

https://github.com/Dr-AlaaKhamis/ISE518/tree/main/5_Datafication

Lecture 6 – Wednesday September 10, 2025

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Outline

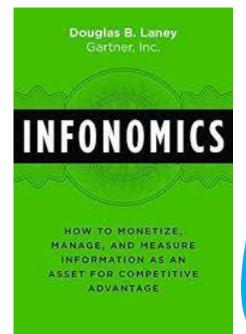
- Datafication
- Condition Monitoring Sensors
- Data Types
- Design of Experiment (DOE)
- Data Governance

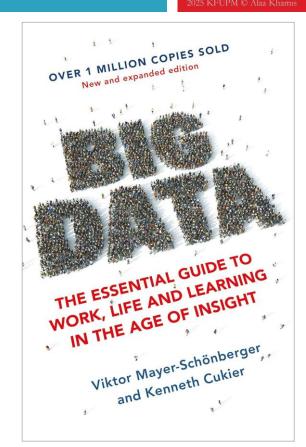
Outline

- Datafication
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Datafication is the broad, technology-driven process of turning actions, interactions, objects and even thoughts into quantified data streams that can be stored, analyzed and monetized. The term was popularized by Viktor Mayer-Schönberger and Kenneth Cukier in Big Data: A Revolution That Will Transform How We Live, Work and Think (2013).

Infonomics is "the theory, study and discipline of asserting economic significance to information," applying "economic and asset-management principles and practices to the valuation, handling and deployment of information assets.







- **Data explosion:** Today, around 147–181 zettabytes of data are estimated to exist globally, with projections reaching 181 ZB by 2025.
- Recent generation: While exact definitions vary, many estimates suggest that ~90% of this data was generated in just the past two years.
- **Digitization dominance:** Virtually all modern data is digital—already by 2014, data in digital format accounted for over 99% of all stored information.
- Unstructured and user-generated: Around 90% of global data is unstructured, and about 70% is user-generated (e.g., social media, videos, emails)



IoT sensors generate ~200 million TB every day



Autonomous Vehicles: 4-20 TB per day



Facebook: 350 M images uploaded per day



X community generates more than 12 terabytes of data per day



YouTube: 300 hours of video uploaded every minutes

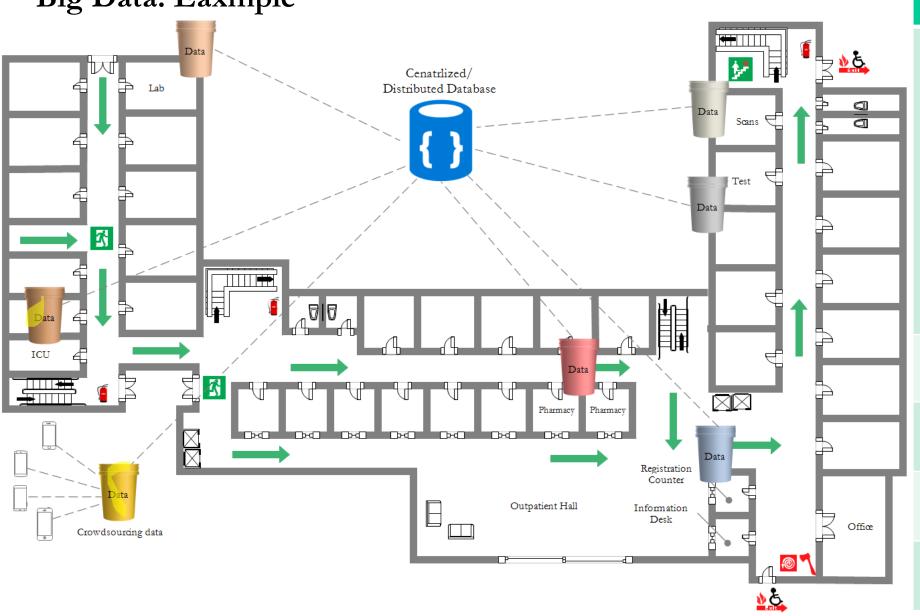


Walmart: 2.5 Petabytes of customer data hourly

• Big Data: Structured vs. Unstructured Data

Industry	Structured data (rows & columns, well-defined schema)	Unstructured data (free-form text, images, sound, etc.)
Manufacturing	SCADA sensor logs (timestamp, machine ID,	Maintenance-crew voice notes and equipment
	temperature, vibration, rpm) stored in a SQL	photos describing faults; PDF equipment manuals
	historian	
Retail / e-commerce	Point-of-sale transactions (SKU, price, quantity,	Customer reviews and star ratings; product-demo
	storeID, time)	videos and images
Banking / fintech	Core-bank ledger records (account #, debit, credit,	Chat-bot transcripts, KYC selfie images, call-center
	balance, currency)	audio recordings
Healthcare	EMR/EHR vitals table (patient ID, visit date, BP,	Radiology DICOM images, doctor's free-text
	HR, lab values)	notes, pathology slide images
Transportation /	Telematics table (vehicle ID, GPS lat/long, speed,	Dash-cam videos, driver voice logs, shipping-label
logistics	fuel level, timestamp)	scans
Energy / utilities	Smart-meter readings (meter ID, kWh, reactive	Drone imagery of power-line inspections, PDF
	power, interval)	regulatory filings
Media & entertainment	Subscriber database (user ID, plan tier, join date,	Streaming-service watch-history text, movie &
	churn flag)	show video files, social-media posts about releases

