INTRODUCTION TO ARTIFICIAL INTELLIGENCE METHODS

2025 RESEARCH IN FIRE ENGINEERING SERIES

SFPE Foundation

JENSEN HUGHES

Thank You

Thank you for attending our presentation introducing artificial intelligence methods in the online webinar for the 2025 SFPE Research in Fire Engineering Series on February 12, 2025. We appreciate your attendance and participation in this important discussion. We look forward to continuing this conversation concerning the use of artificial intelligence technologies in the fire safety industry at the upcoming GCI AI Summit in May 2025.

For more information, please visits our website (**https://www.jensenhughes.com/digital-solutions/**) and don't hesitate to reach out if there is anything we can do to make your community more safe, secure, and resilient. You can reach the presenter at **jhodges@jensenhughes.com** or through our contact an expert portal at **www.jensenhughes.com**.

Abstract

Recent advancements in Artificial Intelligence (AI) technology have paved the way for innovation in technology and tools in numerous sectors. The rate at which these technologies are evolving the workflow of industry professionals in the fire protection industry is remarkable. The SFPE Foundation is hosting an AI summit in May 2025 to discuss the intersection of AI technologies and the fire protection industry. The purpose of this webinar is to provide technical background on these methods and point members to additional resources which can be used to learn more in preparation for the upcoming summit.

During this presentation, we provided a high-level overview, definitions, and a brief background on AI and machine learning (ML) methods. The discussion then moved to a technical presentation on the different types of models that exist. This included a high-level survey of the different models, examples of how the models work, and resources that attendees could use to learn more. The objective of the technical discussion was to provide an entry point for the fire protection engineer to data science and opening the black box to start the process of demystifying AI for our industry.

Speaker Bio: Jonathan L. Hodges, PHD

Dr. Hodges began his career as an intern in the Research, Development, Testing, and Evaluation (RDT&E) division at Jensen Hughes while working towards his Ph.D. in Mechanical Engineering at Virginia Tech where his research focused on the intersection of artificial intelligence, robotics, and fire modeling. He began working full-time in the RDT&E division after graduating in 2018. He has developed models for commercial and government clients and has been managing the modeling service line within the RDT&E division since 2021. His team continues to focus on the intersection of fire risk assessment, computational modeling, and artificial intelligence.

Dr. Hodges is an international expert in model verification and validation. He is a member of the Society of Fire Protection Engineers (SFPE) task group updating the engineering guidance on Fire Model Substantiation, with his primary involvement in the model verification and validation chapter. He has published two handbook chapters on "Intelligent Firefighting" and "The Role of Artificial Intelligence in Firefighting". He has also presented at two of the U.S. Nuclear Regulatory Commission (NRC)'s workshops on Artificial Intelligence. He has also used his extensive experience in fire modeling to support SFPE in developing new guidance on probabilistic risk assessment for local fire exposures.


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May 28-30, 2025
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www.SFPE.org/2025AISummit

1


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2

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INTRODUCTION TO ARTIFICIAL INTELLIGENCE METHODS

2025 SFPE Research in Fire Engineering Series

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3

Agenda

I. Introduction
II. Overview
III. Data
IV. Core Concepts
V. Algorithms
VI. Resources to learn more
VII. Example applications

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Generate me an image demonstrating the effectiveness of sprinklers controlling a residential Christmas tree fire.

5

Generated with AI

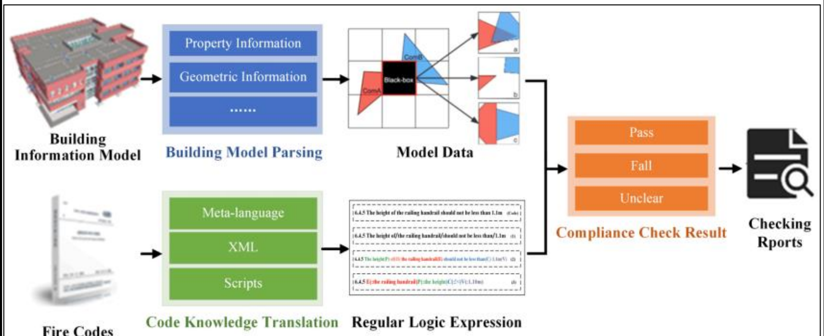
Generate me a pre-incident plan of a battery storage warehouse.

6

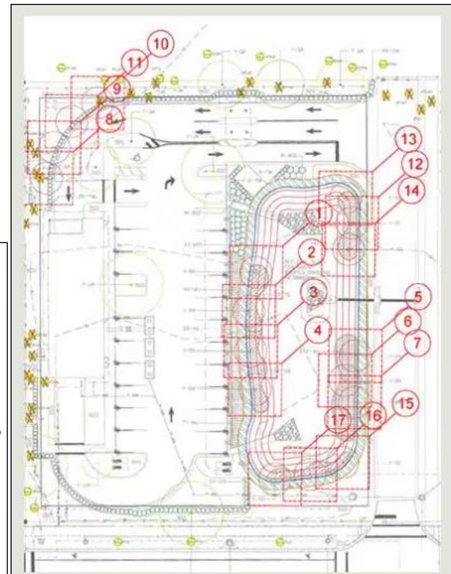
Code Review and Assessment

Automated Mark-Up of Areas of Non-Compliance

+ Potential benefits
  - Streamlined process for authority
  - Educational / training resource
  - Facilitate self-screening to improve submission quality



Y. Wang, Y. Liu, H. Cai, J. Wang, and X. Zhou, "An Automated Fire Code Compliance Checking Jointly Using Building Information Models and Natural Language Processing," Fire, vol. 6, no. 9, p. 358, Sep. 2023.

