Artificial Intelligence trends in the aerospace sector

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All material in: https://tinyurl.com/y6kem32d

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- Artificial Intelligence (AI)
  - Overview: main definitions, applications
  - Sketch of math behind

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  - NASA Langley Technical Areas
  - Earth observation, satellite image analysis
  - Satellite gateway fault prediction
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  - NASA vision of Aerospace Data Analytics: challenge of Physics-Based Algorithms

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  - Live demo of a XAI software platform
- Conclusions: aerospace @ CNR, view into the future

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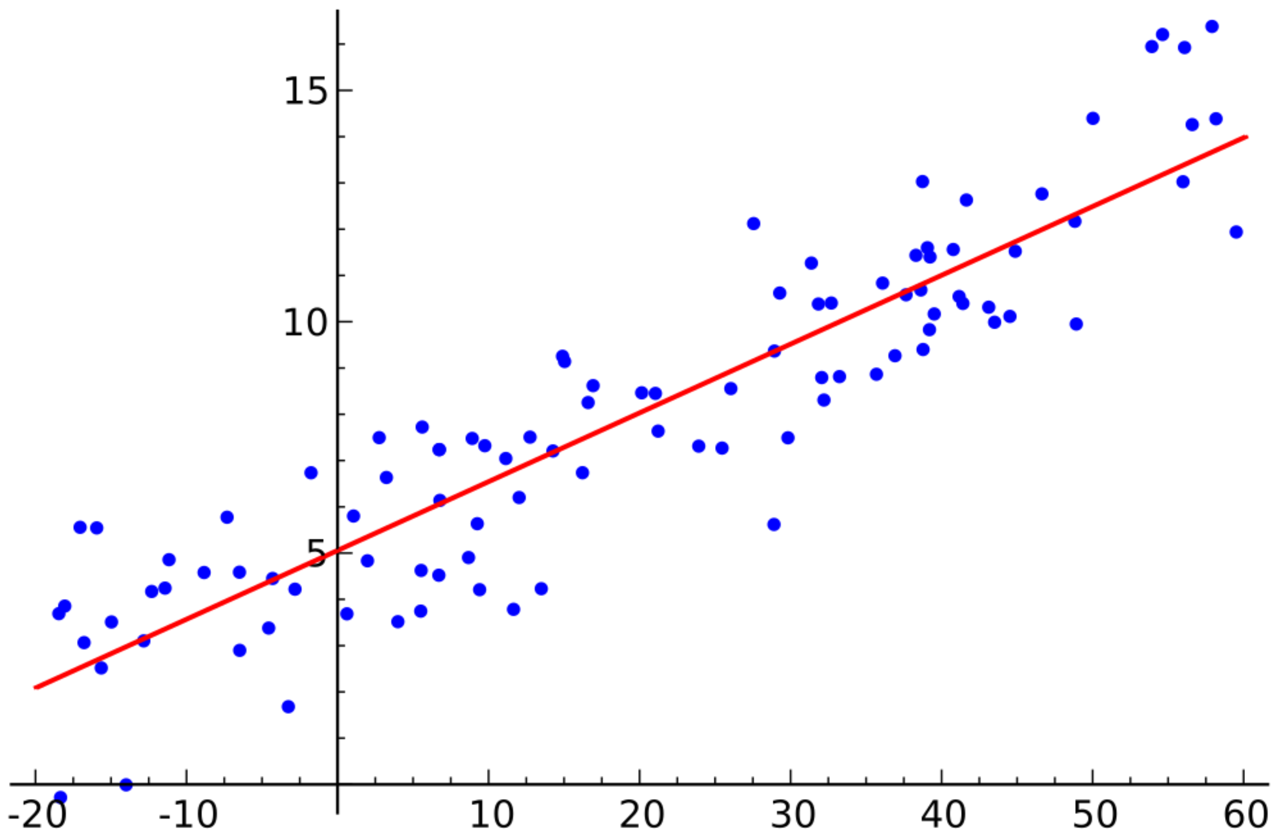
Intro Machine Learning slide

Linear regression and neural network

Linear regression

Linear regression is a linear approach to modeling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables).



