

Artificial Intelligence in Support of the Nuclear Energy Sector

> Prof. Nawal Prinja Jacobs, UK 24 February 2022



Meet the Presenter

Prof. Nawal Prinja has 40 years of academic and industrial experience in the nuclear sector. He is the Technology Director of Jacobs (Clean Energy) and holds a position of Honorary Professor at four British universities. Currently he is chair of WNA/CORDEL working on harmonisation of Nuclear Codes. He has been on IAEA missions to China, South Africa, UAE, Spain and Poland. He was appointed as an advisor to the UK Government to help formulate their long-term R&D strategy for nuclear industry and continues to advise as a member of the Fusion Advisory Board of UKRI and chairs Artificial Intelligence Technology Focus Group for Nuclear Propulsion for Ministry of Defence. He participates in a number of international committees notably the ASME code committee for developing new Plant Systems Design code and represents the UK at the Senior Industry Advisory Panel of the Generation IV International Forum.

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Contents

- Need for AI in nuclear energy sector
- Introducing AI, ML and DL
- Practical experience in using AI in Engineering
- Current Developments/ Examples
- Way Forward





GEN IV International Forum My Introduction

Current Position	 Technology Director, Jacobs Honorary Professor in the School of Engineering at Aberdeen University. Honorary Professor in the College of Engineering, Brunel University London. Honorary Professor, School of Engineering, Bolton University. Honorary Professor, School of Computer Science and Electronic Engineering, the International Centre of Nuclear Engineering, Bangor University.
Experience	 40 years of engineering and technology experience in aerospace, automotive, oil & gas and nuclear power. Over 50 Technical publications including 3 books.
Appointments	 Advisor to the Ministry of Defence (MOD) on the Nuclear Propulsion Research & Technology programme for the nuclear submarines and chair of AI Technology Focus Group for nuclear propulsion. Member of the Nuclear R&D Advisory Board to the UK Government. Chairman of CORDEL at WNA. Technical Expert invited by the IAEA (United Nations) to chair expert meetings on safety classification and Technology Readiness Levels and to participate in Nuclear Knowledge Management and Seismic expert missions to UAE, S Africa, China, Spain and Poland. Independent assessor appointed by the Innovate UK of UKRI. Member of the EC funded FENET and EASIT2 projects aimed at developing computer based simulation competencies. Member of the Board of Directors for the Professional Simulation Engineer (PSE) certification scheme. Chair of Industry Advisory Committee for the National Structural Integrity Research Centre at Cambridge. Ex-Member of Technical Assessment Panel of Fusion for Energy (F4E) Member of the Fusion Advisory Board, EPSRE 4 UKRI. UK representative and Vice Chatr of the Senior Industry Advisory Panel of Gen IV International Forum (GIF) Member of Plant Systems Design code committee of ASME.
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Need to Transform How We Use data

Only 57% of projects finish within their initial budgets. Probability of delivering a major project on time, cost and benefits is only 0.5% !!

Source: PMI Pulse of Profession 20

95% of project data is not used (used once then never used again)

Source: RICS report

85 percent of respondents say AI will significantly change the way they do business in the next five years.

Source: PwC CEO Survey 2019

AI could deliver a 10% increase in UK GDP in 2030.

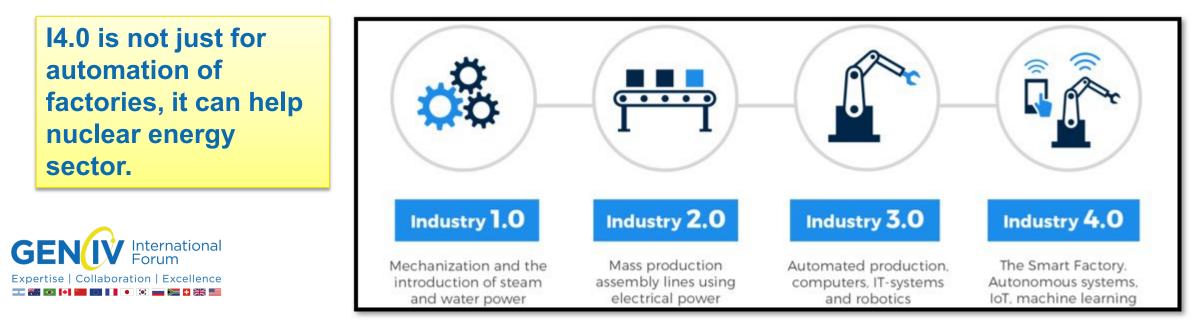
Al Roadmap, Al Council January 2021



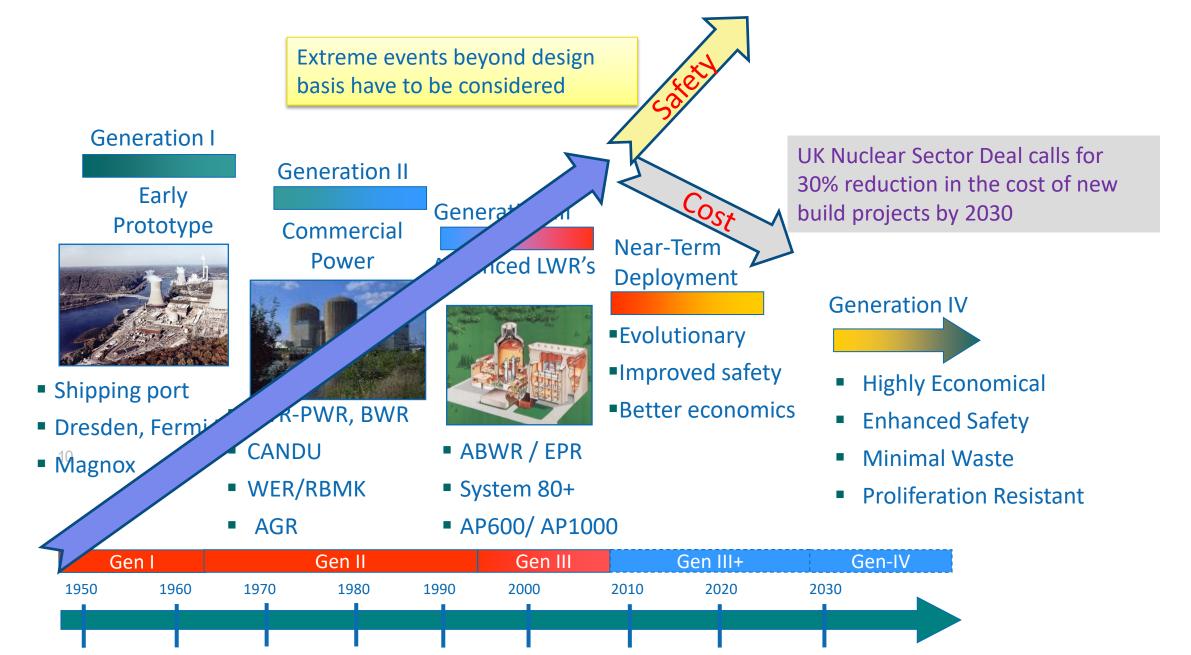
Al and the 4th Industrial Revolution (I4.0)

Al is playing a role in an Industry 4.0 system that meet many of manufacturer's needs:

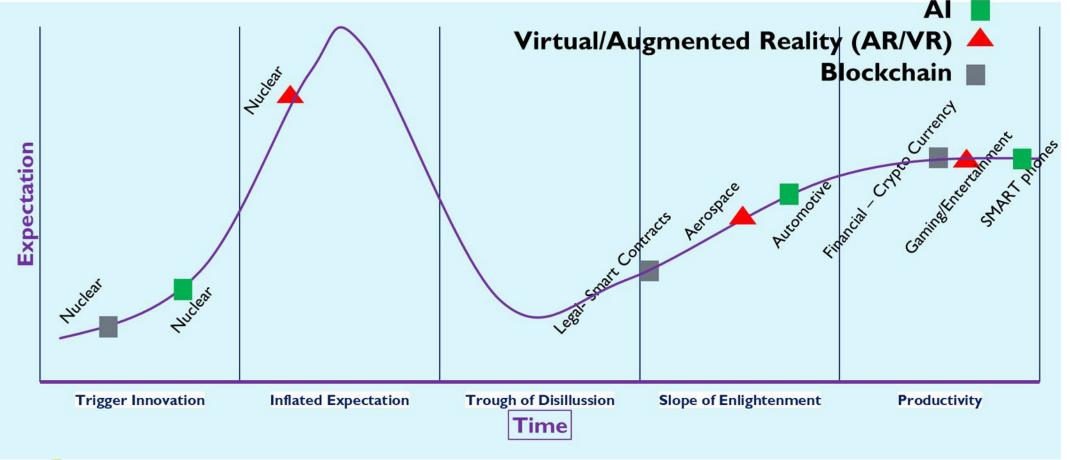
- Historical data collection
- Live data capturing via sensors
- Data aggregation
- Connectivity via communication protocols, routing and gateway devices
- Integration with PLCs
- Dashboards for monitoring and analysis
- Machine learning and other techniques



CHALLENGE: NEED TO INCREASE SAFETY AND DECREASE COST



New Technology : Expectation vs Time Is Nuclear Sector Lagging Behind Others?





