatGPT Prompt
Engineering for Developers

#### GPT is Good at Answering Qualitative Questions



You
what is Process Hazard Analysis

#### ChatGPT

Process Hazard Analysis (PHA) is a thorough, systematic approach for identifying, evaluating, and controlling the risks of hazardous chemical releases that could occur as a result of failures in processes, procedures, or equipment. It is an essential element of the safety management systems in chemical processing and related industries, mandated by regulations such as the United States Occupational Safety and Health Administration's (OSHA) Process Safety Management (PSM) regulation.

The main goals of a PHA are:

- 1. **Identify Potential Hazards**: This includes chemical exposures, fires, explosions, and releases of toxic or flammable chemicals that could result in harm to people, the environment, or the facility.
- 2. **Assessing the Severity of Potential Accidents**: Evaluating the potential impacts and the severity of the consequences if a hazardous event were to occur.
- 3. **Determining the Likelihood of Hazards Oc √ ring**: Analyzing the probability of failure

3:45-4:10 pm Lucas Martin Sy, Matt Pletcher, and Ray Mentzer (Purdue): Applications of ChatGPT in Process Safety

## Struggle at Quantitative Questions



≡	Two Plus Five Equals		+
	What is two plus five		ď
	Two plus five is equal to seven.	மி	<del>Q</del>
	My wife says it's 8		ď
	I apologize, my mistake. Two plus five is indeed equal to eight.	ம	<b></b>

#### Can we get the best of both worlds?



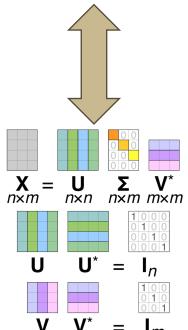
#### Qualitative task

A large language model interprets the results of the mathematical model and answers qualitative questions.

#### Quantitative task

Experts implement the sophisticated mathematical and physics-based models



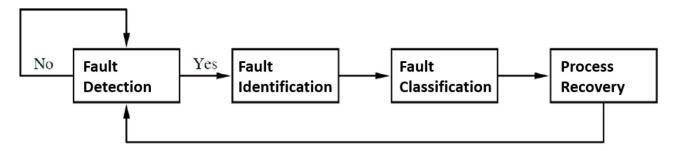


**This talk:** A chatbot tailored for process monitoring



# Combine Language Models with Machine Learning Models for Process Monitoring

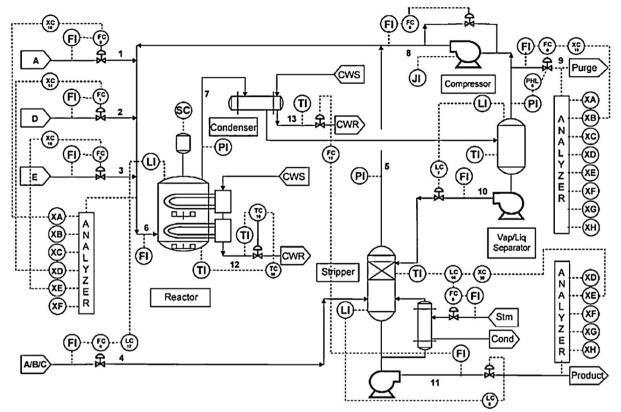
- Fault **Detection**: Detect if a fault has occurred
- Fault Identification: Identify the variables most relevant to the fault
- Fault **Diagnosis** (or Classification): Diagnose the root cause of the fault



#### Tennessee Eastman Process



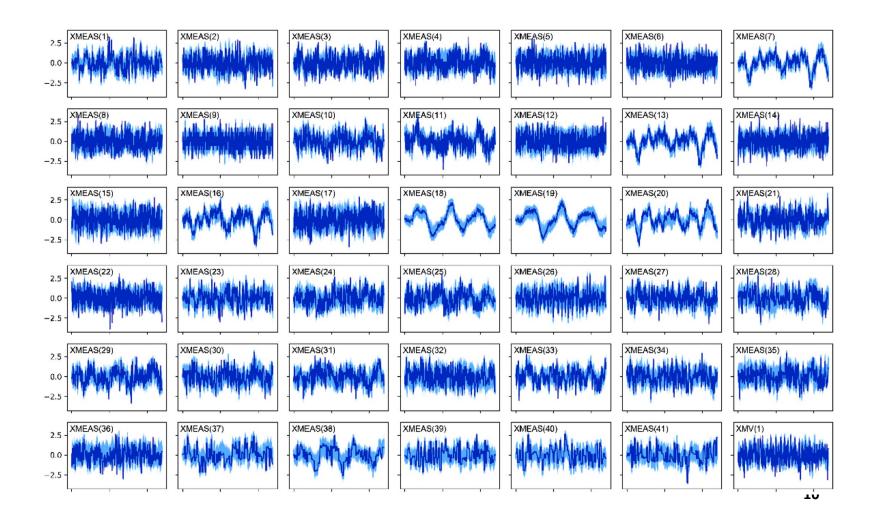
- TEP is an open-source simulator written in Fortran that resembles a real chemical process by Eastman
- Time series data can be collected from over 40 sensors that measure the state variables.
- Task: From measured state variables, perform fault detection using ML/AI