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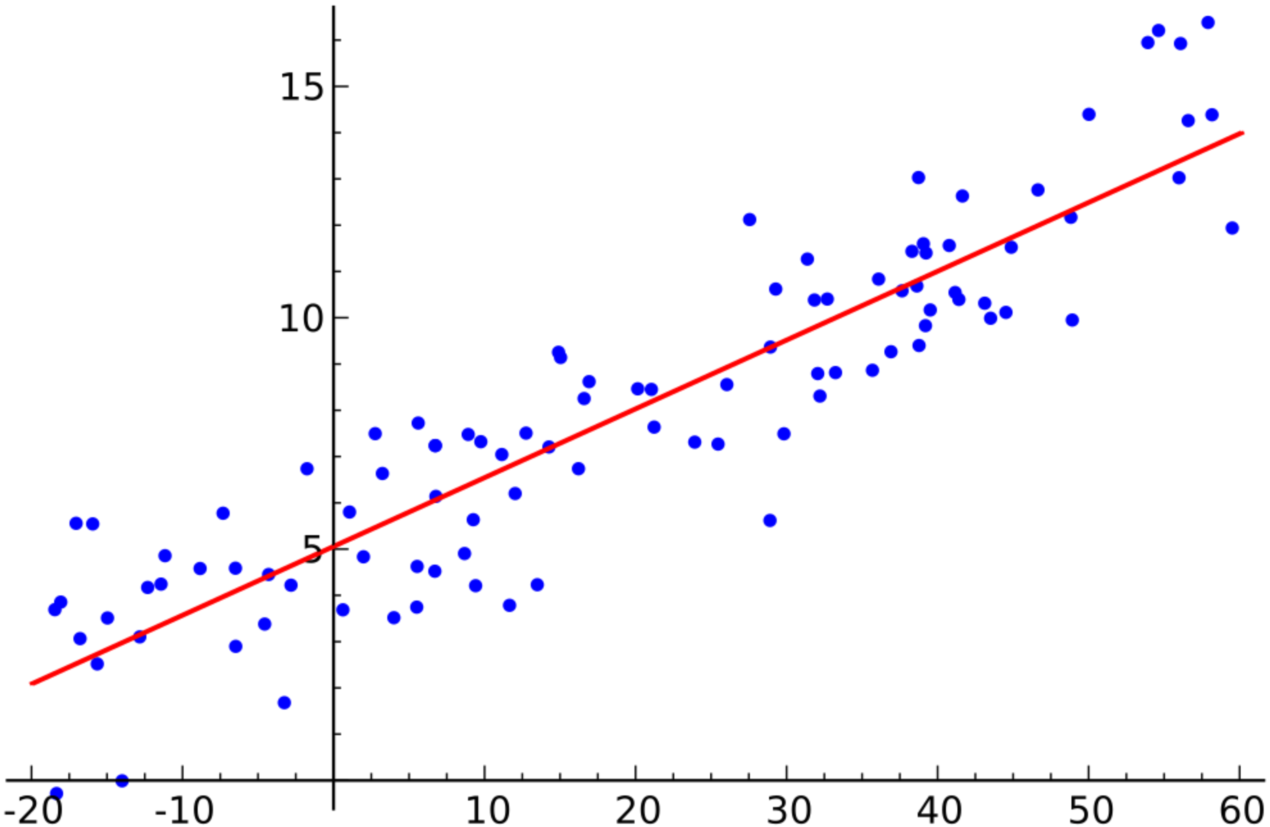
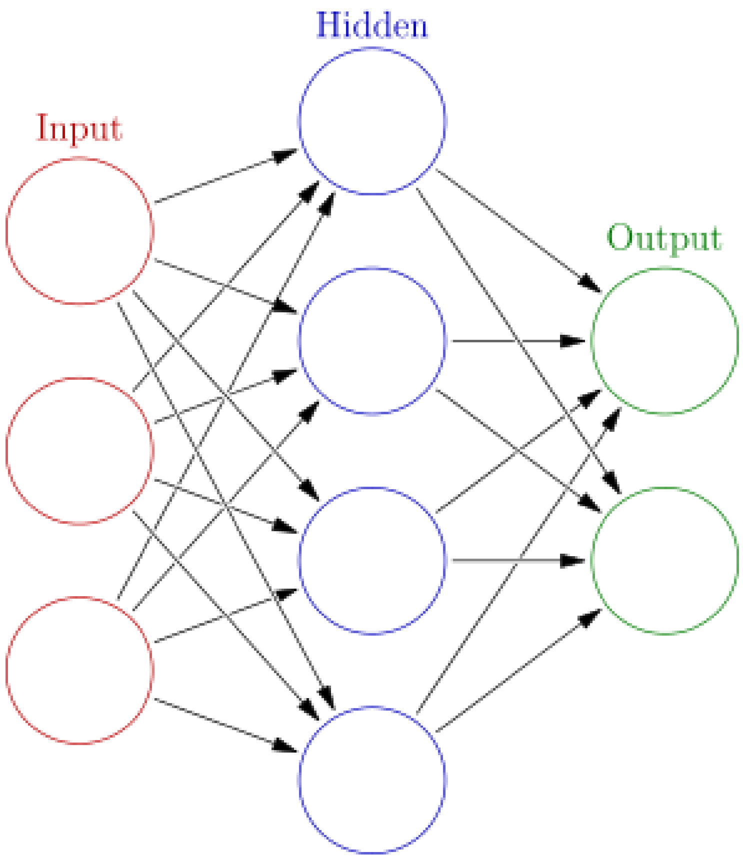
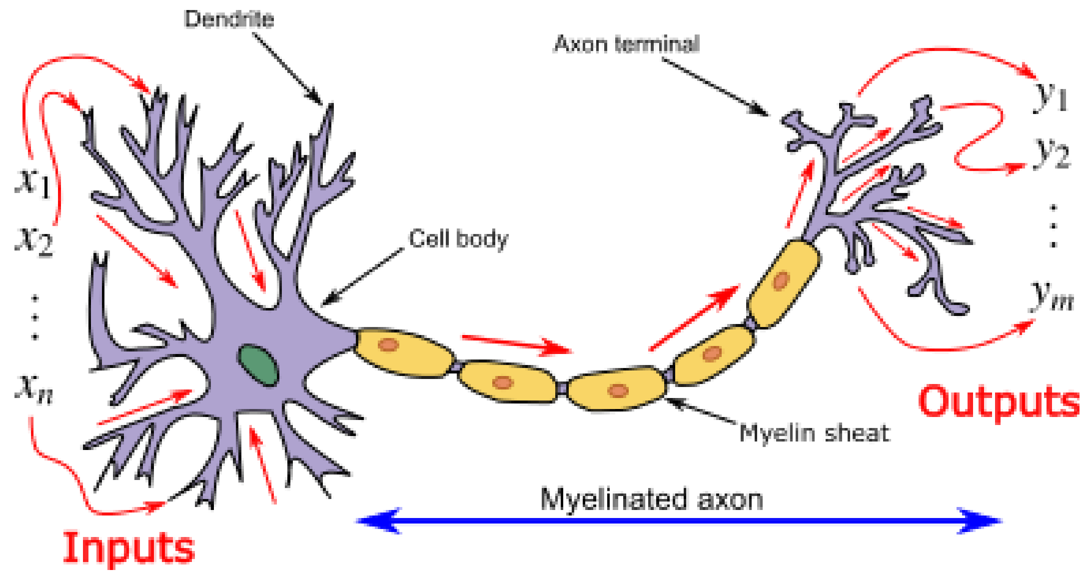
Linear regression slide for details…