UK's Al Journey

Present: The Office for AI is now October, 2017: The considering the Hall-Pesenti AI Review recommendations from the AI The Office for AI and the recommends the creation of Council' AI Roadmap and is Centre for Data Ethics and an AI Council to promote engaging with the broader Innovation are established. growth and coordination in the ecosystem to work on the next Chapter of the UK's AI Journey. sector. April, 2018: The UK Nov 2017: Industrial Strategy Government and AI community published, naming AI and Data agree a £1bn Sector Deal to as one of the four Grand boost the UK's global position Challenges. as a leader in developing AI technologies.

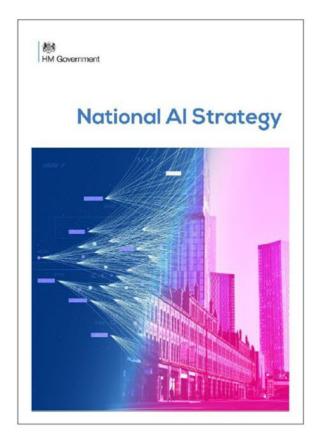


Millingthesis for Artificial Intelligence

The National Al Strategy

The new AI strategy will focus on:

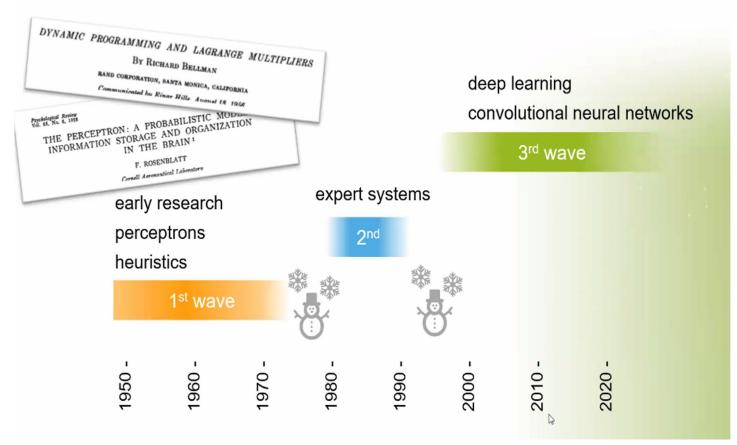
- Growth of the economy through widespread use of AI technologies
- Ethical, safe and trustworthy development of responsible AI
- Resilience in the face of change through an emphasis on skills, talent and R&D





3rd Wave of Al

WAVES OF INNOVATION IN AI/ML



Opportunities for AI

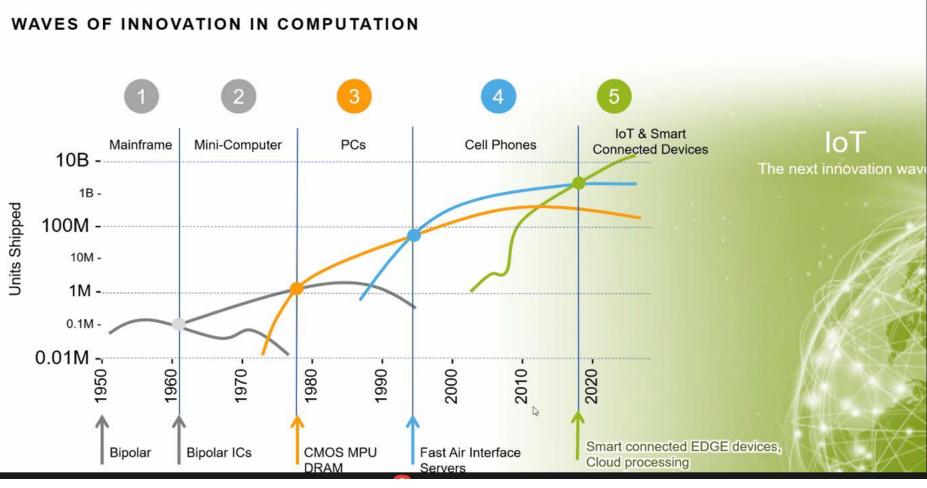
- Autonomous Vehicles: 23%
- Healthcare: 25%
- Manufacturing/Industry 4.0: 41%
- Retail: 9%
- Smart Cities: 23%
- Smart Home: 39%
- Other: 21%

Source: UKRI KTN webinar "Exploring AI at the Edge" 9 Oct 2020 in partnership with EPoSS.



Predicted Al Growth

By next year 1 million devices augmented by AI will be selling every hour !!!

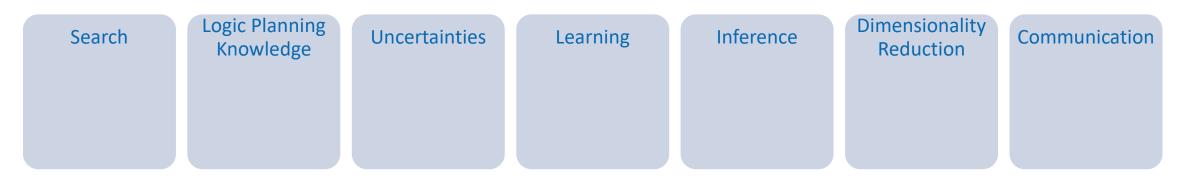






Evolving Categories of Al Methods

- Initial AI methods were primarily rules-based and knowledge-driven.
- Al computational approaches continue to evolve in industry and academia.
- Categorisation by the purpose of the AI system proposed in ISO/IEC TR 24372:2021 are:





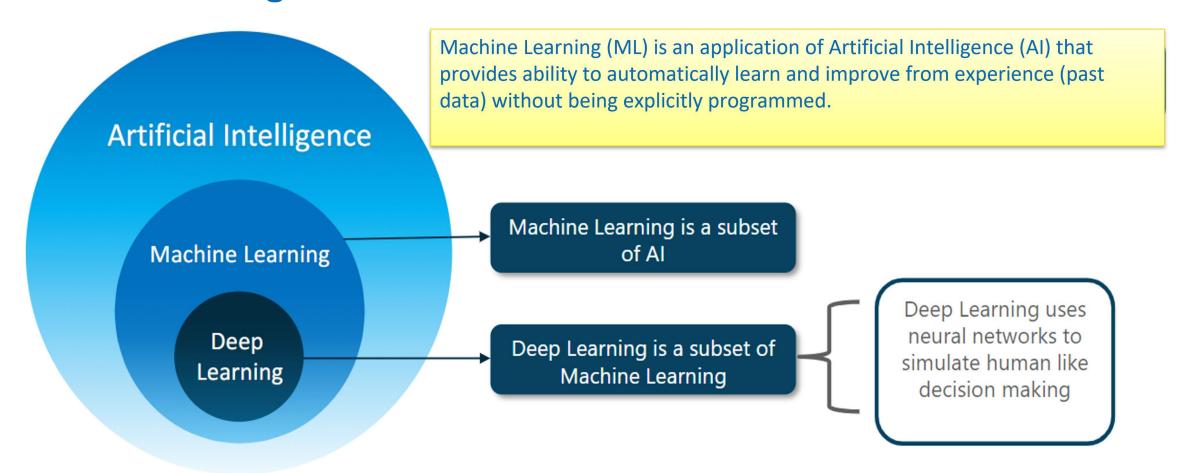


Brief Introduction



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Artificial Intelligence - Subsets





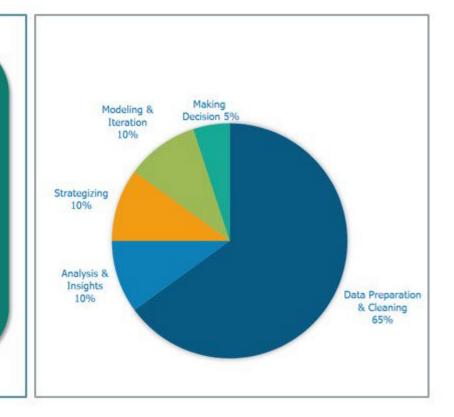
Data Science

- Data science employs many techniques and theories from fields like mathematics, statistics, information science and computer science
- Data Science can be applied to small data sets also yet most people think
 "Data Science is when you are dealing with Big Data or large amounts of data"

Some of the topics/tools that a person need to know when working with Data Science are:

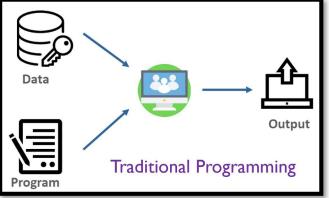
Statistics

- Programming language (R, Python, SAS)
- Softwares: Excel
- Machine Learning
- Big data



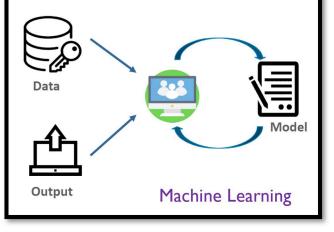


Machine Learning



It focuses on the development of computer programs that can teach themselves to grow and change

when *exposed* to *new data*



Machine learning is a method of data analysis that automates analytical model building

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04

01

02

It enables computers to *find hidden insights using iterative algorithms without being explicitly programmed*

It uses the data to *detect patterns*

in a dataset and *adjust program*

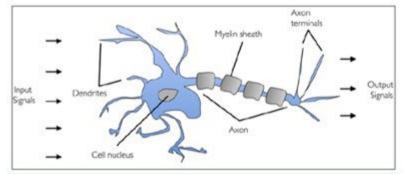
actions accordingly

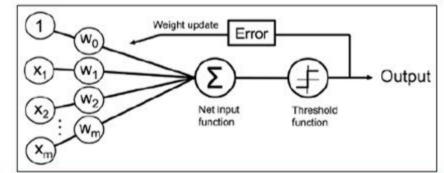


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Deep Learning : Artificial Neural Network

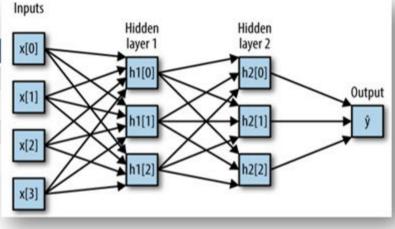




Neurons are interconnected nerve cells in the brain that process and transmit chemical and electrical signals.