• Big Data: Eaxmple



Example	
 X-rays Computerized tomography (CT or CAT scan) Positron Emission Tomography (PET scan) Magnetic Resonance Imaging (MRI) 	
audio or voice reports	
Patient cardTest results	
Medical reportsReviews	
Electronic Medical Records (EMR)	

• Big Data: The 4 V's

40 ZETTABYTES

of data will be created by 2020, an increase of 300 times from 2005



6 BILLION PEOPLE

have cell phones world population: 7 BILLION







2.5 QUINTILLION BYTES

of data are created each day



Most companies in the U.S. have at least

100 TERABYTES

of data stored



As of 2011, the global size of data in healthcare was estimated to be
150 EXABYTES



30 BILLION PIECES OF CONTENT

are shared on facebook every month



Variety

DIFFERENT FORMS OF DATA

4 BILLION + HOURS OF VIDEO

are watched on You Tube each month



4 MILLION TWEETS

are sent per day by about 200 million monthly active users



The New York Stock Exchange captures

1TB OF TRADE INFORMATION

during each trading session _



Velocity

ANALYSIS OF STREAMING DATA Modern cars have close to

100 SENSORS

that monitor items such as fuel level and tire pressure



1 IN 3 BUSINESS LEADERS

don't trust the information they use to make decisions



Veracity

UNCERTAINITY OF DATA

27% OF RESPONDENTS

in one survey were unsure of how much of data was inaccurate





• Big data sizes



Byte of data: one grain of rice





Gigabyte: 3 container lorries



Kilobyte: cup of rice



Terabyte: 2 container ships



Megabyte: 8 bags of rice



Petabyte: covers Manhattan



Exabyte: covers Germany twice



Zettabyte: fills the Pacific ocean

• How much training data is required for machine learning?

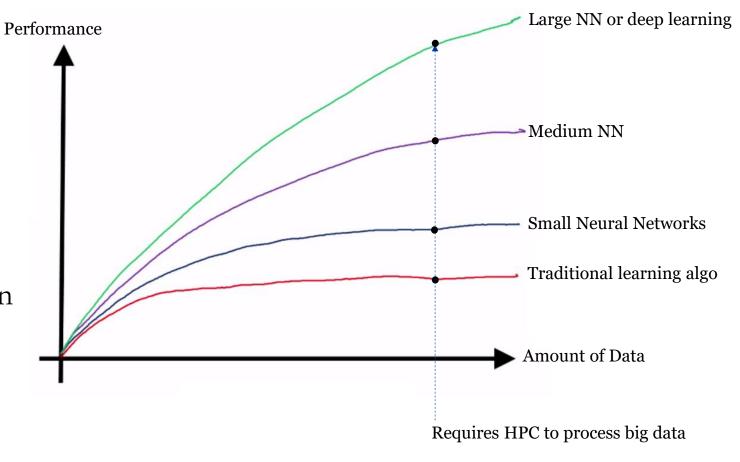
Better Data != More Data

Data Without a Sound Approach = Noise

• How Much Training Data is Required for Machine Learning?

The amount of data required for machine learning depends on many factors, such as:

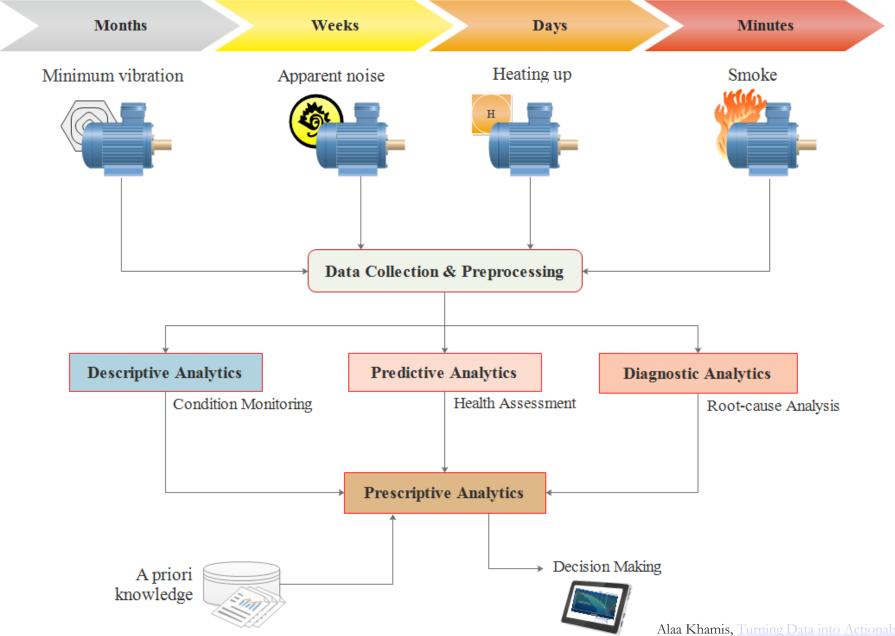
- The complexity of the problem, nominally the unknown underlying function that best relates your input variables to the output variable.
- The complexity of the learning algorithm, nominally the algorithm used to inductively learn the unknown underlying mapping function from specific examples.