Neural network

An artificial neural network is an interconnected group of nodes, inspired by a simplification of neurons in a brain.





Neural network

An artificial neural network is an interconnected group of nodes, inspired by a simplification of neurons in a brain.

These mathematical models are too simple to gain an understanding of biological neural networks, but they are used to try to solve artificial intelligence engineering problems such as those that arise in different technological fields.

Neural network

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Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules.

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For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images.

Applications in aerospace

NASA Langley Technical Areas

Aerosciences

Systems Analysis & Concepts

Measurement Systems

Entry, Descent & Landing

Intelligent Flight Systems

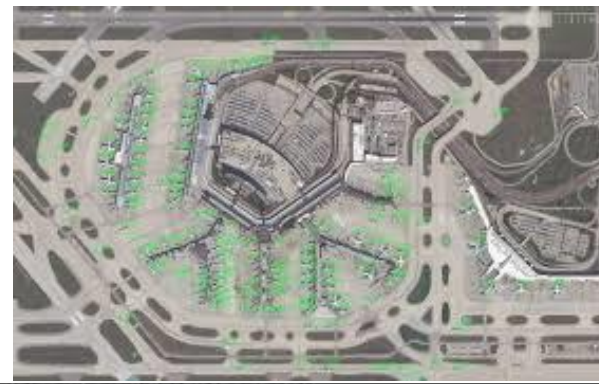
Atmospheric Characterization

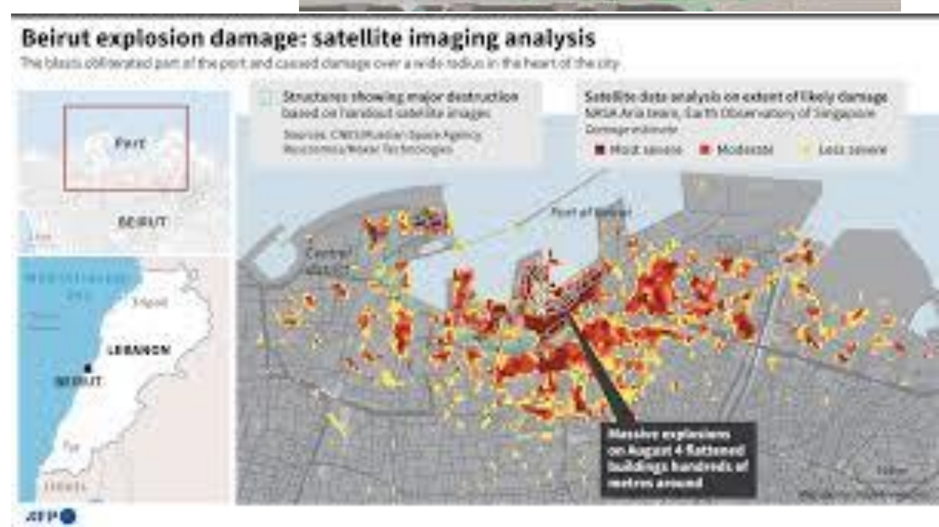
Advanced Materials & Structural Systems

Earth observation - satellite image analysis

Vast amount of digital satellite and aerial imagery is being acquired by modern Earth Observation sensors every day.

Analyze the raw imagery quickly, extract useful, actionable information with higher accuracy, and apply decision making and applications.





Satellite gateway fault prediction

Satellite fault prediction slide

Mars express power challenge

Predict the power or fuel consumption of the spacecraft.

Three years of spacecraft telemetry are released, can you predict the fourth year?

Automate operations and extend satellite life time, which in turn increases the scientific return.