Perceptron receives the inputs \mathbf{x} and combines them with the weights \mathbf{w} to compute the net input. The net input is then passed on to the threshold function, which generates a binary output +1 (Go) or -1 (No-go).

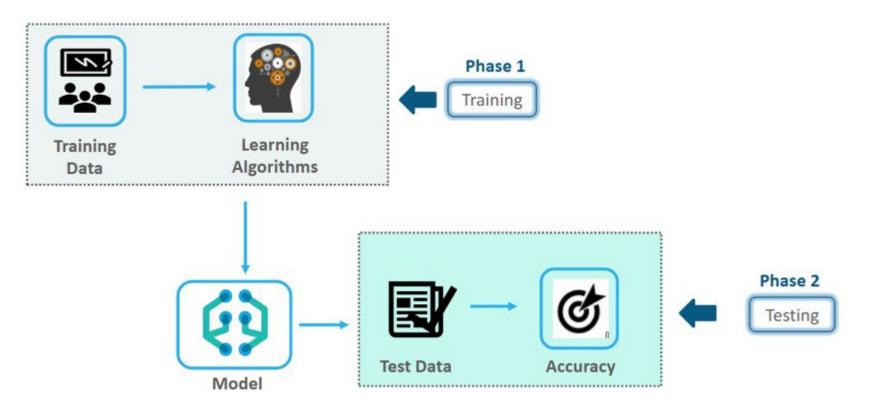
	Brain	Computer
No. of units	~1011	~109
Туре	Neurons	Transistors
Switch time	~10 ⁻³ s	~10 ⁻⁹ s
Model	Parallel	Serial



- Large neural networks made up of many hidden layers of computation inspired the term "deep learning."
- No need to explicitly program.
- They learn from training samples.



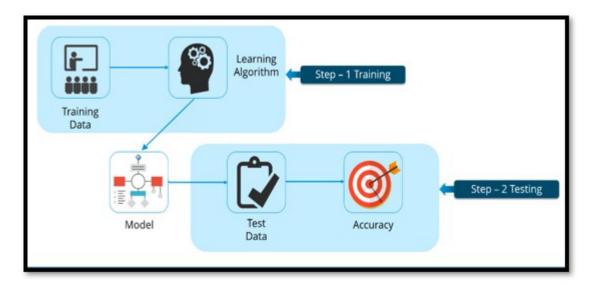
Phases of Machine Learning



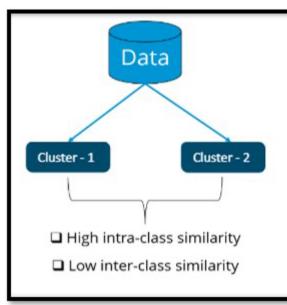


Machine Learning

1. **Supervised learning**: An algorithm learns to map input variables to output variables



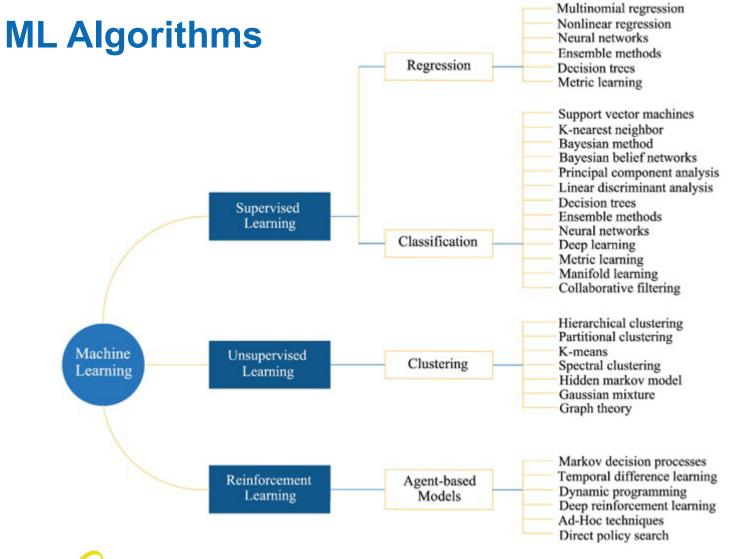
2. Unsupervised learning is training of a model using information that is neither classified nor labelled. Model can learn to cluster input data in classes.



3. Reinforced learning is by interacting with space or an environment. Actions selected on past exploitation or new exploration. The RL agent learns from the consequences through reward or penalty.





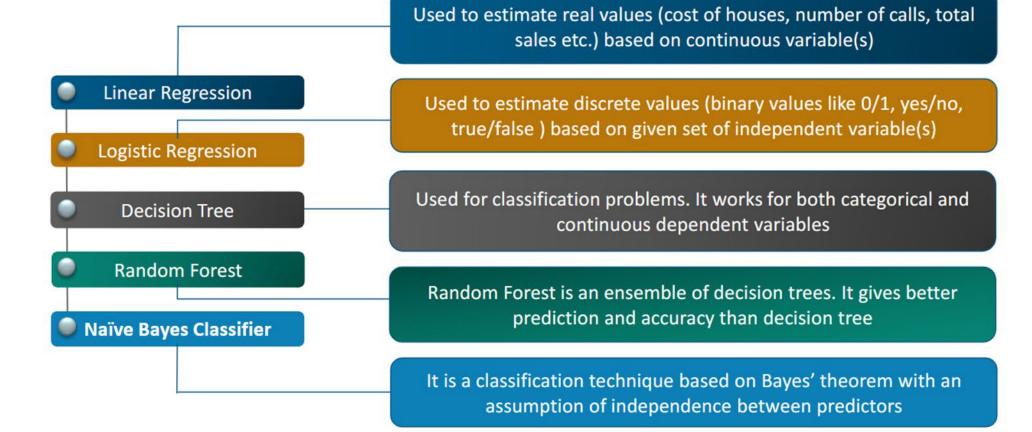


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How to select an algorithm ?

- 1. Training data quantity with no bias
- 2. Level of accuracy
- 3. Complexity Tuning of parameters
- 4. Nonlinearity
- 5. Number of features
- 6. Sacalability

Supervised Learning Algorithms



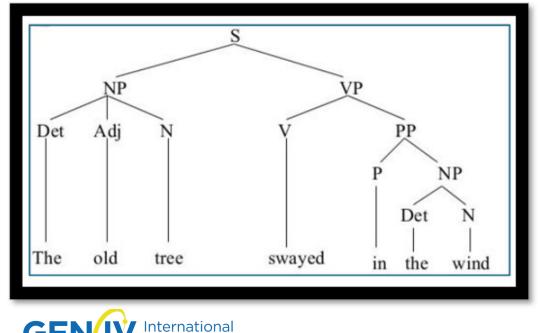


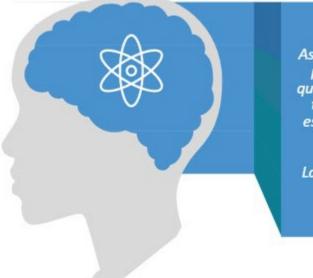
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Text Mining and NLP

Need for text mining and information extraction:

- Most of the information data is in unstructured textual format.
- Need to extract useful information from large amount of textual data.