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Condition Monitoring Sensor Examples: power meter, non-intrusive CTs, Magnets vibration sensor,

temperature sensors.



Power meter



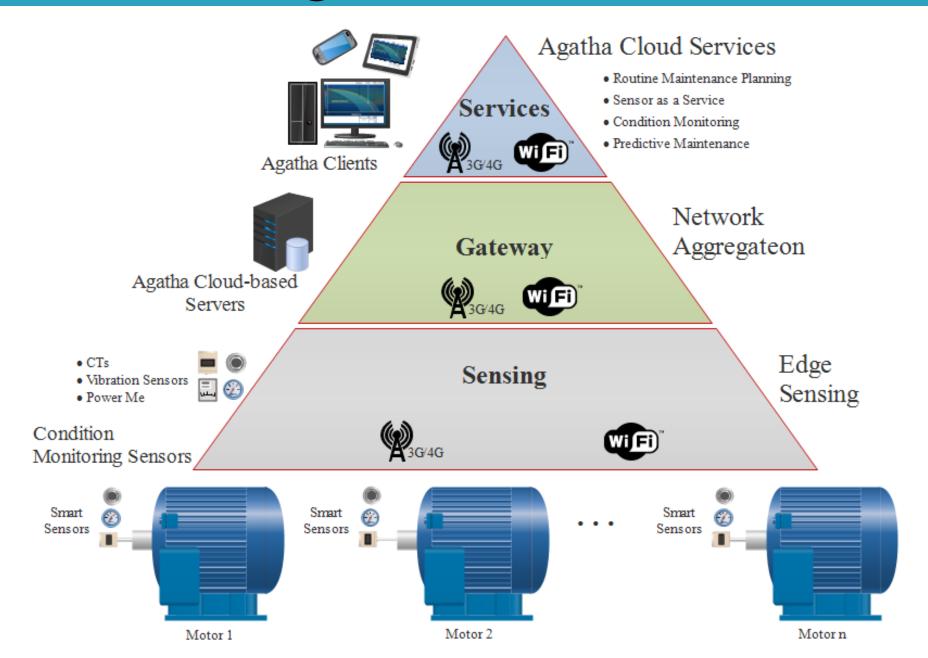
CT sensors



Vibration Sensor



Temperature Sensor



Non-intrusive CT (Current Transformer) Sensors: clamp around conductors to measure current safely without cutting wires. They transmit real-time data for energy monitoring, load management, and fault detection, making them ideal for smart grids and building management.



- **Vibration Sensor:** Continuous Vibration Monitoring and Protection of Critical Equipment Monitors and protects 24/7
 - Operates off standard 24V loop power
 - Interfaces with plant monitoring &PI systems
 - Installs quickly and easily
 - Provides critical machine information
 - Avoids costly
 - catastrophic failures

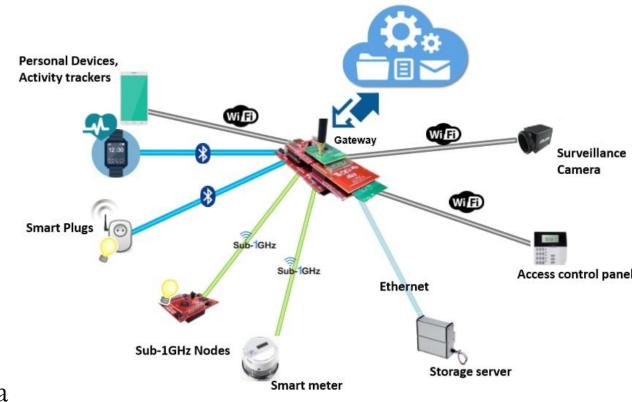


• **Power Meter:** 3 phase power meter with current and voltage transducers are mandatory to monitor the electric panels status (On/Off, normal or overload)