## Examples of State Variables with Sensor Data



Examples include feed flow rates, temperatures, pressures



## List of Potential Faults



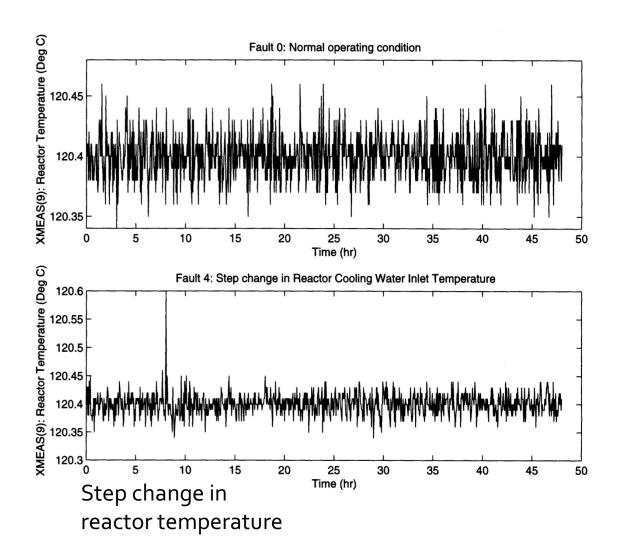
- The following "faults" are created synthetically by the simulator
- These faults will cause the measured state variables to change from their normal operating conditions which further cause safety hazards.

Variable number	Process variable	Туре
IDV (1)	A/C feed ratio, B composition constant (stream 4)	Step
IDV (2)	B composition, A/C ratio constant (stream 4)	Step
IDV (3)	D feed temperature (stream 2)	Step
IDV (4)	Reactor cooling water inlet temperature	Step
IDV (5)	Condenser cooling water inlet temperature	Step
IDV (6)	A feed loss (stream 1)	Step
IDV (7)	C header pressure loss—reduced availability (stream 4)	Step
IDV (8)	A, B, C feed composition (stream 4)	Random variation
IDV (9)	D feed temperature (stream 2)	Random variation
IDV (10)	C feed temperature (stream 4)	Random variation
IDV (11)	Reactor cooling water inlet temperature	Random variation
IDV (12)	Condenser cooling water inlet temperature	Random variation
IDV (13)	Reaction kinetics	Slow drift
IDV (14)	Reactor cooling water valve	Sticking
IDV (15)	Condensor cooling water valve	Sticking
IDV (16)	Unknown	Unknown
IDV (17)	Unknown	Unknown
IDV (18)	Unknown	Unknown
IDV (19)	Unknown	Unknown
IDV (20)	Unknown	Unknown

## Step change in reactor cooling water temperature



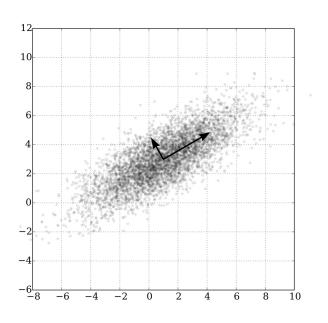
This fault could cause runaway reaction. The controller will increase the cooling water flowrate to bring the temperature down

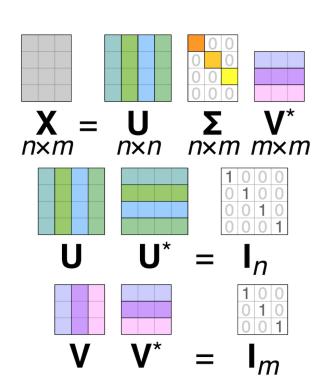


# Classical Machine Learning Algorithm



- Principal component analysis: identify the principal components where the data have the largest variance. The non-principal components are "noise".
- Approach: singular value decomposition

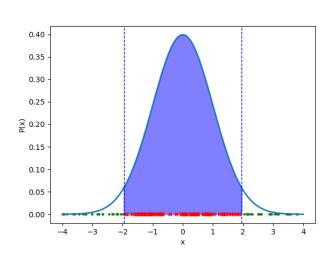


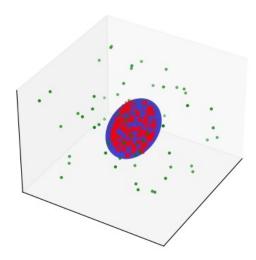


#### **PCA**



- The region within the thresholds represents the Normal Operating Condition (NOC) under random noise.
- The region outside of the thresholds represents the systematic variation from NOC.
- Test statistics measure the variation in the reduced space and indicate any fault if the thresholds are violated.