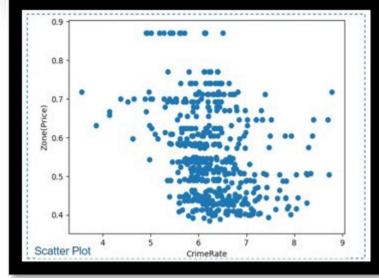


As, Text Mining refers to the process of deriving high quality information from the text . The overall goal is, essentially to turn text into data for analysis, via application of Natural Language Processing (NLP)

- Tokenisation (break into small structures)
- Bigrams, Trigrams and Ngrams (consecutive words)
- Stemming (base/root form) fish, fishing
- Lemmatization (inflected forms of words)-give, gave, giving
- Stopword Removal (a, and, is, the)
- Parts of Speech tagging (grammatical type)
- Named Entity Recognition
- Syntax Trees
- Chunking and Chinking

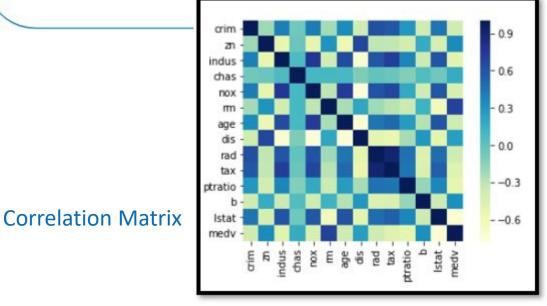
ML Example: House price prediction (Boston Dataset)

1													1
0.00632	18.00	2.310	0	0.5380	6.5750	65.20	4.0900	1	296.0	15.30	396.90	4.98	24.00
0.02731	0.00	7.070	0	0.4690	6.4210	78.90	4,9671	2	242.0	17.80	396.90	9.14	21.60
0.02729	0.00	7.070	.0	0.4690	7,1850	61.10	4.9671	2	242.0	17.80	392.83	4.03	34.70
0.03237	0.00	2.180		0.4580	6.9980	45.80	6.0622	3	222.0	18.70	394.63	2.94	33.40
0.06905	0.00	2.180	.0	0.4580	7,1470	\$4.20	6.0622	3	222.0	18.78	396.90	5.33	36.20
0.02985	0.00	2.180	.0	0.4580	6.4300	58.70	6.0622	3	222.0	18.70	394.12	5.21	28.70
0.08829	12.50	7,870	0	0.5240	6.0120	66.60	5.5605	5	311.0	15.20	395.60	12.43	22.90
0.14455	12.50	7.870		0.5240	6.1720	96.10	5.9505	5	311.0	15.20	396.90	19.15	27.10
0.21124	12,50	7.870		0.5240	5.6310	100.00	6.0821	5	311.0	15.20	386.63	29.93	16.50
0.17004	12.50	7,870	.0	0.5240	6.0040	85.90	6.5921	5	311.0	15.20	386.71	17.10	18.90
0.22489	12.50	7.870		0.5240	6.3770	94,30	6.3467	5	311.0	15.20	392.52	20.45	15.00
0.11747	12,50	7.870	.0	0.5240	6.0090	82.90	6.2267	5	311.0	15.20	396.90	13.27	18.90
0.09378	12.50	7,870	.0	0.5240	5.8890	39.00	5.4509	5	311.0	15.20	390.50	15.71	21.70
0.62976	0.00	8.140		0.5380	5,9490	61.80	4,7075	- 4	307.0	21.00	396.90	8.26	20.40
0.63796	0.00	8.140	0	0.5380	6.0960	84.50	4.4619	- 4	307.0	21.00	380.02	10.26	18.20
0.62739	0.00	8.140		0.5380	5.8340	56.50	4.4986	- 4	307.0	21.00	395.62	8.47	19.90
1.05393	0.00	8.140		0.5380	5,9350	29.30	4.4986	- 4	307.0	21.00	386.85	6.58	23.10
0.78420	0.00	8.140	0	0.5380	5.9900	81.70	4.2579	- 4	307.0	21.00	386.75	14.67	17.50
0.80271	0.00	8.140		0.5380	5.4560	36.60	3.7965	- 4	307.0	21.00	288.99	11.69	20.20
0.72580	0.00	8.140	.0	0.5380	5.7270	69.50	3,7965	- 4	307.0	21.00	390.95	11.28	18.20
1.25179	0.00	8,140	0	0.5380	5,5700	98.10	3,7979	- 4	307.0	21.00	376,57	21,02	13.60

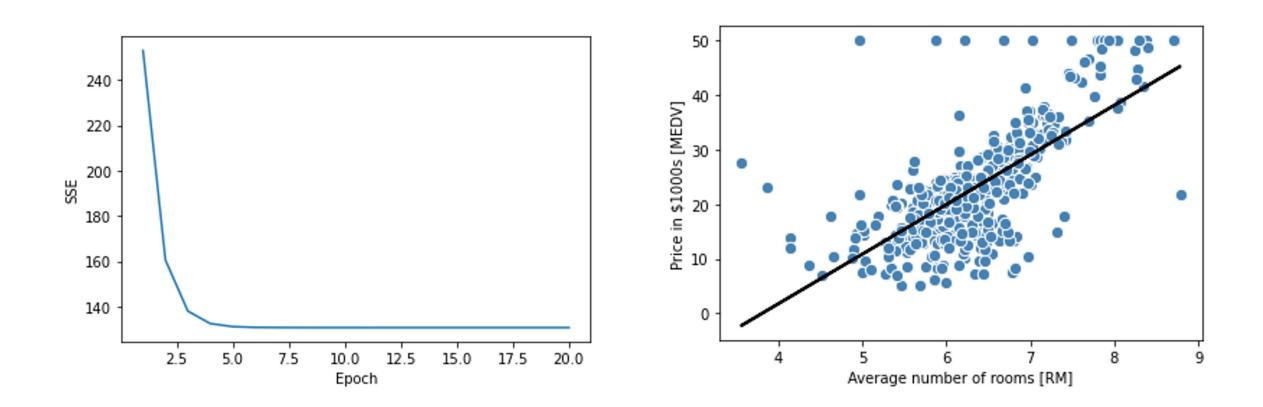


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- CRIM per capita crime rate by town
- ZN proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS proportion of non-retail business acres per town.
- CHAS Charles River dummy variable (1 if tract bounds river; 0 otherwise)
- NOX nitric oxides concentration (parts per 10 million)
- RM average number of rooms per dwelling
- AGE proportion of owner-occupied units built prior to 1940
- DIS weighted distances to five Boston employment centres
- RAD index of accessibility to radial highways
- TAX full-value property-tax rate per \$10,000
- PTRATIO pupil-teacher ratio by town
- B 1000(Bk 0.63)² where Bk is the proportion of blacks by town
- LSTAT % lower status of the population
- MEDV Median value of owner-occupied homes in \$1000's



House Price Prediction





My Experience/Examples of Using Al

<u>Completed Projects</u>

- 1. Rock / Mine Classification for Submarines using Sonar Data
- 2. Predicting non-conformance of electron beam welds
- 3. Accelerating ultrasonic testing of welds
- 4. Predicting environmental impact on fatigue/fracture behaviour of steel
- 5. Material properties predictor for power plant steels (M4Ps)
- 6. Using Natural Language Processing (NLP) for quick translation of documents
- 7. NLP for cognitive search and relevant information retrieval from large repositories of documents (using Goldfire supplied by IHS)
- 8. Root cause of failures in TIG welding

Future Projects

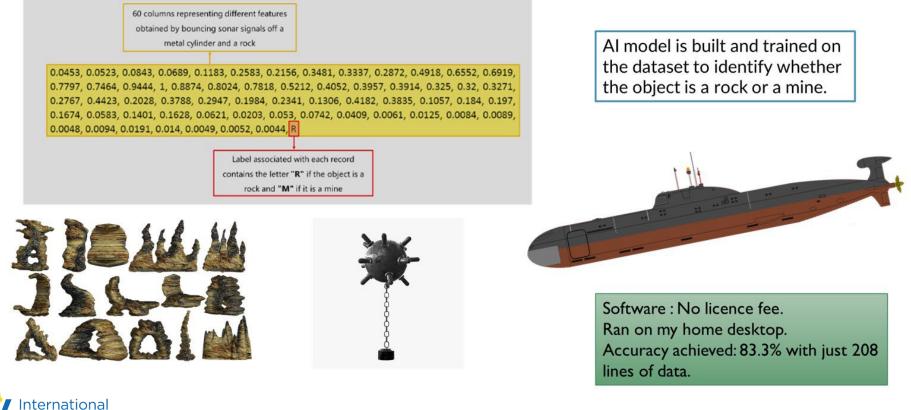
- 1. Recognition of human actions
- Probabilistic AI for Prediction of Material Properties (PROMAP)



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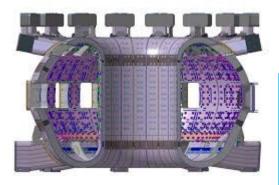
Example 1 : Rock / Mine Classification for Submarines using Sonar Data

Data with 208 observations on 61 variables. The first 60 represent the energy within a particular frequency band, integrated over a certain period of time. The last column contains the class labels : 'R' for rock and 'M' for mine.



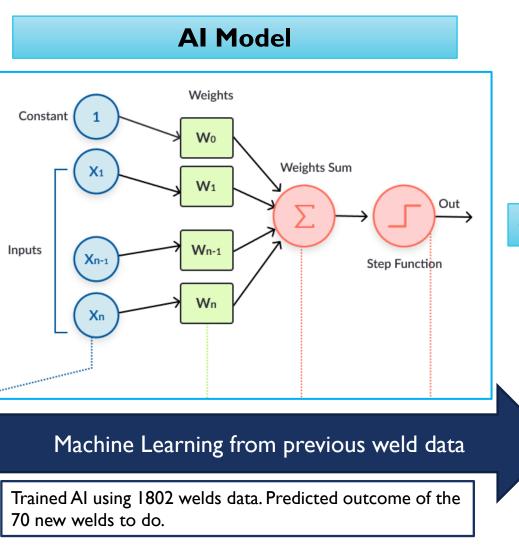
Example 2: AI model to accelerate construction of Vacuum Vessel for Fusion

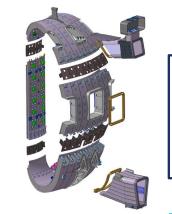
Based on input of parameters of planned welding it can use previous experience to predict the outcome and help with decision to proceed or not leading to better planning, de-risking and accelerating the programme.