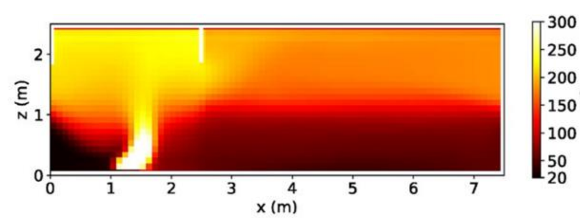


https://warrington.ufl.edu/due-diligence/2023/11/14/using-ai-to-review-construction-plans/

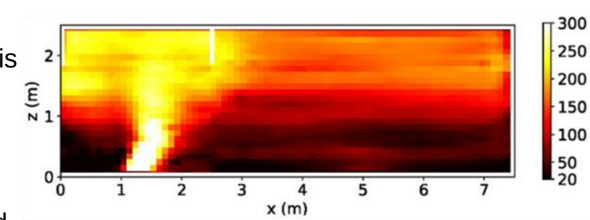
7

Digital Twins

+ Monitor cameras and sensors to:
  - Identify transient fuel loads
  - Identify inadequate fire barriers
  - Identify inoperable equipment
+ Integrate with BIM model and design basis documents
  - Notify fire marshal if hazard exceeds design basis
  - Inform updates to pre-incident plans
+ Inform the Incident Commander of egress paths which are likely to be uninhabitable due to heat and smoke



High-Fidelity CFD Fire Model



Rapid Machine Learning-Based Surrogate Model

J. L. Hodges, B. Y. Lattimer, and K. D. Luxbacher, "Compartment fire predictions using transpose convolutional neural networks," Fire Saf. J., vol. 108, no. November 2018, pp. 1–22, 2019.

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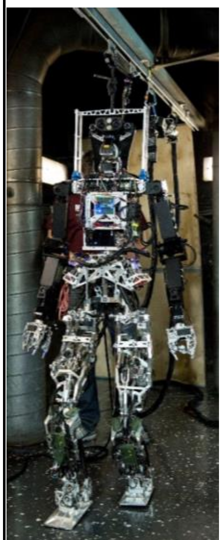
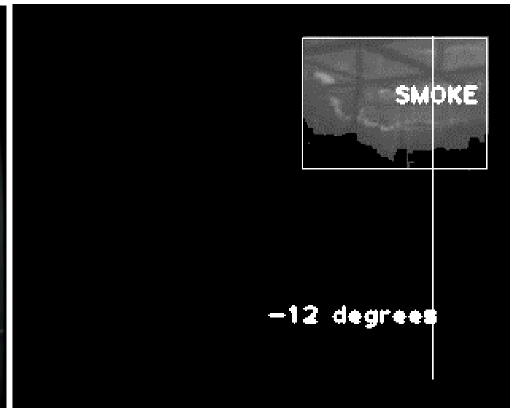
8

Robotic Fire Environment Classification



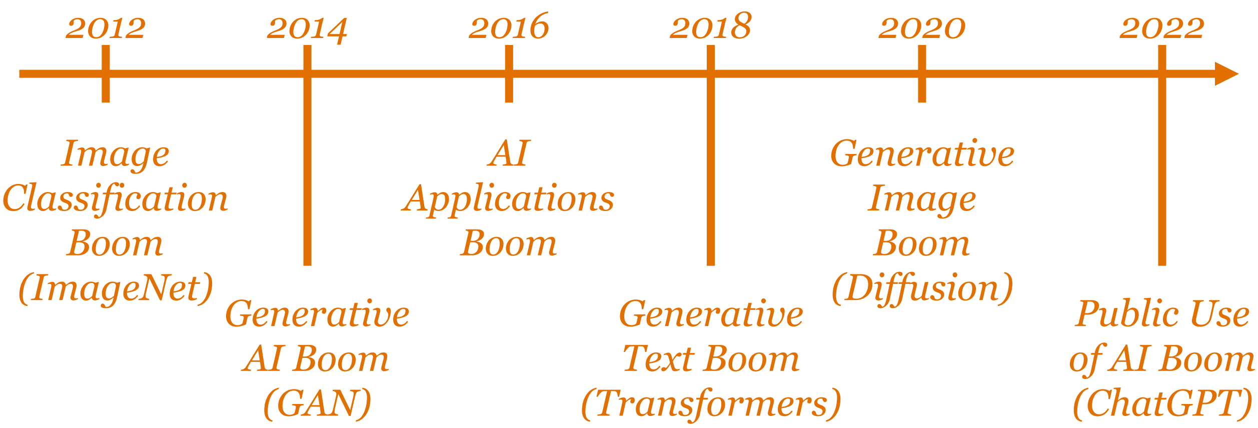


Virginia Tech, 2016. Shipboard Autonomous Firefighting Robot (SAFFiR) Robotic Systems for Damage Control and Maintenance.