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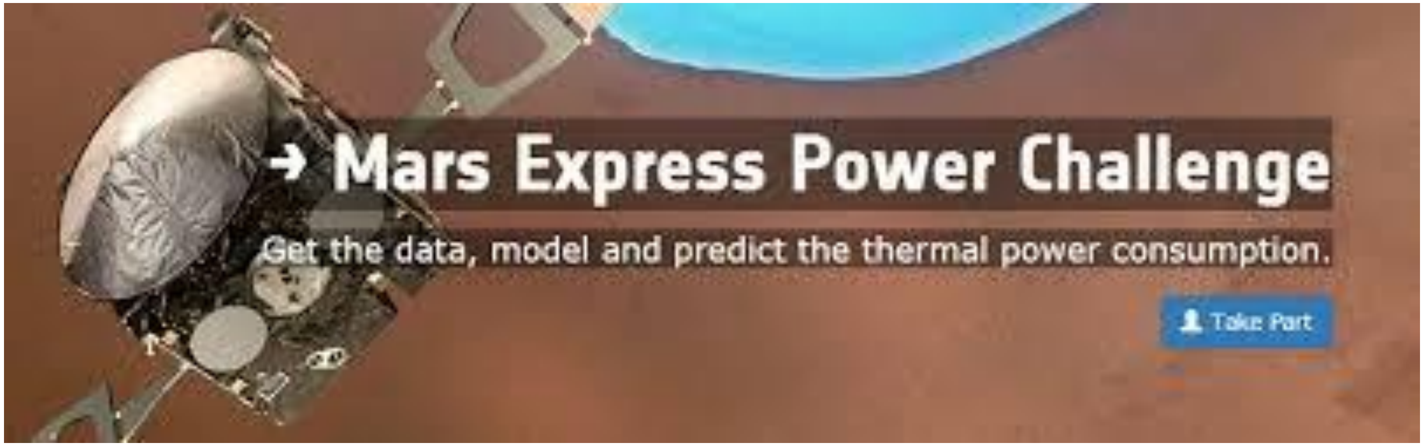


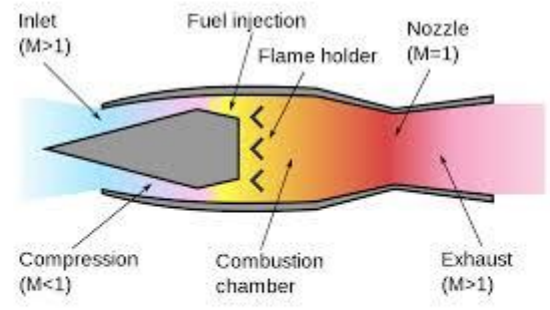
https://kelvins.esa.int/mars-express-power-challenge/

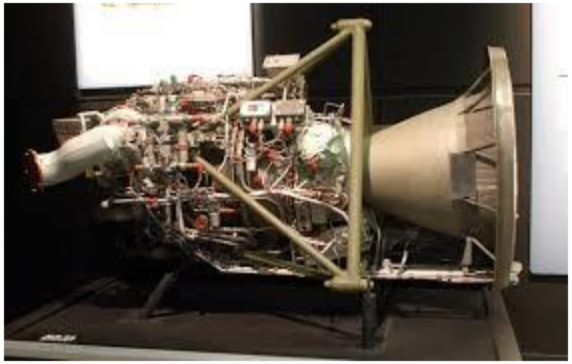
Physics-Informed Machine Learning

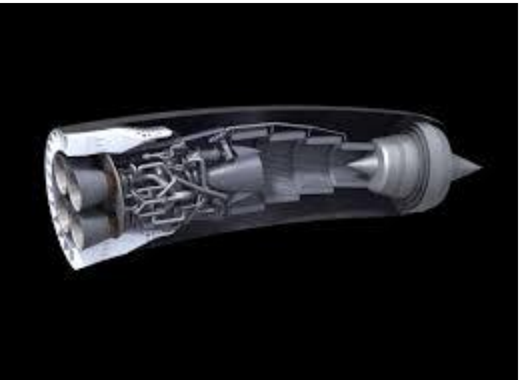
Physics-Informed Machine Learning

Assist but respect models: Machine learning should be used to correct/improve existing models, not to replace them.

Cost effective & exact solution: Turbulent flow & Solid Mechanics modeling, Optimal design of Aircraft & Rocket engine.