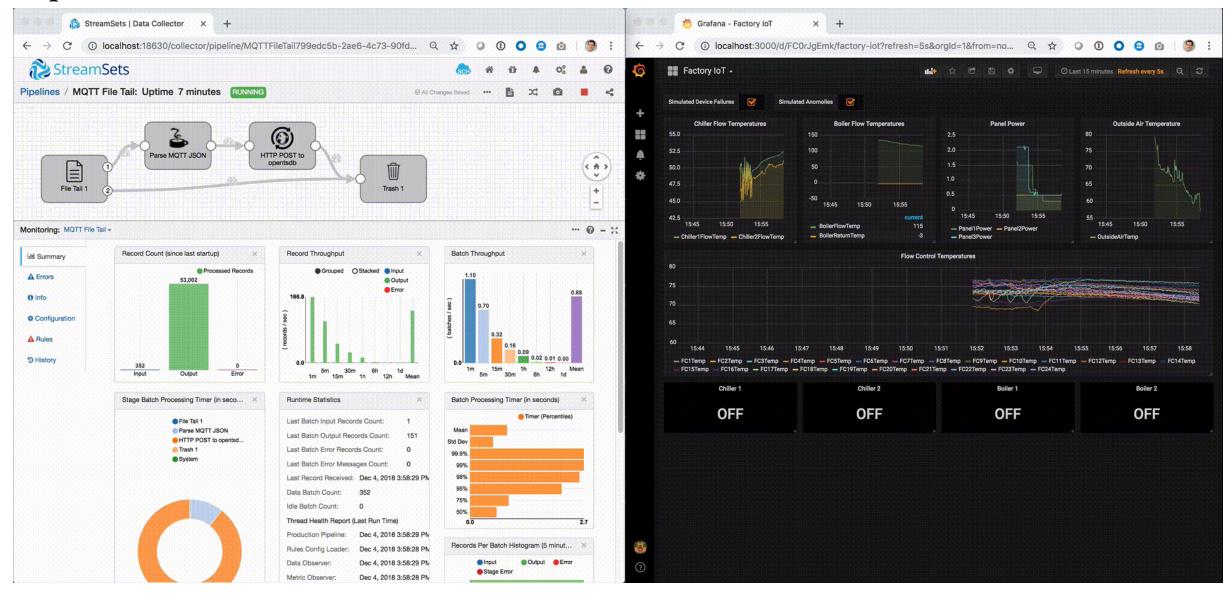


- **Temperature Sensors:** provide continuous, real-time data on equipment heat levels without disrupting operations. By detecting abnormal temperature rises, they help predict failures, prevent downtime, and improve safety, making them essential for motors, bearings, and other critical assets.
 - Thermocouples: durable, wide temperature range, common in heavy industry.
 - RTDs (Resistance Temperature Detectors): highly accurate and stable, used where precision is critical.
 - Thermistors: sensitive and fast-responding, suited for narrow-range monitoring.
 - Infrared (IR) sensors: non-contact, useful for moving parts or inaccessible surfaces
 - Wireless IoT sensors: enable remote, real-time monitoring and integration with predictive maintenance systems.

- **IoT Gateway:** Multi-communication channels to collect the data from the different sensors and direct this data to the cloud server to be analyzed. The following technical specifications are required:
 - Wi-Fi, Ethernet, RS 485, 3G/4GConnectivity
 - 12 industrial sensor Analog input (4-20 ma)
 - 8 Relay Output 220V/3A
 - Configurable over LAN and WAN
 - Secure access control
 - Sampling rate: up to 10 seconds sensors data
 publish rate



• Operational Dashboard:

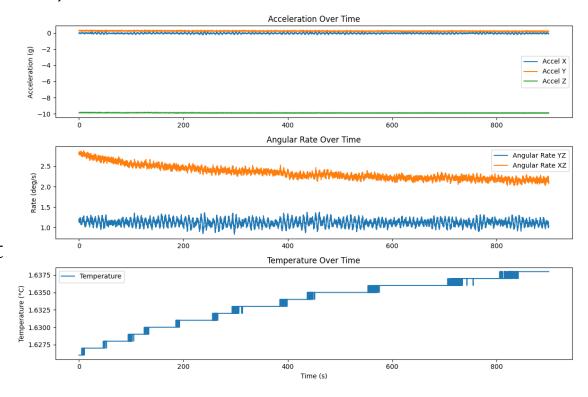


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Data Type	Example Sources
Time-Series	Vibration, temperature, pressure, flow, voltage
Acoustic/Ultrasonic	Leak detection, bearing diagnostics
Thermal/Imaging	IR cameras, visual inspections
Event/State Logs	PLC alarms, operational status
Historical Structured	CMMS data, asset metadata
Analytical/Lab	Oil/lubricant, wear debris analysis
Human/Annotation	Operator notes, RCA, inspection logs

- Time-Series Sensor Data
 - Continuously sampled measurements over time, essential for trend and anomaly detection.
 - Vibration data (accelerometers, velocity, displacement)
 - Temperature readings (thermistors, RTDs)
 - Pressure data
 - Flow rate measurements
 - Electrical current & voltage (e.g., motor current signature analysis)
 - RPM / speed / torque sensors
 - Environmental data (humidity, ambient temperature)