Input: EB welding
parameters.

EB Parameters	EB Conditions
Length	Sector/ Segment
Current	Orientation
Welding Velocity	Supplier
Focussing System Current	Type of weld
	Position



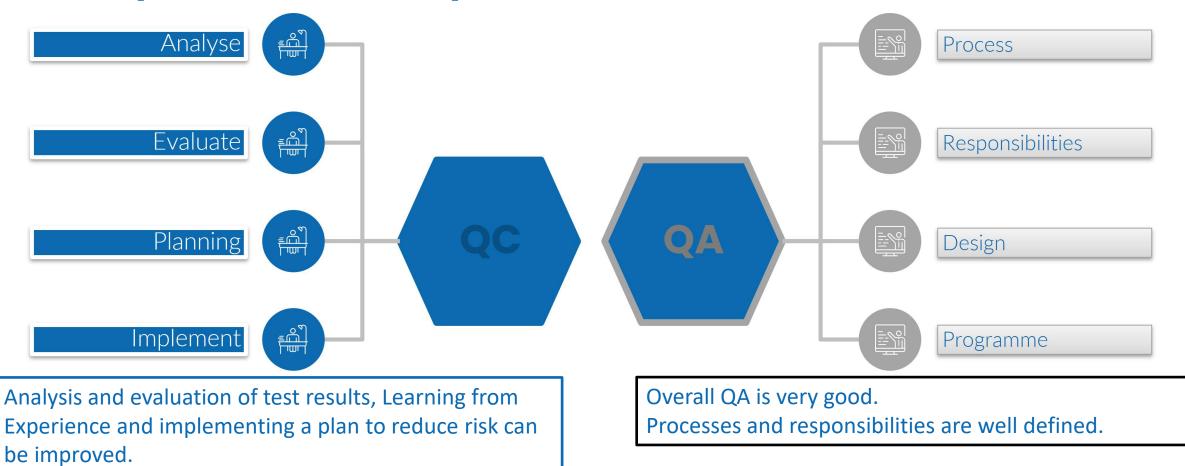


There are 9 sectors. Each sector requires over 10000 different types of welds with full 100% inspection.

Output: Probability of non-conformance

	Result	ce			
	NC_EBW_R	Not conform - Defect related to EB			
		Process - Weld to be repaired			
	NC_OTH_R	Not conform - Defect not related to			
		EB Process - Weld to be repaired			
	NC_OTH_NR	Not conform - Defect not related to			
		EB Process - No repairing need			
	NC_DOC_NR	NC related to documentation - No			
	NC_DOC_NK	repairing need			
7	С	ccepted			
Р	rediction	Actual			
С	One weld with 90%	Failed			
	6 others with 56% illure.	7 out of 16 failed			

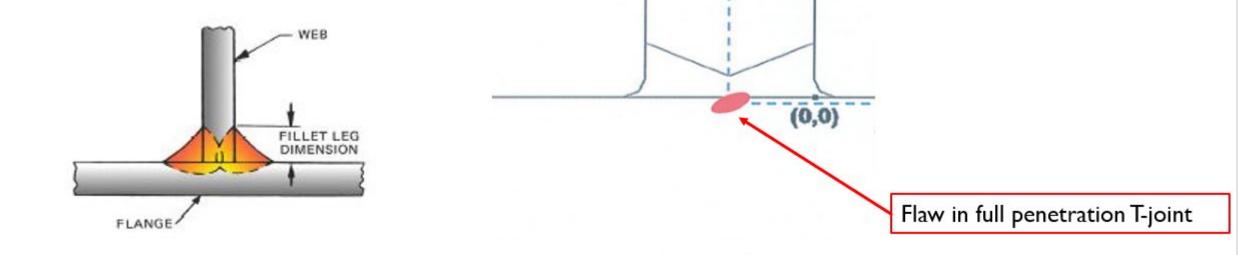
Quality Control vs Quality Assurance





Al can de-risk and accelerate projects

Example 2: Applying AI to Accelerate UT Inspection of welds

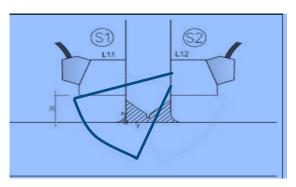


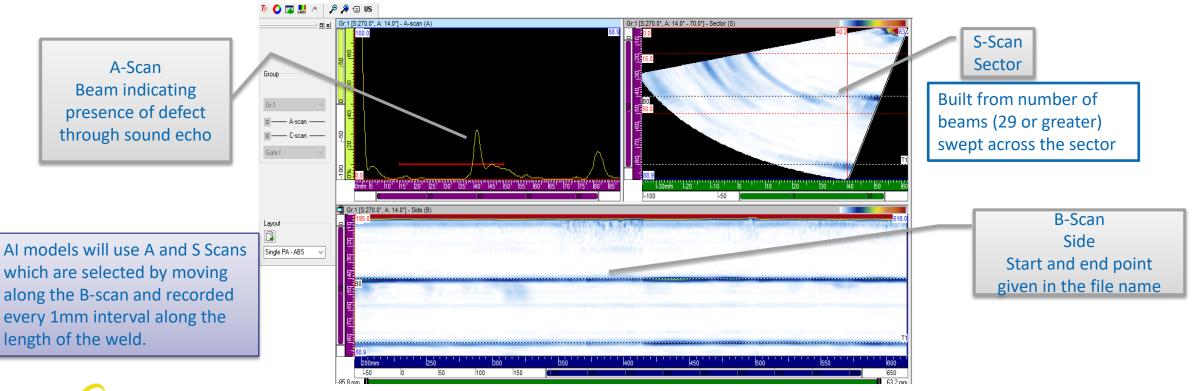
- UT is preferred over radiographs
- It can cost I\$m to 5\$m to train and qualify an inspector
- UT acquisitions and analysis can take days



Typical UT Acquisitions

Recently, for a particular weld form, AI model identified defects with accuracy of 98%

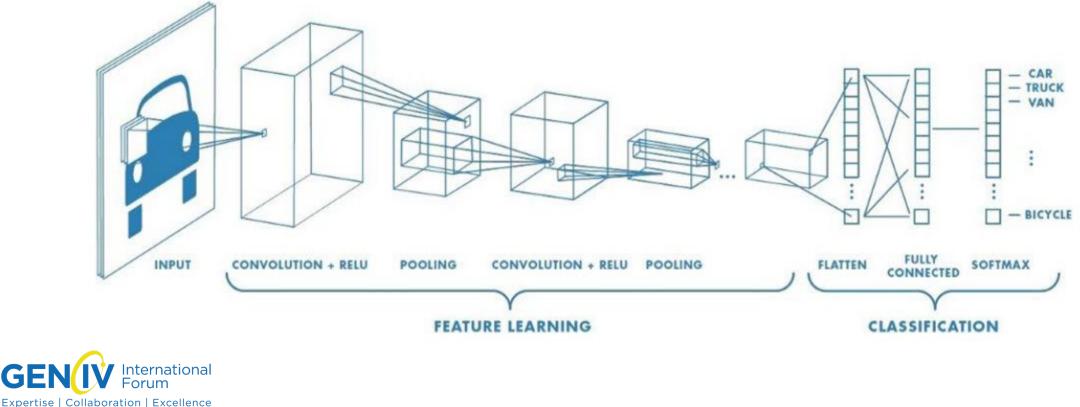




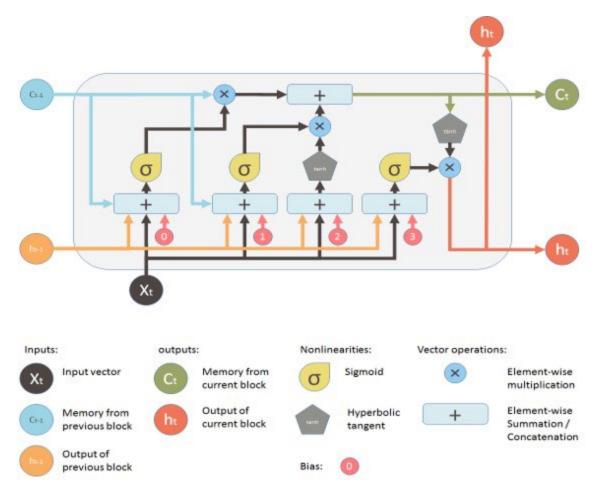


CNN for Image Analysis

A Convolutional Neural Network (CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.