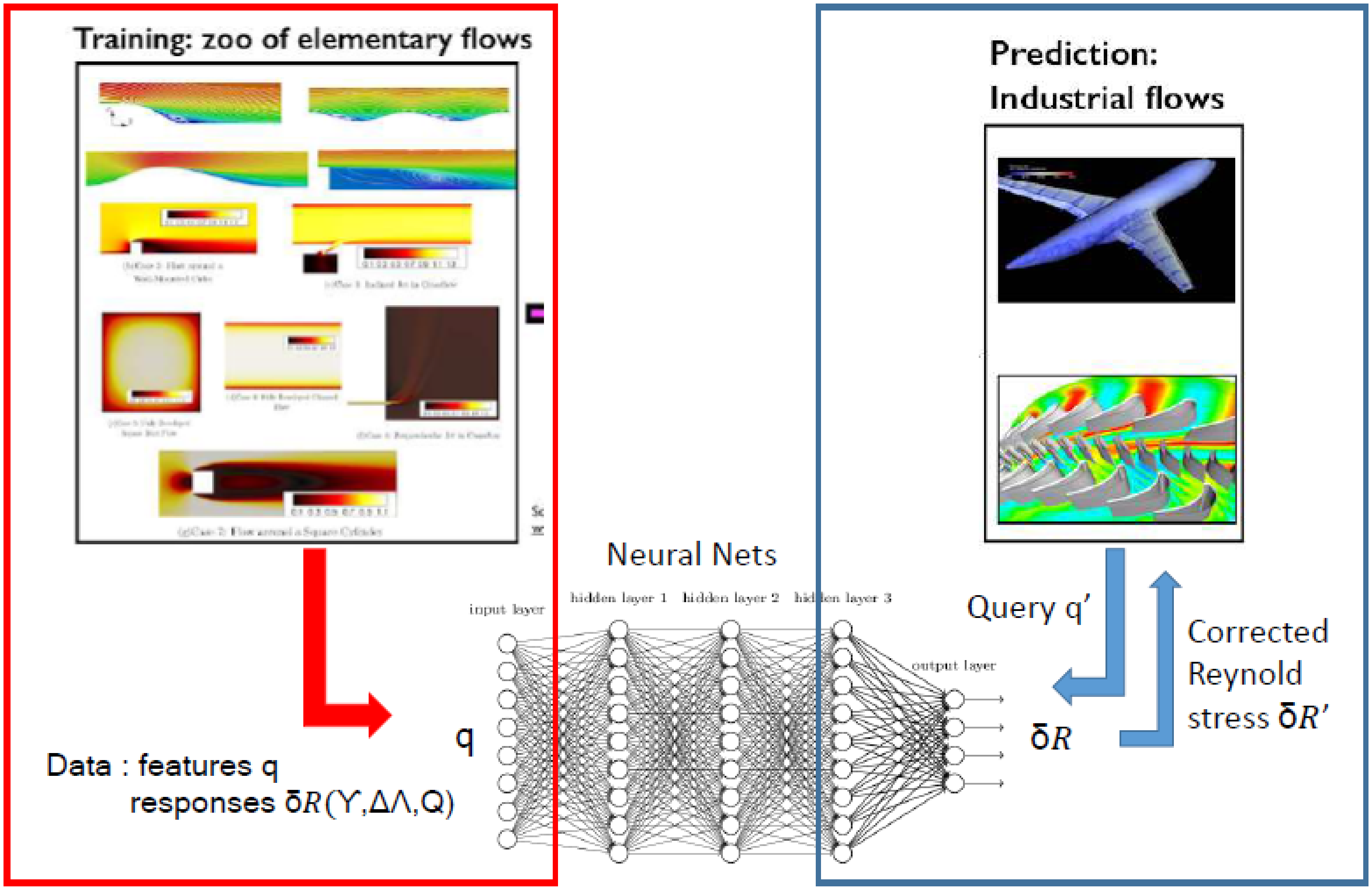




Physics-Informed Machine Learning

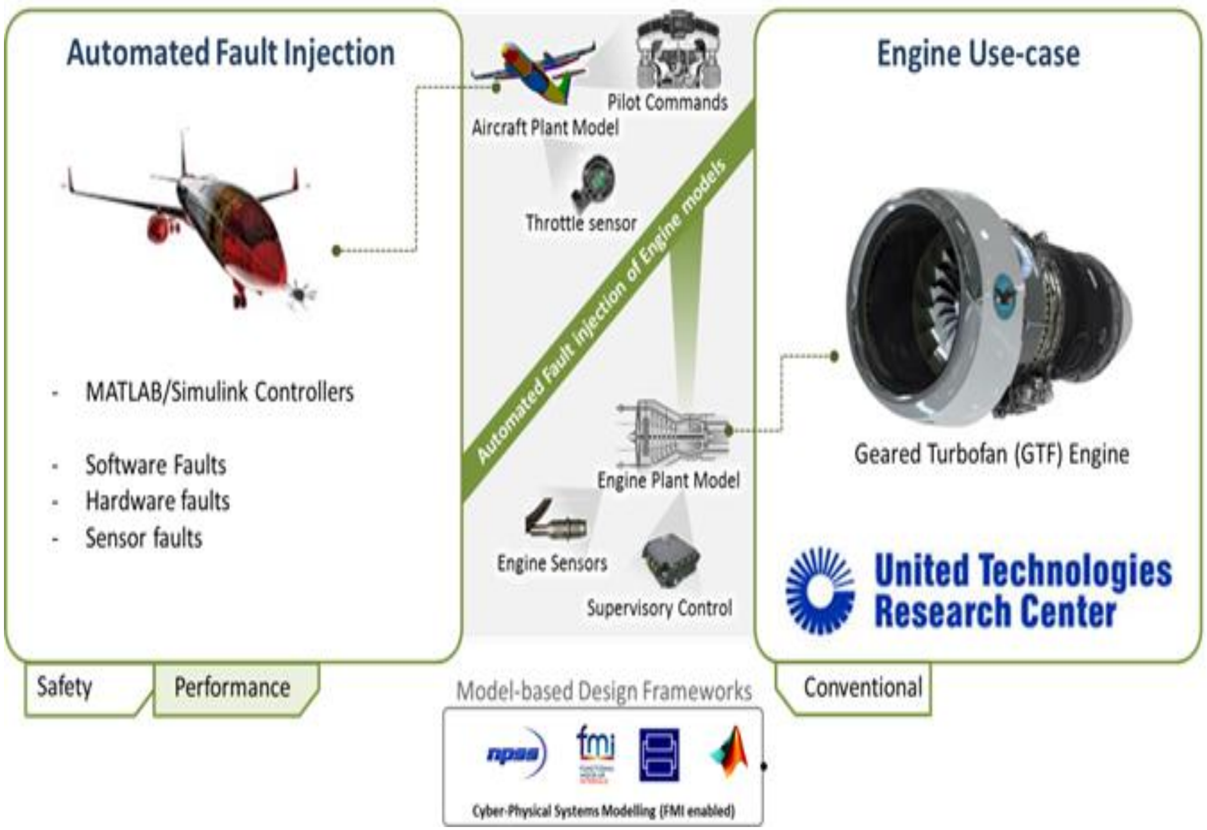
Phase I :
Training with Machine learning