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Acoustic & Ultrasonic Data

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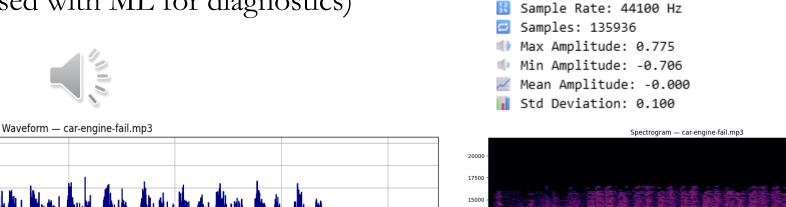
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High-frequency signals, often analyzed in waveform or spectrogram formats.

Ultrasound sensor data (bearing inspection, leak detection)

1.5

- Acoustic emissions (early-stage fault detection in mechanical parts)
- Sound recordings (used with ML for diagnostics)



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File: data/audio/car-engine-fail.mp3

Duration: 3.08 s



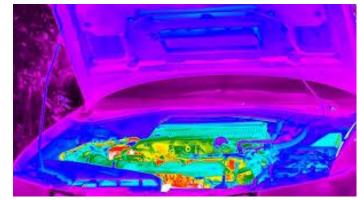
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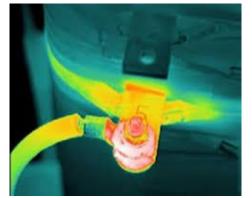
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• Thermal/Imaging Data

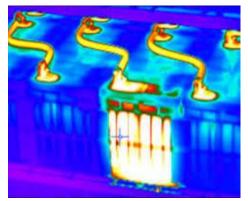
Spatial or pixel-based data capturing thermal signatures or visual cues.

- Infrared thermography (IR images/videos)
- Visual inspections (RGB cameras)
- Thermal maps of components or systems

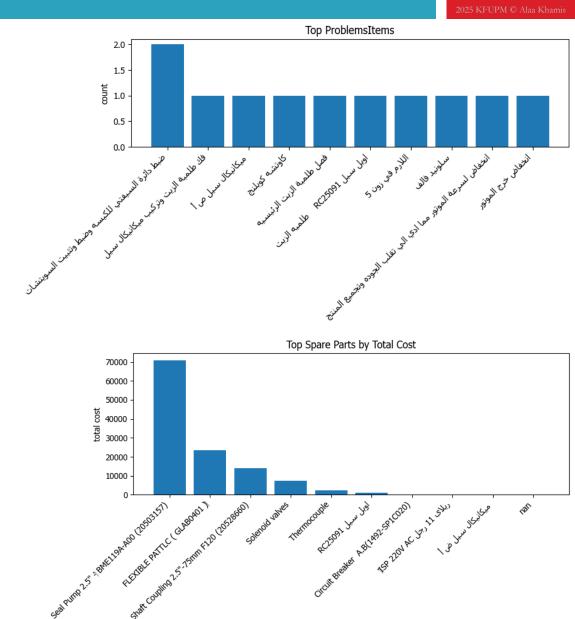








- Logo/Event/State Data
 - Discrete logs or flags representing system state changes or events.
 - PLC/DCS alarms and event logs
 - Fault codes and error messages
 - Start/stop events
 - Operating mode/status (idle, running, error)



- Structured Historical/Maintenance Data
 - Tabular data, useful for failure modeling and supervised ML.
 - CMMS / EAM data (work orders, failure reports, mean time between failures)
 - Asset metadata (make, model, age, location, specs)
 - Maintenance logs (corrective, preventive actions taken)
 - Downtime records

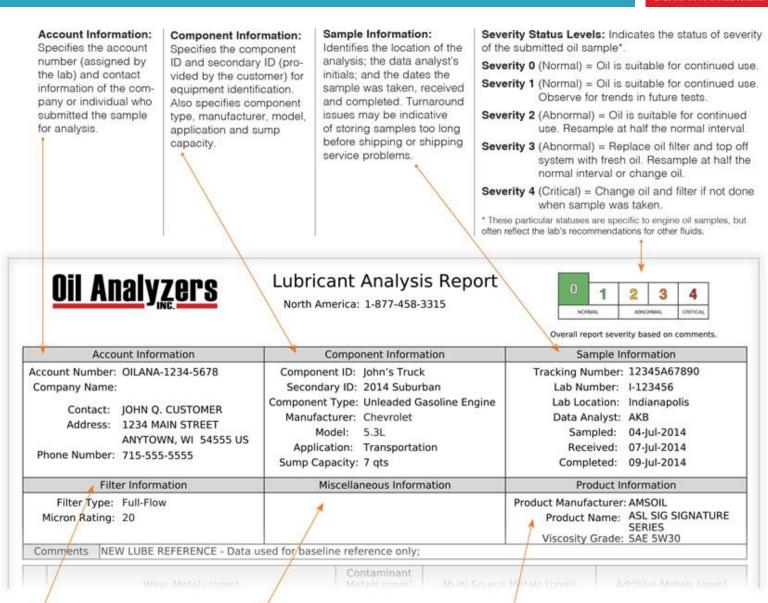


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Normal

- Analytical/Lab Data
 Intermittently collected and labanalyzed, often stored in
 structured format.
 - Oil/lubricant analysis (particle count, water content, viscosity)
 - Wear debris analysis
 - Coolant contamination analysis