LSTM for Time Series (Wave) Analysis



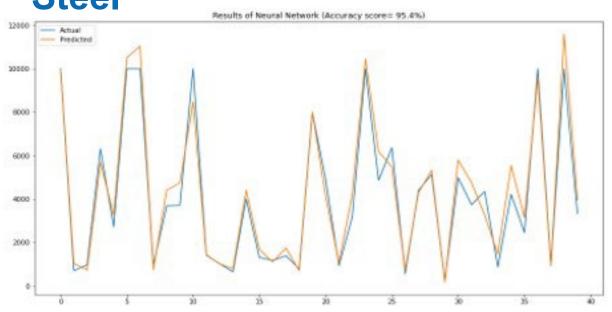
International

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- Instead of having a single neural network layer, there are four layers (0 to 3) that interact in a very special way.
- 0 Forget Layer with Forget Valve
- 1 Input gate Layer to Update
- 2 New Values and New memory Valve
- 3 Output Valve
- There is a memory unit and three information gates or valves.
- The gates are different neural networks that decide which information is allowed in the cell state. The gates can learn what information is relevant to keep or forget during training.
- The key to LSTMs is the cell state, the horizontal line running through the top of the diagram. It is a kind of conveyor belt running straight down the entire chain, with only some minor linear interactions (x or +).

You can train LSTM to predict share values in stock market but do it at your own risk.

EXAMPLE 4: Environmental Impact on Fatigue/Fracture Behavior of Steel



- Results of 38 tests were predicted with 95.4% accuracy from previous data.
- At £15000/test, over half a million pounds could have been saved.



- 246 tests conducted to establish environmental impact on number of cycles it took for a specimen to reach failure.
- 135 input features were being monitored. Data analysis was done to perform correlation, principal component analysis and feature importance to reduce the number of features to 9.
- A sequential Artificial Neural Network (ANN) model with 10 dense layers of neurons was developed.
- The data was split 80%-20% to train and test the model.
- 95.4% accuracy was achieved by the ANN model

The INCEFA PLUS data was generated under the INcreasing safety in NPPs by Covering gaps in Environmental Fatigue Assessment (INCEFA) project funded by H2020 which is the EU funding programme for research and innovation. Data courtesy of Alec McLennan

Example 5: Material Properties Predictor for Power Plant Steels (M4Ps)

- Al models trained to predict material properties from known chemical composition and processing history.
- 58 steel types in the data base containing a number of steel product forms (tubes, plates, bars etc) used in power plants.
- AI models predicted three sets of material properties : tensile properties (Proof Stress, Ultimate Tensile Strength, Elongation% and RA%), creep rupture properties (Fracture time, Elongation% and RA%) and hardness (HRB/HRC).
- Accuracy ranged from 85% to 98%

Data courtesy of Andrew Wisbey

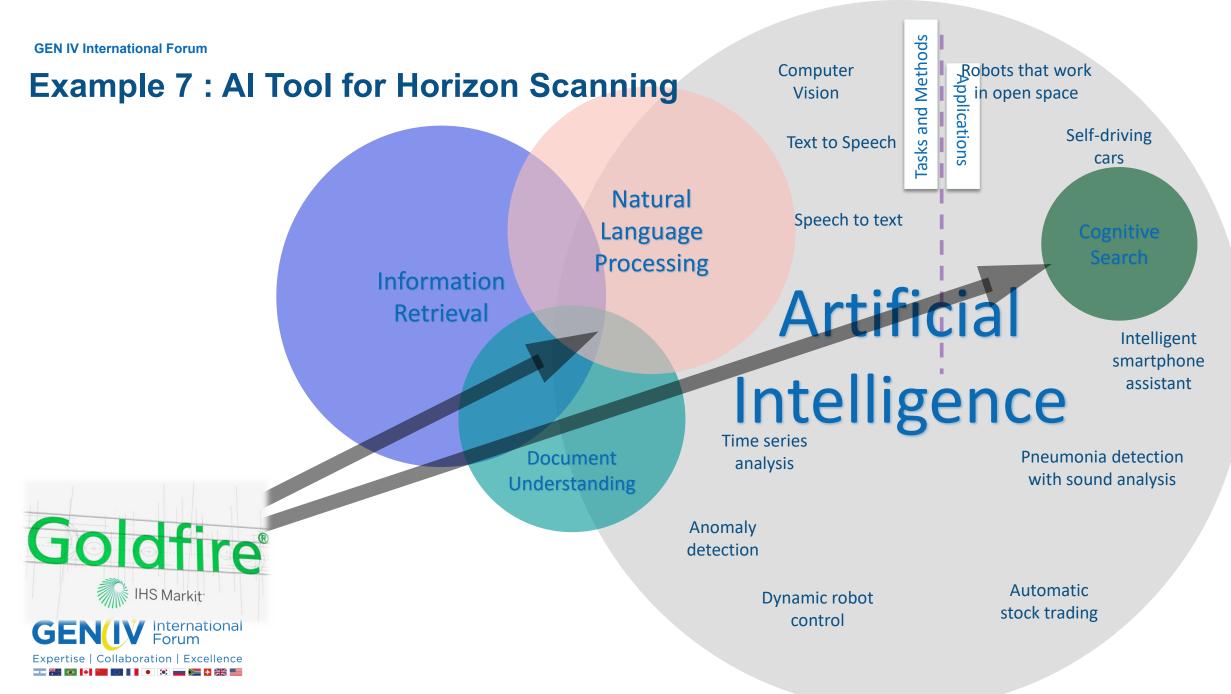
Such AI models can help develop new materials for Gen IV reactors.

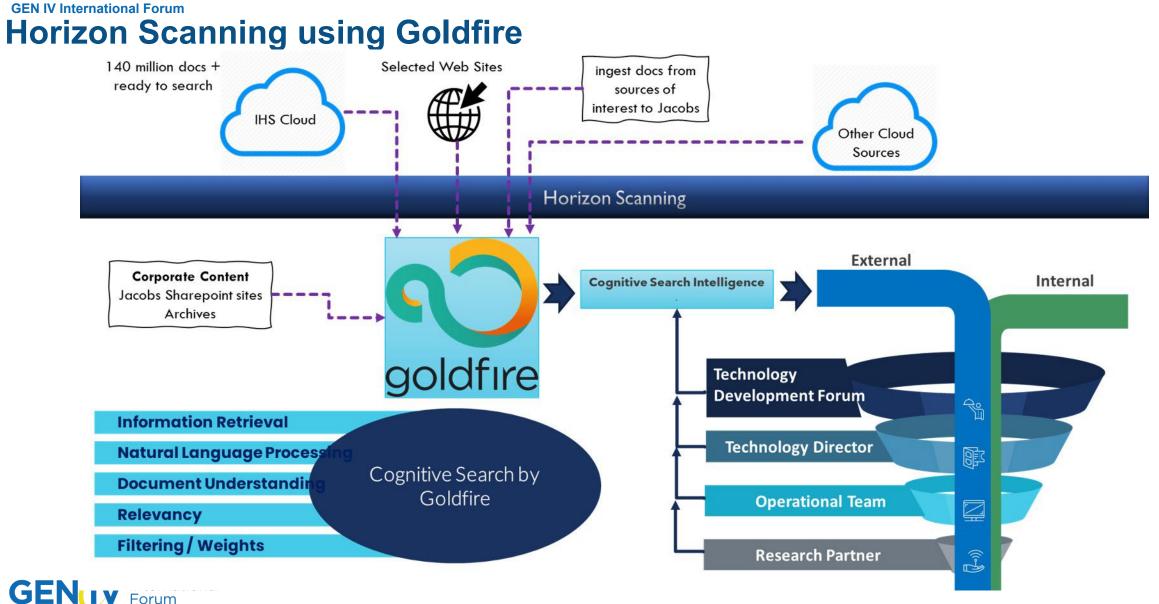


Example 6 : NLP for Translation

- Translation of technical documents including figures and tables into English
- Translation of old research papers into English
- Charity work for NHS to help translate Covid vaccination guides from English to a number of foreign languages (Bengali, Urdu, Gujarati, Tamil, Kurdish etc)







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What can Goldfire tell us about Primary Water Stress Corrosion Cracking (PWSCC)?