Agenda

I. Introduction
II. Overview
  A. Timeline
  B. Definitions
  C. Types of AI Tasks
  D. Performance Metrics
III. Data
IV. Core Concepts
V. Algorithms
VI. Resources to learn more
VII. Example applications

Recent Developments in AI



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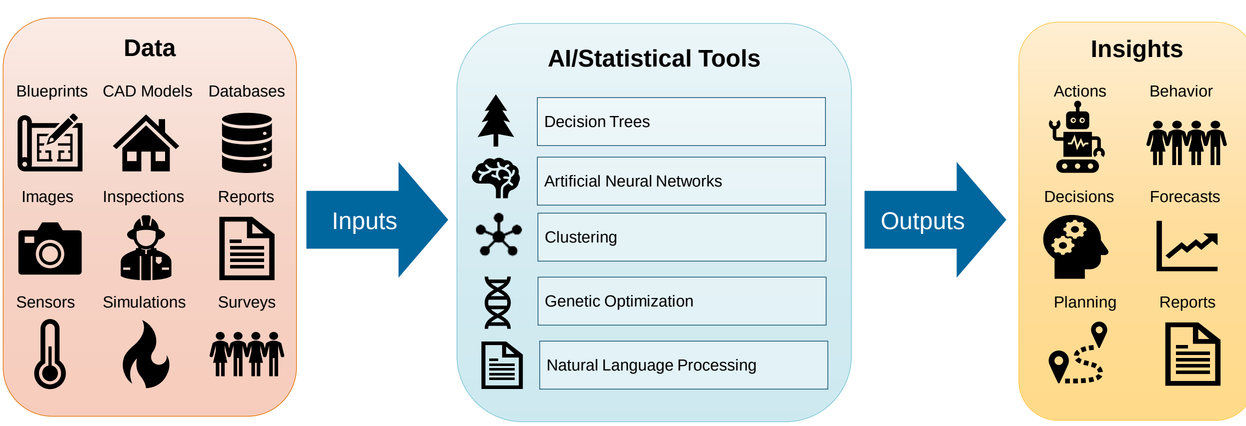
11

Artificial Intelligence

Objective: Use data to predict trends, behavior patterns, and automate processes



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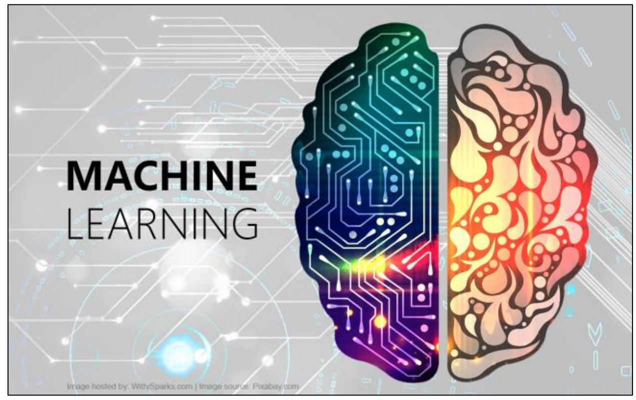
12

Learning Algorithms

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. – Mitchell 1997



https://towardsdatascience.com/introduction-to-machine-learning-for-beginners-eed6024fdb08

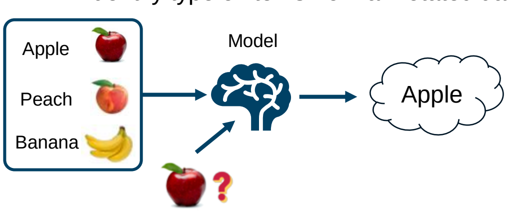
Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016. See the Deep Learning book freely available online for more detail on these topics: https://www.deeplearningbook.org/