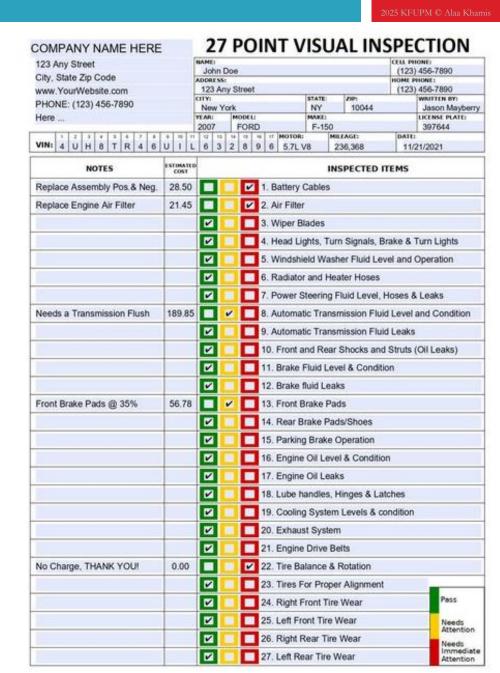
Filter Information: Identifies the filter used and its micron rating. **Miscellaneous Information:** Details additional miscellaneous information.

Product Information: Identifies the sample lubricant and its properties.

Human Input / Expert Annotations

Qualitative or semi-structured data, increasingly used in supervised learning.

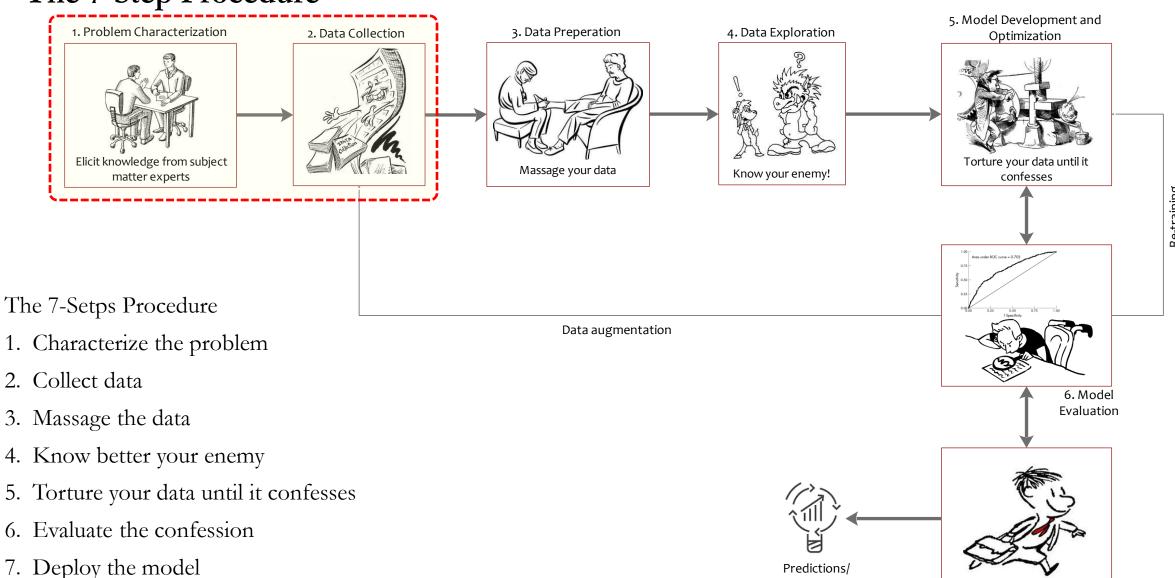
- Operator observations
- Manual inspection notes
- Failure root cause analysis (RCA) reports
- Expert labeling of fault types



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• The 7-Step Procedure



Actionable insights

7. Model Deployment

Controlled Factors

Independent variables that represent design parameters changeable during data collection process

Signals

Independent variables or stimuli required for fulfilling the model functionality

RUL Prediction Model

Response

Dependent variables that represent primary intended functional output of the model

Noise Factors

Independent variables that influence prediction model, controllable during data collection process and uncontrollable after deploying the model