Phase II :
Prediction with ML assisted
RANS Simulation



Aircraft engine controller

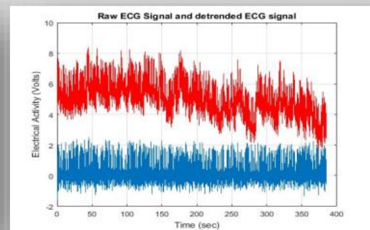
- Gas turbine engine coupled with an engine controller.
- Several type of faults and attacks (e.g., hot start, hung start and start stall) will be tested in the different flight modes (take-off, cruise, landing).
- Interaction between cyber models.



Aerospace Data Assistant

Aerospace Data Assistants Projects

Cognitive Assessment of Crew State Monitoring



Build classification models for predicting cognitive state using physiological data collected during flight simulations

Goals

- Identify unsafe cognitive states in aircrew real-time
- Apply results for more effective pilot training

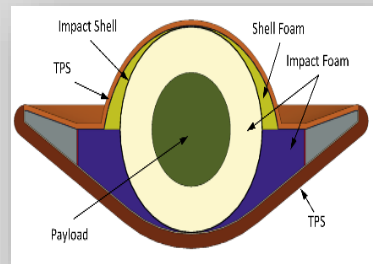
Techniques

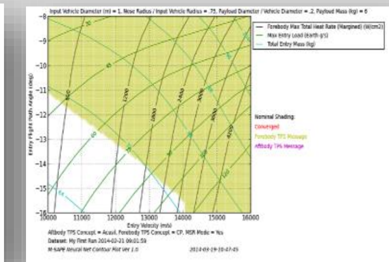
- Ensemble of machine learning tools (deep neural network, gradient boosting, random forest, support vector machine, decision tree)
- Data pre-processing using detrending and power spectral density

Accomplishments & Next Steps

- Initial data mapping, statistical analysis, and signals processing
- Explore combining multiple signal models using ensemble
- Developing models from test subjects data from different days

Rapid Exploration of Aerospace Designs





Develop a generalized machine learning platform to be used for analyzing mod-sim data for design optimization

Goals

- Provide surrogate modeling to explore the trade space of aerospace vehicle designs with easy-to-use web interface
- Use fast machine learning models instead of computationally-intensive code for rapid exploration and optimization

Techniques

- Supervised machine learning algorithms, SVM, and Neural Networks trained on labeled data

Accomplishments & Next Steps

- Python 2.7 with SKLearn algorithms are being used
- Web interface using PHP being developed for SME use

Linear regression

Application 1:

Non-Destructive Evaluation (NDE) Image analysis

Goal:

Automate delamination detection

Method: Fit data with linear regression and detect outlier regions. Regression performed on 1D and 2D signals; Uses C ++ and R

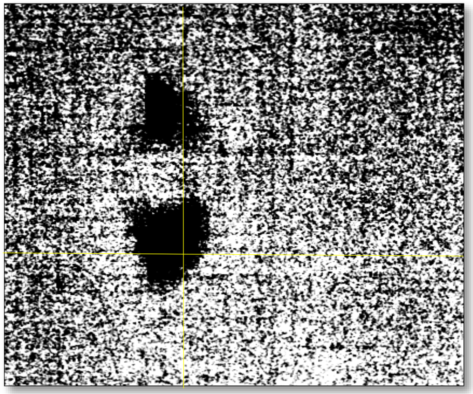
Application 2:

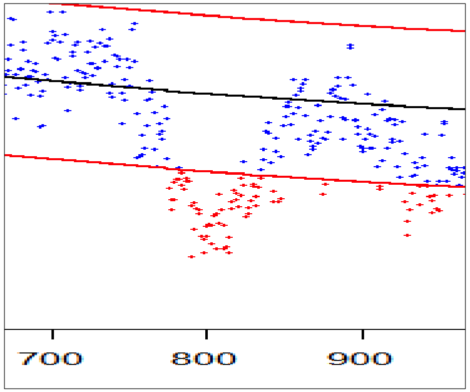
Aeroelastic Flutter Data Analytics

Goal:

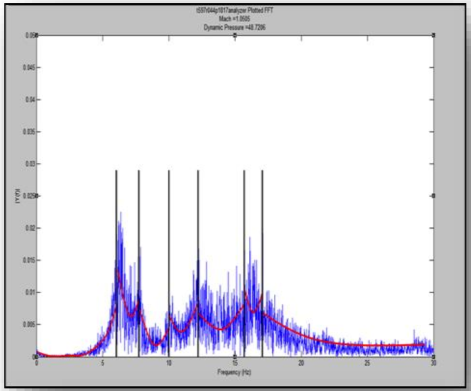
Detect precursors and onset of aeroelastic flutter