13

Types of AI Tasks

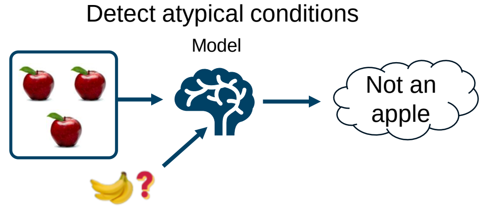
1) Classification

Identify type of items from annotated dataset



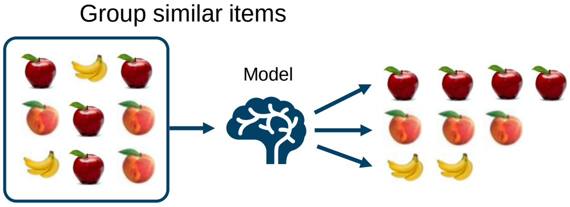
2) Anomaly Detection

Detect atypical conditions



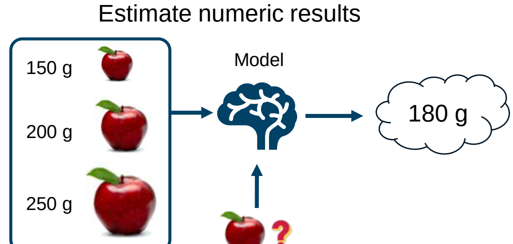
3) Clustering

Group similar items



4) Regression

Estimate numeric results



14

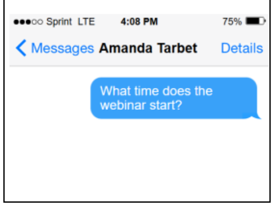
Types of AI Tasks

Images generated with AI

5) Transcription

Transform unstructured data

Speech Recognition
Text-to-Speech

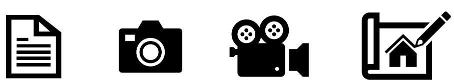


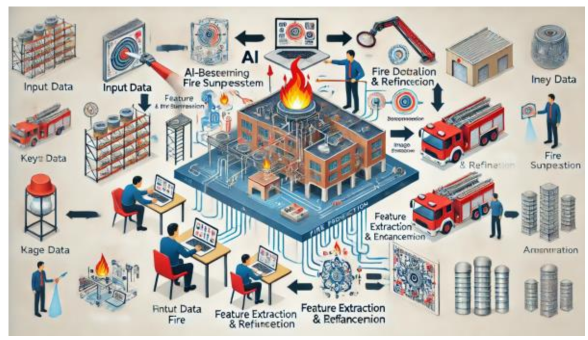
Language Translation

6) Generation

Create new content synthesizing old examples

Reports Images Videos Designs





AI-Generated image of "generate a schematic of the process of image generation using AI with an example of interest to fire protection engineers"

Performance Metrics

- Accuracy
  - Bad metric for skewed data
  - 99% accurate by predicting NO ignition
- False Negative Rate (FNR)
  - Fraction of ignitions which are not detected (i.e., number of fires which reach a critical size prior to discovery)
- False Discovery Rate (FDR)
  - Fraction of false alarms to be investigated by fire service (i.e., measure of nuisance)

		Ground Truth	
		Ignition	No Ignition
Model	Ignition	True Positive (TP)	False Positive (FP)
	No Ignition	False Negative (FN)	True Negative (TN)

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

$$FNR = \frac{FN}{(TP+FN)}$$

$$FDR = \frac{FP}{(TP+FP)}$$

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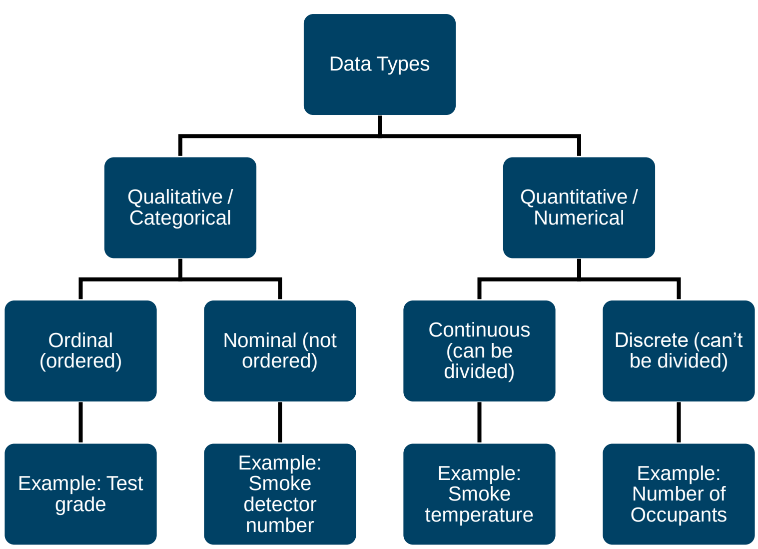
Types of Data – Quantity Type



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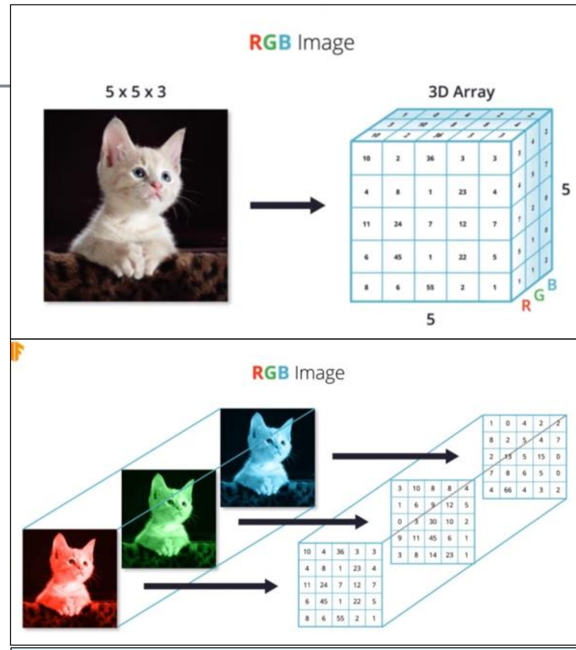
Tensors

+ Tensors
  - Multi-dimensional arrays of numbers
  - Relative position in arrays matter
  - Rank is the number of dimensions
+ Images
  - Rank 3 tensor
    - rows, columns, channels
+ Videos
  - Rank 4 tensor
    - rows, columns, channels, time



https://dev.to/sandeepbalachandran/machine-learning-going-furthur-with-cnn-part-2-41km