Error States

Failure modes or effects of failure as defined by enduser when using the model



CO: Safe Driving



C1: Text Right



C2: Phone Right



C3: Text Left



C4: Phone Left



C5: Adjusting Radio



C6: Drinking



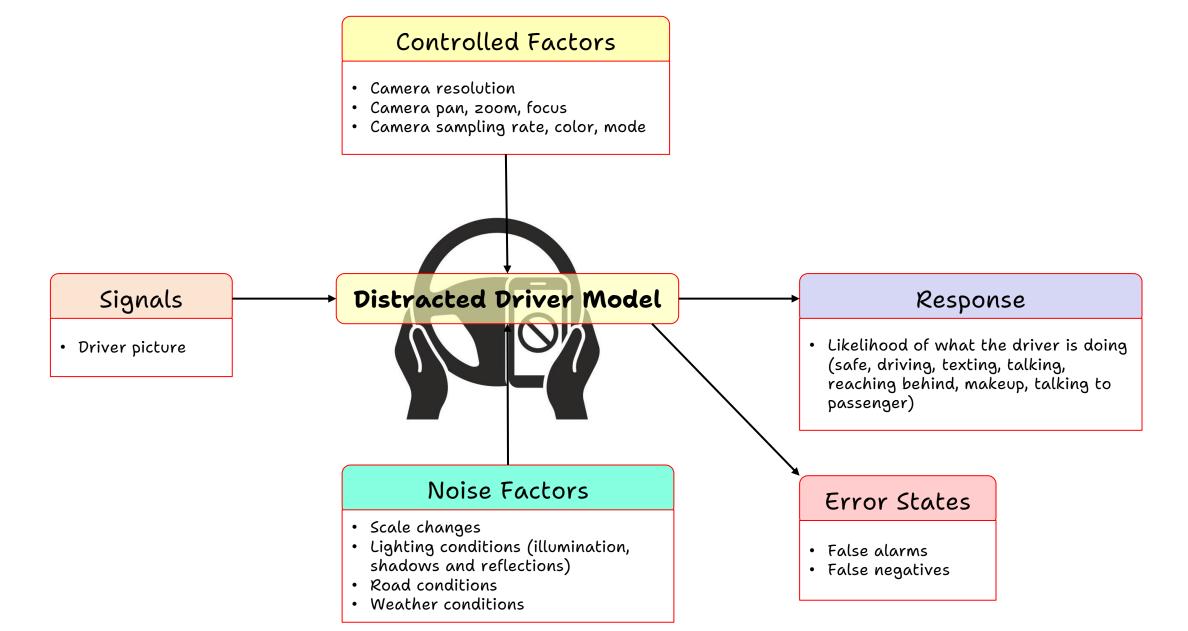
C7: Reaching Behind



C8: Hair or Makeup



C9: Talking to Passenger



Controlled Factors

- Motor Type
- · Supply voltage
- · Ambient temperature
- · Ambient humidity
- · Sensor type and placement
- Sampling frequency

Signals

- · Motor vibration signals
- · Temperature readings
- · Current and voltage measurements
- Rotational speed (RPM)
- · Acoustic signals

RUL Prediction Model

Noise Factors

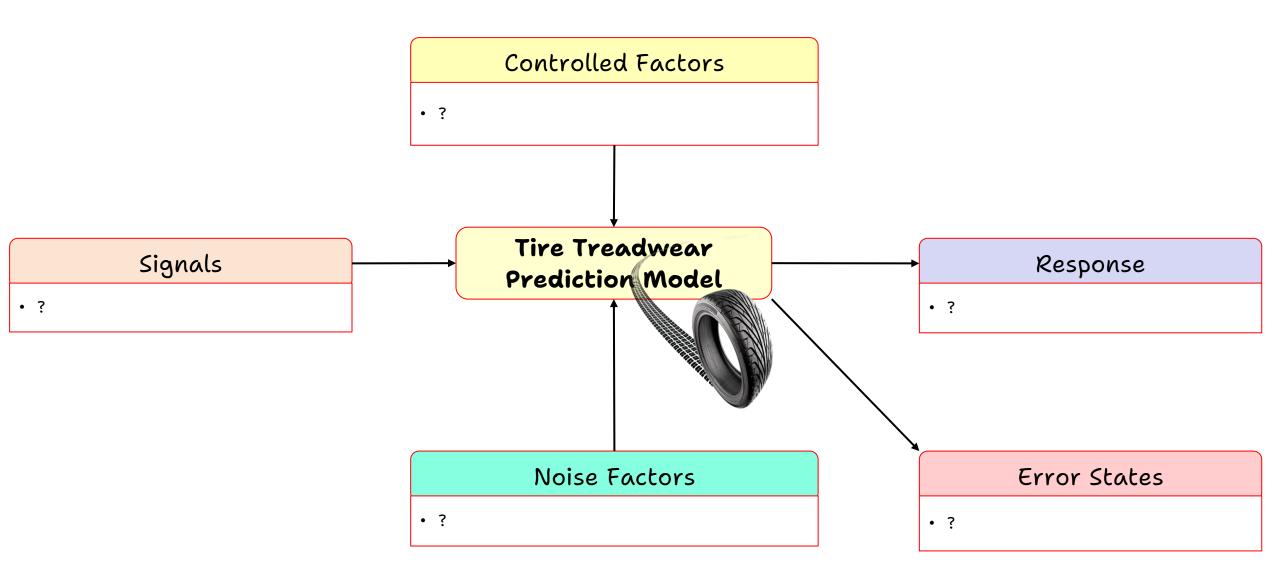
- Random load fluctuations from production process
- · unexpected voltage dips/spikes
- · operator handling differences
- · environmental dust/contaminants