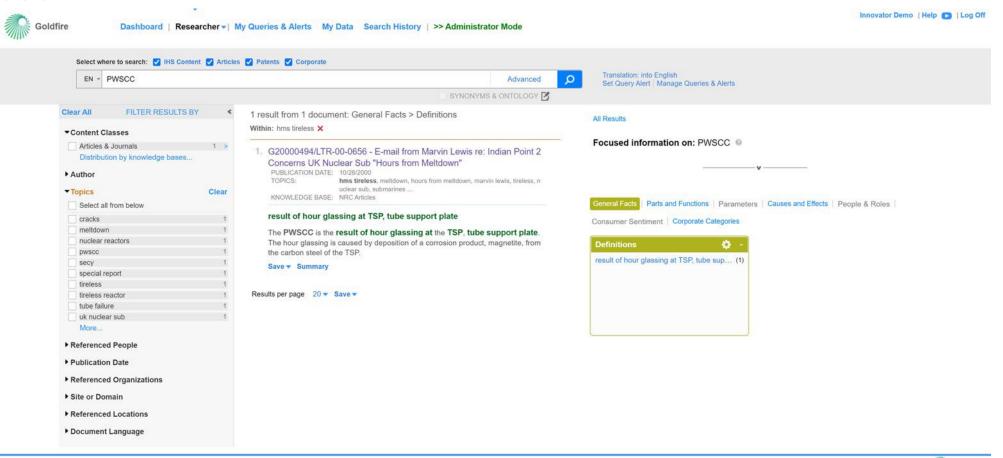
Idfire Dashboard Researcher -	My Queries & Alerts My Data Search History >> Administrator Mode	7595 results			
Select where to search: 🕑 IHS Content 🕑 Artie	cles 🗹 Patents 🗹 Corporate		<u>.</u>		
EN + PWSCC	Advanced	P Translation: into English Set Query Alert Manage Que	ries & Alerts		
FILTER RESULTS BY	SYNONYMS & ONTOLOGY 🗹				
FILTER RESOLTS BT	7,595 results	All Results			
Content Classes Codes & Standards Engineering Books 22 >	 New Code Case Development for the Mitigation of PWSCC and CISCC in ASME Section III Components by Advanced Surface Stress 	Focused information on: P	WSCC 0		
Patents & Applications 161 Other IHS Sources 100 Articles & Journals 7,204 Distribution by knowledge bases	Improvement Technology PUBLISHER: ASME PUBLICATION DATE: 714/2019 TOPICS: pwscc, pwscc and ciscc, ciscc, mitigation, asme section xi, asme section on iii components, asme section			v	
Distribution by knowledge bases	KNOWLEDGE BASE: American Society of Mechanical Engineers Articles	General Facts Parts and Function	ns Parameters	Causes and Effects People & Role	'S
▶ Author	ASME Section III has formed two Task Groups with the intent to reduce PWSCC	Consumer Sentiment Corporate Categories			
► Topics	and CISCC in operation by mitigating residual stresses during new construction of		1000		
▶ Referenced People	components. <u>More (2)</u> Save - Summary	Definitions	Q +	Properties	Q +
Publication Date		More Specific	0 -	Concepts	0 -
Publisher	⊘ 2. Advanced Inlay System for Inlet/Outlet Nozzles of RV for Preventive	axial PWSCC	(290) 🔶	PWSCC initiation	(357) 🔺
	Maintenance Ágainst Alloy 600 PWSCC in Japanese PWR Plants PUBLISHER: ASME PUBLICATION DATE: 7/14/2013 TOPICS: pwscc, alloy 600 pwscc, advanced inlay, inlay system, advanced inlay system, advanced inlay system. KNOWLEDGE BASE: American Society of Mechanical Engineers Articles	circumferential PWSCC	(179)	PWSCC crack	(348)
 Referenced Organizations 		potential PWSCC	(160)	PWSCC susceptibility	(291)
▶ Site or Domain		Alloy PWSCC	(59)	PWSCC cracking	(261)
▶ Referenced Locations		U-bend PWSCC	(53)	PWSCC flaw	(253)
Document Language	PWSCC can be prevented by improving one of the elements. MHI has been	Circ PWSCC	(40)	PWSCC indication	(240)
Standard Status	developing stress improvement methods, for example, Water Jet Peening (WJP), Shot Peening by Ultrasonic vibration (USP), and Laser Stress Improvement	weld PWSCC	(27)	PWSCC water stress corrosion cra	. (219)
	Process (L-SIP). More (4)	potential undetected PWSCC	(27)	PWSCC resistance	(175)
Publication	Save - Summary	expansion zone PWSCC	(22)	PWSCC degradation	(159)
Knowledge Collections		future PWSCC	(20) 👻	PWSCC growth	(155) 👻
▶ Standard Class	€ 3. The Effect of Zinc Addition to Simulated PWR Primary Water on the	Less	a ten.	Less	8 CL.
▶ ICS Code	PWSCC Resistance, Crack Growth Rate and Surface Oxide Films Characteristics of Prefilmed Alloy 600	Advantages	0.	Disadvantages	o

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Primary Water Stress Corrosion Cracking (PWSCC) Reported in HMS Tireless

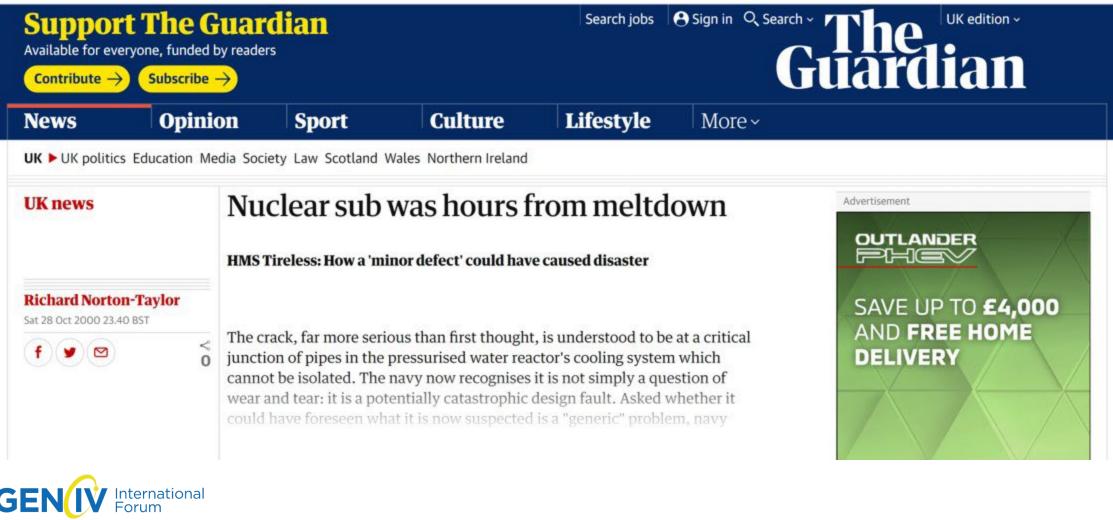


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What information can Goldfire Lead Us to Regarding this Incident?



Expertise | Collaboration | Excellence

GEN IV International Forum

Goldfire AI helps to provide possible answers to questions

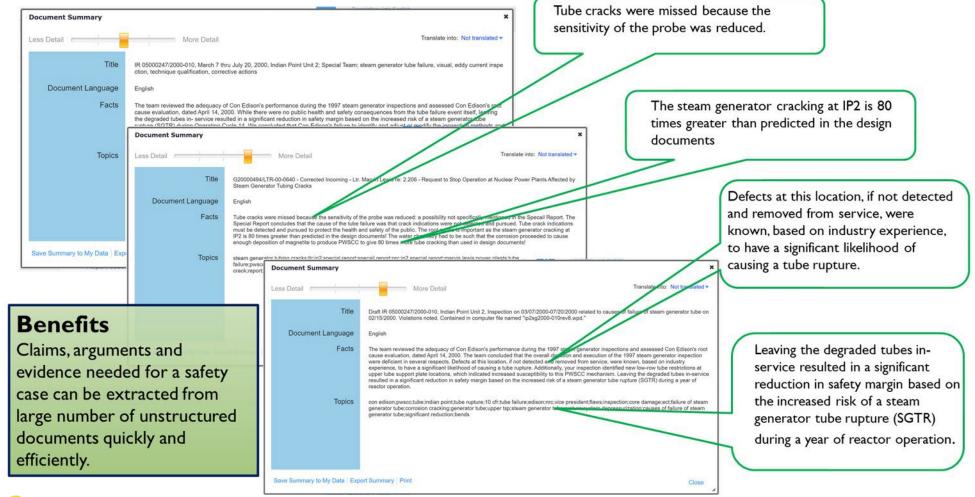
e Dashboard Resear	cher +∣ My Queries & Alerts	My Data Search History >> Administrat	or Mode					
Select where to search: IHS Content	- Articles 🗌 Patents 🗌 Corpor	rate						
EN * why were cracks missed?			Advanced O	Translation: into English Set Query Alert Manage Que	eries & Alerts			
		SYNONYMS	& ONTOLOGY					
FILTER RESULTS BY	< 8,467 results			All Results				*
Content Classes								
 Articles & Journals 8 Distribution by knowledge bases Author Topics 	Operation at Cracks PUBLICATION D TOPICS:	LTR-00-0640 - M Lewis Ltr. re 2.206 Request Nuclear Power Plants Affected by Steam Ger VATE: 10/15/2000 steam generator tubing cracks, cracks, tube crack, s g20000494, power plants	nerator Tubing	Focused information on:	why were crac	ks missed? ▼		
Referenced People	KNOWLEDGE B	ASE: NRC Articles		General Facts Parts and Function	ns Parameter	s Causes and Effects People & Ro	oles	
		reduction of sensitivity of probe		Consumer Sentiment Corporate Categories				
a data		Tube cracks were missed because the sensitivity of the probe was reduced: a possibility not specifically mentioned in the Specail Report. More (11)		Contraction of the second				
1956 2019	Save - Summ	and a final second s	(<u>11</u>)	Answers	• •	Methods	Q -	
⊖ In ● Between	oure - ourier	 Marvin Lewis re: 2.206 - Request to Stop Operation at Nuclear Power Plants Affected by Steam Generator Tubing Cracks PUBLICATION DATE: 10/21/2000 TOPICS: steam generator tubing cracks, cracks, tube crack, ltr, ip2, special rep 		reduction of sensitivity of probe	(5)	testing of areas	(1)	
1956 - 2019	2. Marvin Lewis			limitation of boroscope	(2)			
1950 - 2019				human error	(1)			
Publisher				inadvertent placement of clipboa				
Referenced Organizations		ort, special report ASE: NRC Articles	, ipz, apolai iep	degradation phenomenon	(1)			
Select all from below	and other of				-		-	
NRC	1,020	sensitivity of probe		Conditions	O -	Locations	Q -	
Nuclear Regulatory Commission		vere missed because the sensitivity of the probe		test condition	(2)	in inspection	(6)	
U.S. Nuclear Regulatory Commission	a possibility no	t specifically mentioned in the Specail Report. More	<u>,10</u>)	255 degrees	(1)	in tendon anchorage hardware	(3)	
Westinghouse	2,796 Save - Summ	ary		155 degrees	(1)	at sludge pile	(2)	
DOE	2,063			145 degrees	(1)	in CRDM nozzle weld	(2)	
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EPA	1,818 Questions.			More	(1)	More	(2)	
Quality Assurance	1,784 PUBLISHER:	NRC/RGN-I		inore		INDIG		-