Text Encoding and Tokenization

+ Tokens – Unit of a text broken down from larger pieces.
  - Character(s), Syllable(s), Word(s), Phrases(s), Clause(s)
  - Limit the context available to a large language model
+ Tokenizers separate text into smaller tokens
+ Commercial LLMs typically limit the number of tokens that can be provided
  - Individual users ~10,000 tokens
  - Industrial users 100,000+ tokens

Text	~# of Tokens
4 characters	1 token
75 words	100 tokens
1-2 sentence	30 tokens
1 paragraph	100 tokens
1,500 words	2,048 tokens

https://help.openai.com/en/articles/4936856-what-are-tokens-and-how-to-count-them

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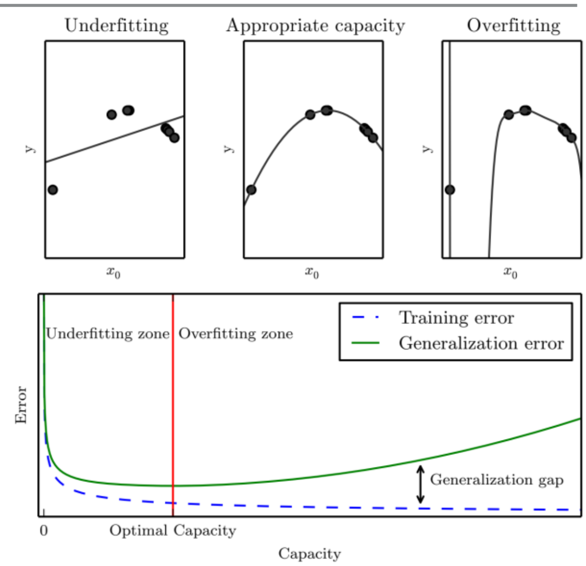
Capacity, Generalization, and Overfitting

- Capacity
  - Ability of a model to store information
  - High-capacity models will memorize the training set
  - Low-capacity models will fail to fit the training set
- Generalization
  - Ability to perform well on *new, previously unseen* inputs
  - Difference between training and testing errors

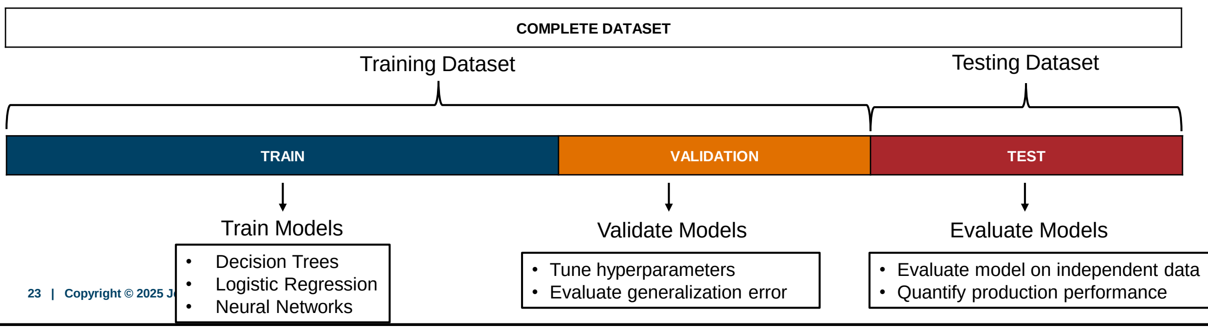


A. C. Ian Goodfellow, Yoshua Bengio, "The Deep Learning Book," *MIT Press*, vol. 521, no. 7553, p. 785, 2017.

22

Data Separation

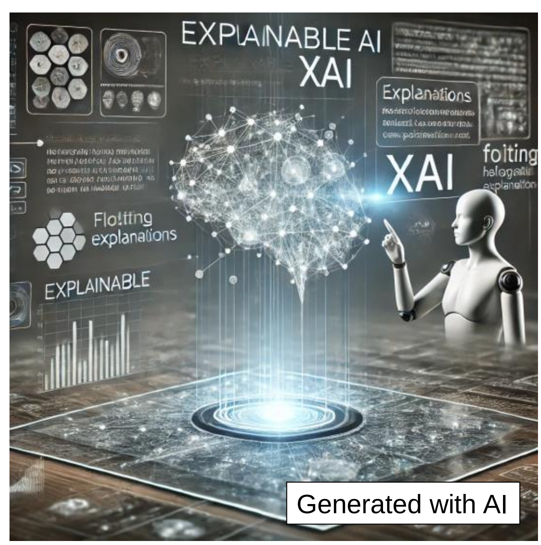
+ Need three sets of data for AI applications
+ Validation data used during training to examine generalization error
  − Not fully independent from training!
+ Testing data is fully independent from training process
  − Used to evaluate the production performance of the models



Explainability

+ Can a human understand the decision made by AI?
  − Many of the best performing models are "black box"
  − Implications in fire life safety!

+ NIST – Four Principles of Explainable Artificial Intelligence
  − Explanation: Evidence or reason(s) for outputs
  − Meaningful: Explanations are understandable
  − Explanation Accuracy: Correctly reflects the reason for generating the output
  − Knowledge Limits: Operates within design basis and when there is confidence in its output.