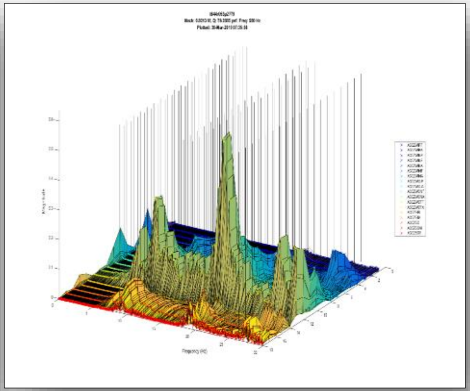
Method: Fit best quadratics between structural modes to detect mode coalescence; Uses MatLab

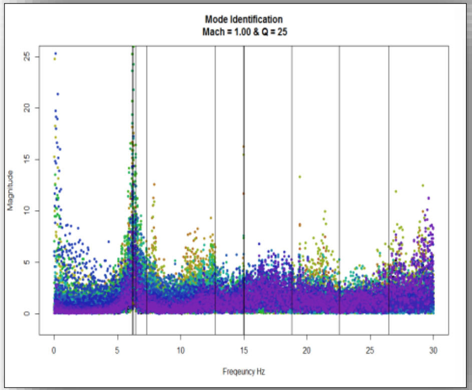


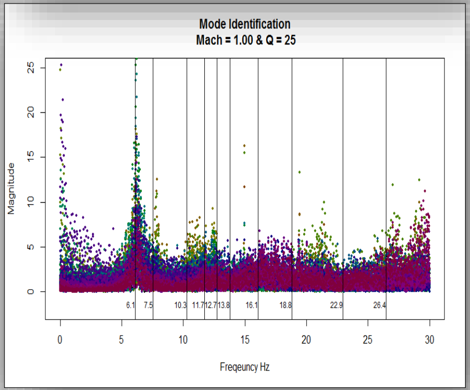


Top: Linear regression of 1D-signals for anomaly detection in carbon fiber; *Bottom*: Mode identification in flutter time-series data using linear regression







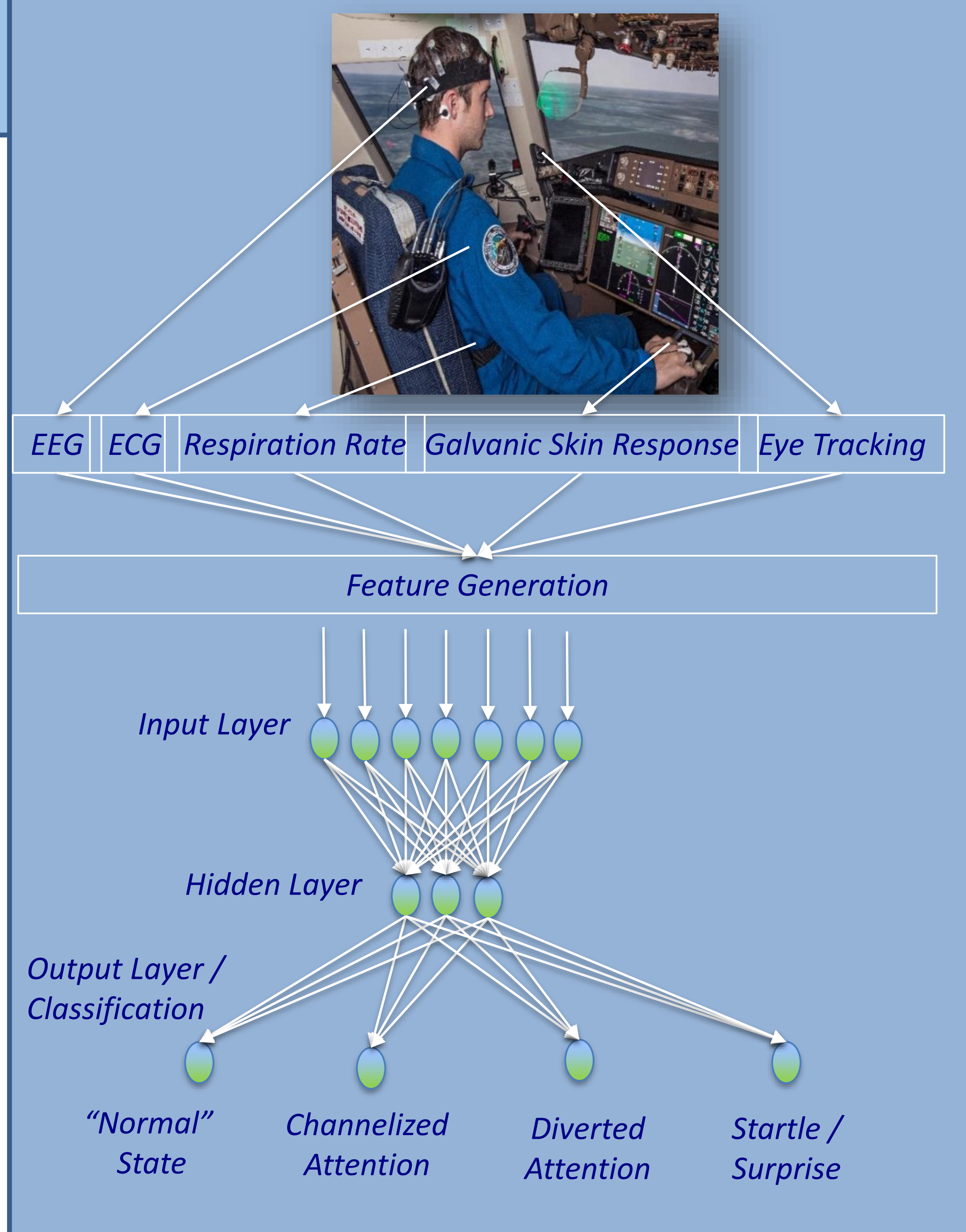


Artificial neural networks

Application 1: Crew State Monitoring

Goal: Build classification models capable of accurate, real-time prediction of aircrew cognitive state using physio data collected during flight simulations