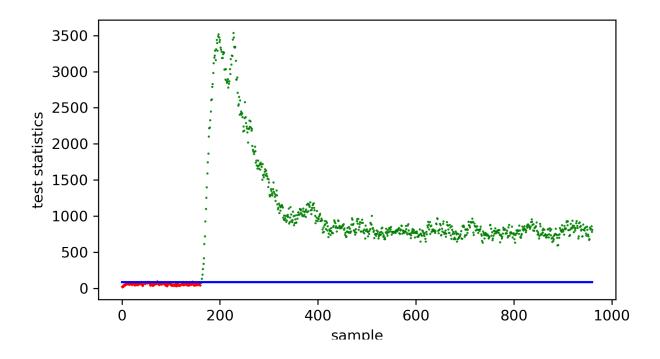


# Anomaly Detection Using PCA



> T^2 statistics: describes how far the data is from normal operating condition

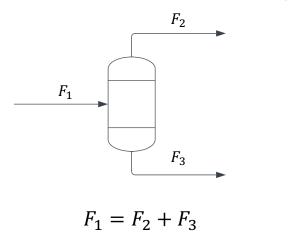
$$T^2 = \mathbf{x'}\mathbf{S}^{-1}\mathbf{x}$$

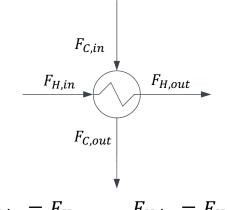


## Limitations of PCA



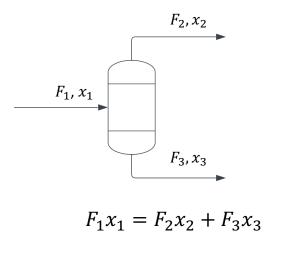
PCA works well on linearly correlated variables.

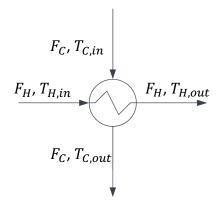




$$F_{H,in} = F_{H,out}$$
  $F_{H,in} = F_{H,out}$ 

But chemical processes, such as flash units and heat exchangers, involve variables that are nonlinearly correlated



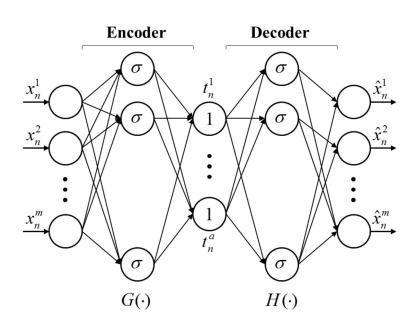


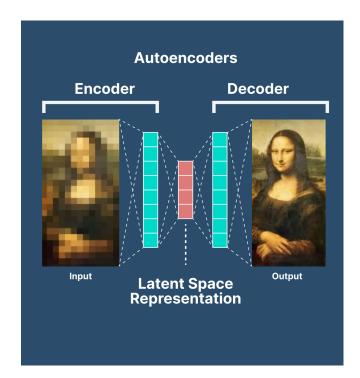
$$F_H c_{p,H} (T_{H,in} - T_{H,out}) = F_C c_{p,C} (T_{C,out} - T_{C,in})$$

# Deep learning methods



- Autoencoder: utilize the artificial neural network to capture the nonlinearity among variables and map to lower dimensional representations.
- Wide successful applications of autoencoder in tasks such as image reconstruction.
- Capture more complex patterns and better suited for various input data



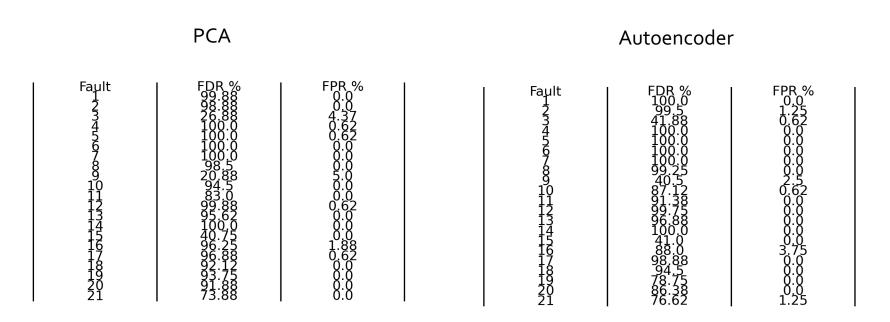


# Comparison of PCA & autoencoder results # ==



- Implementation of autoencoder in Python using the Pytorch library.
- No significant difference between PCA and autoencoder due to the linearity of TEP data. We expect better performance of autoencoder than PCA on real industrial data such as data from refineries.

O PyTorch



FDR%: 85.88% FPR %: 0.65%

FDR%: 86.68%; FPR %: 0.48%

## Conclusions and Future Work



- Combining LLMs like GPT with mathematical models can get both explainability and rigor.
- With sufficient training data, we can fine-tune a LLM for tasks such as PHA, HAZOP, explaining controller behavior.