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Level of Autonomy

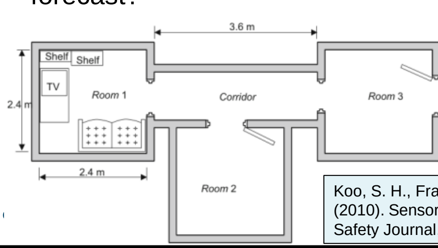
Human Involvement ↑ | Machine Independence ↓

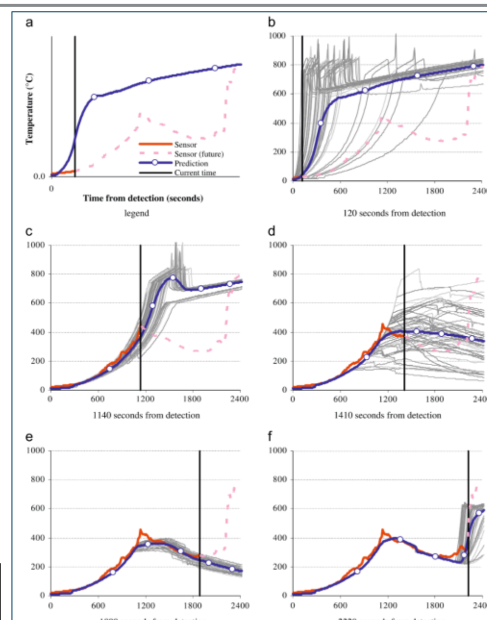
Level	AI and Autonomy Level	Potential Uses of AI and Autonomy
Level 0	**AI Not Used**	No AI or autonomy integration in systems or processes
Level 1	**Insight** Human decision-making assisted by a machine.	AI integration in systems used for optimization, operational guidance, or business process automation that would not affect safety.
Level 2	**Collaboration** Human decision-making augmented by a machine.	AI integration in systems where algorithms make recommendations that could affect safety/security and control are vetted and carried out by a human decisionmaker.
Level 3	**Operation** Machine decision-making supervised by a human	AI and autonomy integration in systems where algorithms make decision and conduct operations with human oversight that could affect safety/security and control.
Level 4	**Fully Autonomous** Machine decision-making with no human intervention	Fully autonomous AI in systems where the algorithm is responsible for operation, control, and intelligent adaptation without reliance on human intervention or oversight that could affect safety/security and control.

Slide credit: M. Dennis, *AI Characteristics for Regulatory Consideration,* presented at the 4th U.S. Nuclear Regulatory Commission Workshop on AI, 2023.

Implicit Assumptions

+ Is the system predicting the future results based on…
  - Unchanging conditions?
  - Constant gradient changing conditions?
  - Dynamic changes in conditions?
+ Example – Predicting the occurrence of flashover
  - Conditions can change rapidly with changes in ventilation.
  - What ventilation configuration is assumed in the forecast?





Koo, S. H., Fraser-Mitchell, J., & Welch, S. (2010). Sensor-steered fire simulation. Fire Safety Journal, 45(3), 193–205.

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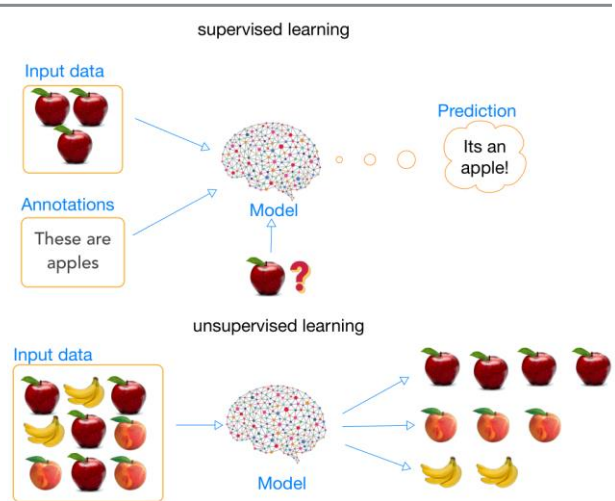
27

Supervised vs Unsupervised Learning

+ Supervised learning
  − Learn to predict a specific target based on input
  − Human acts as the instructor to the algorithm

+ Unsupervised learning objectives
  − Identify interesting properties of the underlying distribution
  − Algorithm acts as an instructor to the human



Y. Ma, K. Liu, Z. Guan, X. Xu, X. Qian, and H. Bao, “Background augmentation generative adversarial networks (BAGANs): Effective data generation based on GAN-augmented 3D synthesizing,” *Symmetry (Basel).*, vol. 10, no. 12, 2018.