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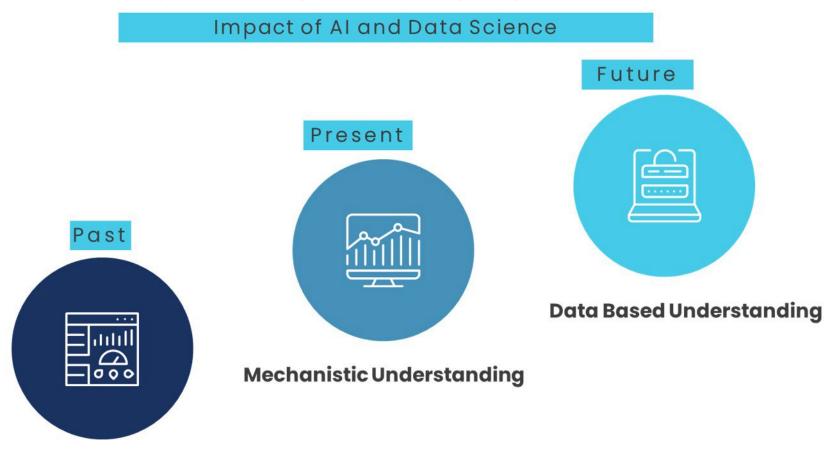
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Goldfire Al Summaries Help to Provide Quick Insights





The Way We Do Engineering is Changing



Empirical Understanding



Current project : Probabilistic AI for Prediction of Material Properties (PROMAP)

A feasibility study sponsored by Advanced Nuclear Skills Innovation Campus (ANSIC).

AIM: To combine AI models with probabilistic methods to help predict the properties of materials used in the nuclear industry

THE PROBLEM: The existing AI are trained with deterministic data and models require a large number of physical tests to cover the natural variability in the material properties. An extra challenge for the nuclear industry is that there is not sufficient material test data available for such a data centric AI approach.

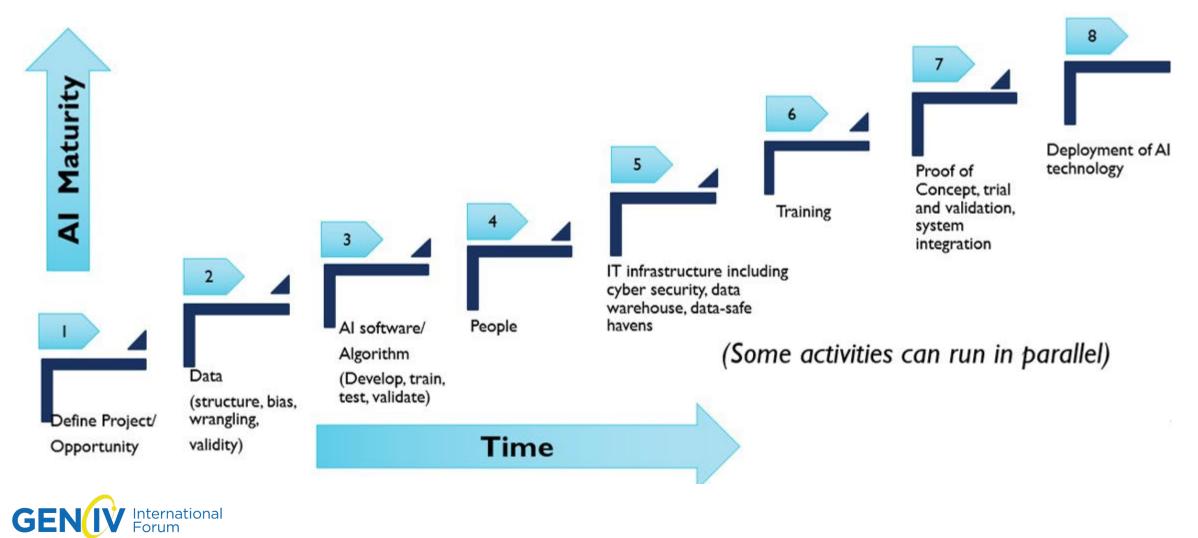
THE SOLUTION: Combine ANN with Bayesian statistics and Interval Predictor Models to enhance the robustness of the response. This allows for the uncertainties from the sparse data and material variability to be accounted for and it allows to provide the necessary confidence associated with the prediction.

University of Strathclyde is leading the project with help from the Risk Institute at Liverpool University and the author. *If you have nuclear material database that needs to be enhanced, please contact the author.*





8 Steps to Deploy Al technology



Expertise | Collaboration | Excellence

Summary : Al in Nuclear energy sector

i. Accident identification

Probabilistic Graphical Models (PGM) is a technique in Machine Learning in which probability distribution over different variables are used to predict behaviour. Example: Hidden Markov Models for accident identification in nuclear power plants.

ii. System Performance

Reinforcement learning can be applied to a dynamic system where learning data provides feedback to achieve a defined goal. Example: Reinforced Learning for plasma control in fusion reactors.

iii. Information retrieval

There are a number of NLP tools available. Example: A pilot project is being run to extract useful safety information and 'lessons learnt' from the previous event reports.

iv. Structural Integrity

Example: ANN was applied to predict Environmental Impact on Fatigue/Fracture Behavior of Steel.



Summary : Al in Nuclear Energy Sector

v. Material Properties

Example: Material Properties Predictor for Power Plant Steels (M4PS) and Probabilistic AI for Prediction of Material Properties (PROMAP).

vi. Predictive maintenance

AI can identify anomalous behaviour. Example: the High Intensity Proton Accelerator at the Paul Scherrer Institute where the particle accelerator instrumentation has very tight operational constraints

vii. Weld Inspection

Example: AI applied to accelerate PAUT inspection of welds.

ix. QA vs QC

Al used to extract lessons learnt from previous data to improve processes. Example: Root cause failure analysis of TIG welds.

x. Robotics in construction and decommissioning

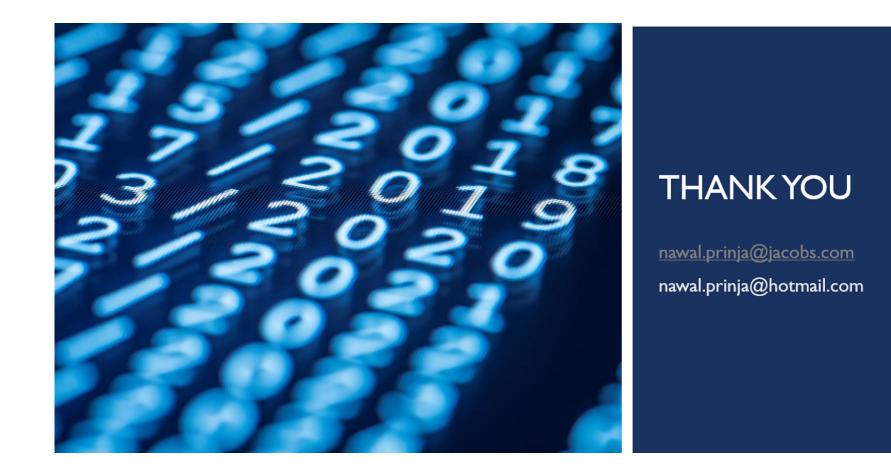
Robotics and AI are two distinct domains. Robots have been in use in industry for quite some time but empowered by AI, they are turning into 'smart robots'.



Conclusion : Al is Powering the Future

- All is playing a crucial role in the 4th industrial revolution (I4.0).
- Data science and machine learning is being used to stay ahead and remain competitive.
- Innovative solutions with AI technology are being developed which previously were thought to be science fiction.
- Every problem is different. Talk to experts to understand which aspect of AI/ML to use.
- Al is powering the future. Nuclear is powering the future. 'Al' and 'Nuclear Energy' are contemporaneous in meeting our future energy needs.







Upcoming Webinars

Date	Title	Presenter
23 March 2022	Scale Effects and Thermal-Hydraulics: Application to French SFR	Mr. Benjamin Jourdy, CEA, France
19 April 2022	GIF/IAEA Joint Webinar: Role of Nuclear Energy in Reducing CO ₂ Emissions	Dr. Shannon Bragg-Sitton, INL Mr. Wei Huang, IAEA Ms. Diane Cameron, NEA
11 May 2022	Development of Nanosized Carbide Dispersed Advanced Radiation Resistant Austenitic Stainless Steel (ARES) for Generation IV Systems	Mr. Jiho Shin, KAIST, Republic of Korea