Response

- Predicted Remaining Useful Life (RUL) in hours or cycles
- Probability distribution of time-tofailure
- · Confidence interval of RUL estimate

Error States

- Prediction error (e.g., RMSE or MAE)
- · Biased RUL estimates
- · False alarms and false negatives



• How do I set up an experiment?

Design of Experiment (DOE)

Full Factorial Design

Fractional Factorial Design

Pros & Cons	Full Factorial	Fractional Factorial
Pros	 All possible combinations can be covered Analysis is straightforward, as there is no aliasing 	 Less memory and effort Less time Runs can be added to eliminate cofounding.
Cons	Cost of the experiment increases as the number of factors increases	 Analysis of higher order interactions could be complex Cofounding could mask factor and interaction effects

Full Factorial Design

$$N_{full} = r \prod_{i=1}^{k} L_i$$

 N_{full} is the number of runs

 L_i is number of levels for factor i

r is number of replicates (optional)

Special cases

Two-level factors only $\Rightarrow N = r 2^k$

Three-level factors only $\Rightarrow N = r 3^k$

Controlled Factors Motor Type Supply voltage Ambient temperature Ambient humidity Sensor type and placement Sampling frequency **RUL Prediction Model** Signals Response · Motor vibration signals Predicted Remaining Useful Life (RUL) · Temperature readings in hours or cycles Current and voltage measurements Probability distribution of time-to- Rotational speed (RPM) Acoustic signals Confidence interval of RUL estimate Noise Factors Error States Random load fluctuations from production · Prediction error (e.g., RMSE or MAE) · Biased RUL estimates unexpected voltage dips/spikes · False alarms and false negatives operator handling differences environmental dust/contaminants

Example: considering only 3 two-levels controlled factors and 3 two-level noise factors with no replicate: $N = r 2^k = 2^6 = 64$ runs. If each run takes 30 minutes, the total duration to collect the data would be 1920 minutes (32 work hours or four 8-hour full days).

• Fractional-factorial (regular resolution) for a two-level fractional design

$$N_{frac} = r2^{k-p}$$

k is the total number of factors

p is number of generators (fractionality)

 $p=0 \Rightarrow$ full, $p=1 \Rightarrow$ half fraction, $p=2 \Rightarrow$ quarter fraction, etc.

Example: considering only 3 two-levels controlled factors and 3 two-level noise factors with no replicate. Number of runs for quarter fraction experiment: $N = r 2^{k-p} = 2^{6-2} = 16$ runs. If each run takes 30 minutes, the total duration to collect the data would be 480 minutes (8 hours or one full day).

• Fractional-factorial (regular resolution) for a three-level fractional design

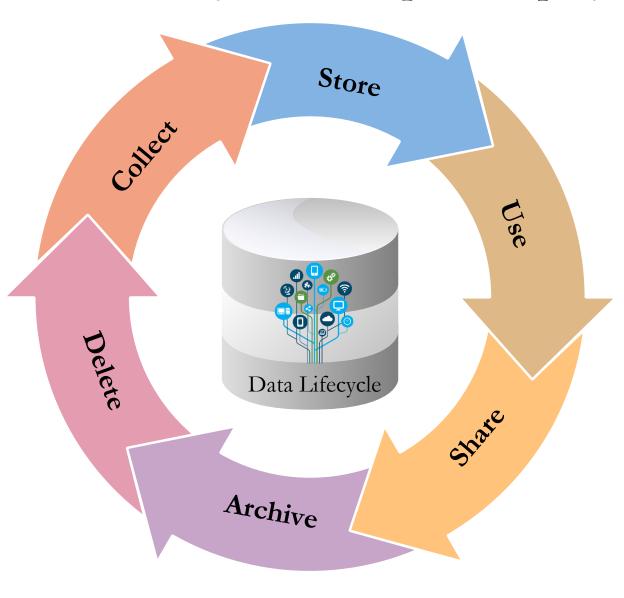
$$N_{frac} = r3^{k-p}$$

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Data Governance

• Data Privacy, Ownership and Equity



- What types of data are collected and shared?
- Why should the data be collected and shared?
- What are the benefits of sharing the data?
- How owns the data?
- With whom the data will be shared?
- When will the data be collected and used?
- How will the data be collected and used?
- Will anonymization and privacy masking be applied on the data?
- What will happen to the user's data or profile when the user dies?