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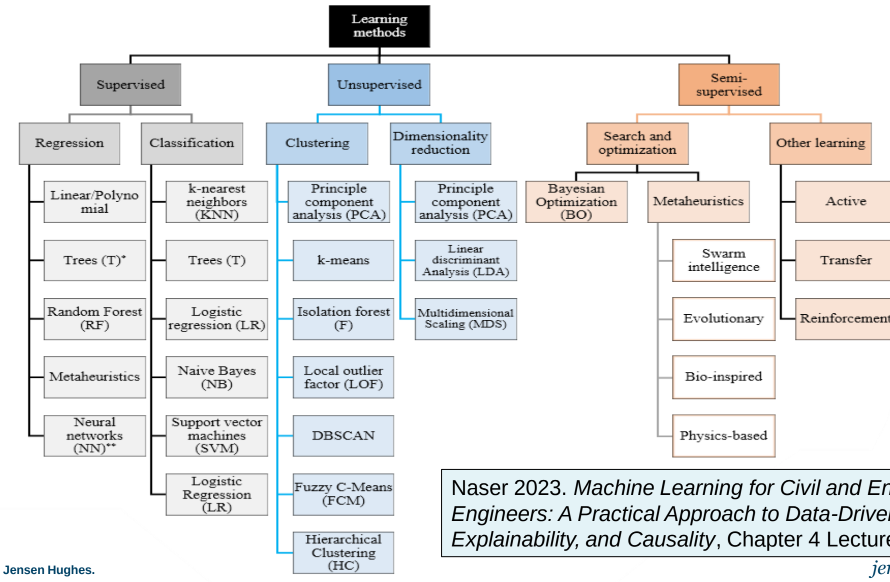
28

Classes of Algorithms



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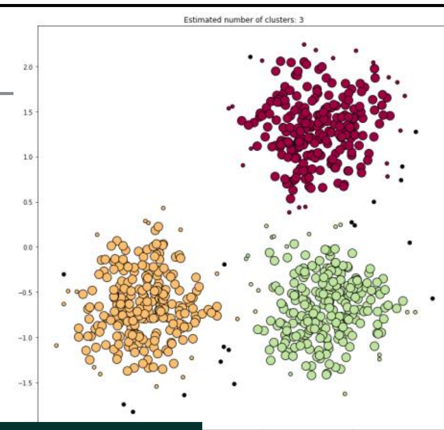
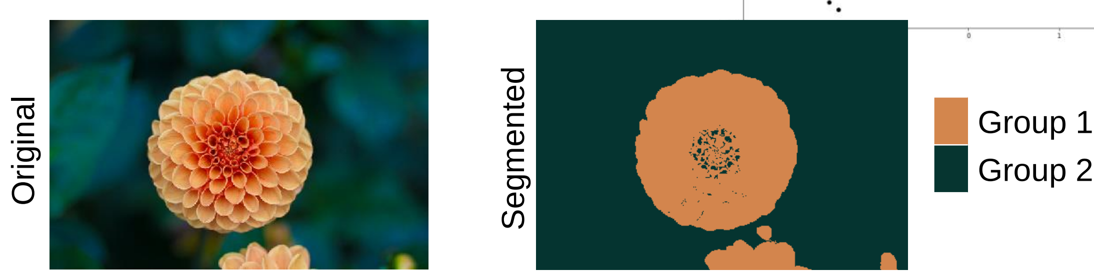
Clustering



+ Identify the optimal number of groups in a dataset
+ Group points near to each other in the considered dimensional space
  - Grouping data in scatter plots (right)
  - Grouping data by color (below)



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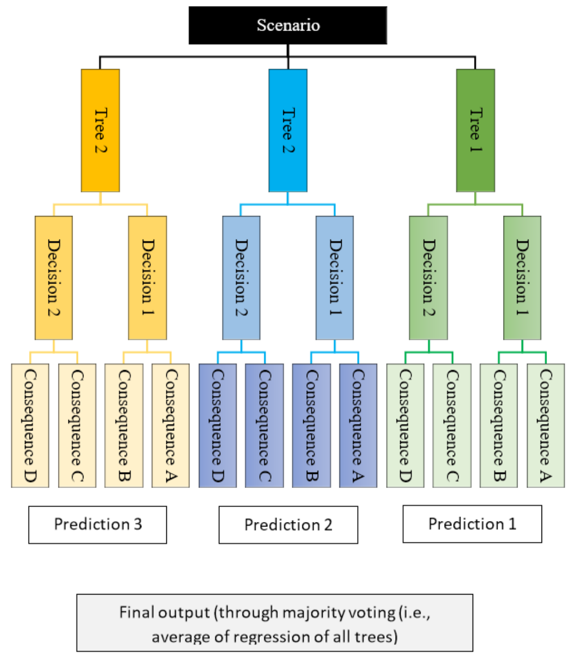
Tree-Like Methods

+ Hierarchical structure, like a fault tree
+ Nodes and branches determined by the algorithm
  - Selected to minimize error
  - Can also be designed to minimize complexity to improve explainability
+ Can use ensembles of trees for better performance, but less explainability



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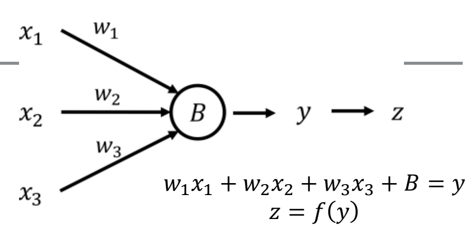
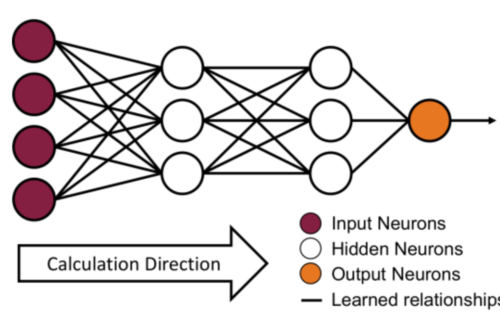
31

Neural Networks

+ Massively parallel system of equations
  - Perceptron/neuron: Represents a single equation
  - Layer: Group of neurons which are processed simultaneously
  - Network Architecture: Functional form of the model, overall system
+ Weights and biases are solved by the computer using known data during training



Example neuron



Example Neural Network

32

Other Neural Networks Designs

+ Convolutional neural networks
  - Tensors / Images as inputs and/or outputs
  - Spatial relationship between inputs is preserved and important

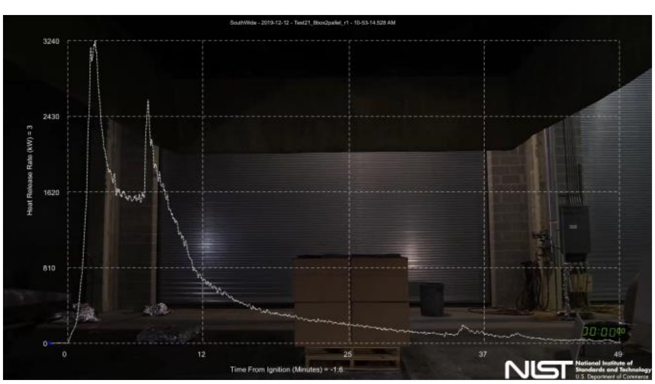
orange → apple

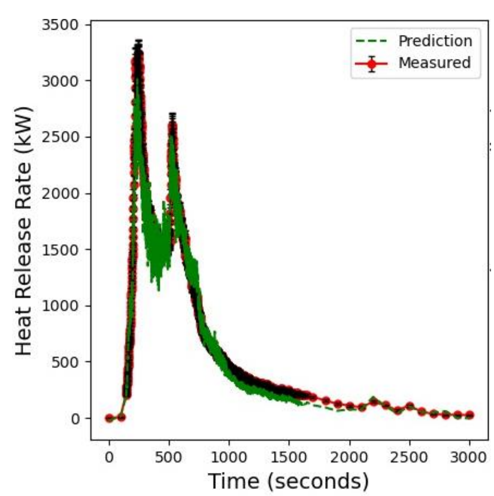
horse → zebra

Jun-Yan Zhu, et al. Unpaired image-to-image translation using cycle-consistent adversarial networks. 2017.

Other Neural Networks Designs

+ Recurrent neural networks
  - Current output depends on previous output
  - Maintains context and information about order





Prasad 2024, Predicting Heat Release Rate from Fire Video Data. https://doi.org/10.6028/NIST.IR.8521

Resources to Learn More

I. Books
II. Lecture Series
III. Interactive Tools
IV. SFPE AI Summit

Books

+ Nielsen – Neural Networks and Deep Learning
  - Easy to read with embedded web tools to help visualize different aspects of the learning process
  - Coding examples and exercises in Python (dated now using an older version of Tensorflow)
+ Goodfellow – Deep Learning
  - Well written and detailed book on machine learning.
  - Great as a reference material, not recommended starting book as it can be dry and a bit dated (2016)
+ James – An Introduction to Statistical Learning
  - Well written more recent book on machine learning
  - Coding examples and exercises in both Python and R
+ Naser – Machine Learning for Civil & Environmental Engineers
  - Targeted towards engineers rather than data scientists / computer scientists
  - Power point slides and lecture notes free online, book not free
+ Raschka – Machine Learning with PyTorch and Scikit-Learn
  - Learn by example with lots of Python example code and exercises
  - Exercises available on GitHub, book not free

Lecture Series

- Full lectures from university entry level course on machine learning
  - Caltech – Machine Learning Course (Computer Science)
  - MIT OpenCourseWare – Machine Learning Course (Computer Science)
  - Stanford Online – Machine Learning Course (Computer Science)
  - Stanford Online – Transformers United Course (Computer Science)
  - Clemson – Machine Learning Course (Civil and Environmental Engineering)
- Other resources
  - Programming with Mosh – Python Full Course for Beginners
  - 3Blue1Brown – Approachable Entry Level Videos on Neural Networks

Interactive Tools

- Hands-on web-tools to help understand components of AI algorithms
  - K-Means Clustering – METU
  - K-Nearest Neighbors Demo – Stanford
  - LLM Visualization – Bbycroft
  - Neural Network Learning – Tensorflow
  - Support Vector Machines Demo – Greitemann
- Thanks to Prof. MZ Naser for the list of tools

Naser 2023. *Machine Learning for Civil and Environmental Engineers: A Practical Approach to Data-Driven Analysis, Explainability, and Causality*, Chapter 4 Lecture Notes.

39

Summary

I. **Defined AI, machine learning, and related technologies**
II. **Introduced the basics of data-driven modeling**
III. **Discussed examples of specific algorithms used in AI models**
IV. **Provided resources that can be used to learn more**

40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2025 SFPE Research in Fire Engineering Series
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41

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