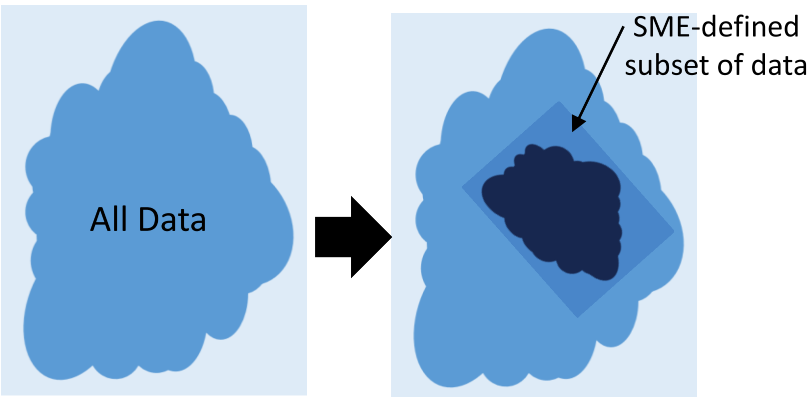
Method: ANN trained to classify cognitive state



NASA vision of Aerospace Data Analytics (cognitive machine learning)

Aerospace Data Analytics: Challenge of Physics-Based Algorithms

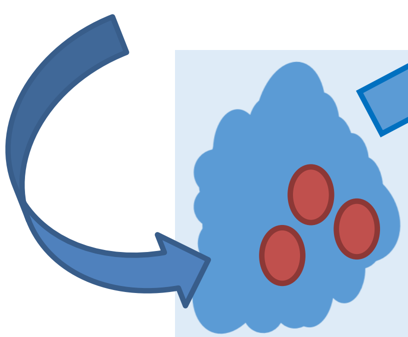
Current State



SME relies on traditional methods to pre-select data; Requires expertise and is time-consuming

Being Developed

Data Mining techniques to detect patterns and correlations which will be validated by SMEs



Data Analytics Team and SMEs working together

Being Developed

Algorithms that mimic SME knowledge:
- Validate the algorithm
- Save SME time

Application of algorithms to data, and to other legacy datasets

Yields New Insights

Long Term Vision

Virtual Expert

Autonomous Assistant to SME that analyzes all possible data and augments decision making

eXplainable AI (XAI)

Intelligible analytics - why

D/SRUPTION

The Next Big Disruptive Trend in Business. . . Explainable AI
With so many different approaches to machine learning – neural networks, complex algorithms, probabilistic graphical models – it's getting increasingly difficult for humans to figure out how machines are coming to their conclusions.

THE WALL STREET JOURNAL.

Capital One Pursues 'Explainable AI' to Guard Against Bias in Models
The effort aims to better understand how a machine-learning model comes to a logical conclusion.

Capital One Financial Corp. is researching ways that machine-learning algorithms could explain the rationale behind their answers, which could have far-reaching impacts in guarding against potential ethical and regulatory breaches as the firm uses more artificial intelligence in banking.

WIRED

Sure, A.I. Is Powerful—But Can We Make It Accountable?
Imagine you apply for insurance with a firm that uses a machine-learning system, instead of a human with an actuarial table, to predict insurance risk. After crunching your info—age, job, house location and value—the machine decides, nope, no policy for you. You ask the same question: "Why?"

Nobody can answer, because nobody understands how these systems—neural networks modeled on the human brain—produce their results.

- EU General Data Protection Regulation (GDPR)
  - In Effect May 2018
  - Penalties as high as 4% of annual revenue

WIRED

Artificial Intelligence Is Setting Up the Internet for a Huge Clash With Europe

The GDPR restricts what the EU calls "automated individual decision-making", And for the world's biggest tech companies, that's a potential problem. "Automated individual decision-making" is what neural networks do. "They're talking about machine learning," says Bryce Goodman, a philosophy and social science researcher at Oxford University.

The regulations prohibit any automated decision that "significantly affects" EU citizens. This includes techniques that evaluate a person's "performance at work, economic situation, health, personal preferences, interests, reliability, behavior, location, or movements." At the same time, the legislation provides what Goodman calls a "right to explanation." In other words, the rules give EU citizens the option of reviewing how a particular service made a particular algorithmic decision.

Example

Rule *r* **if** <*premise*> **then** <*consequence*>

N	Disease (Output)	Condition 1	Condition 2	Covering
1	No	Age $\leq$ 65	Marker > 10.60 units	80%
2	No	Male Gender	Marker $\leq$ 29.40 units	30%

Feature ranking

Rule *r* **if** <*premise*> **then** <*consequence*>

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Importance of a condition *c*: error variation with and without *c*

$$\Delta E(c) = E(r') - E(r)$$

Relevance: error variation and covering *C(r)*

$$R(c) = \Delta E(c) C(r)$$

Relevance R_v of feature x_j

$$R_v(x_j) = 1 - \prod_k (1 - R(c_{kl}))$$

Feature ranking

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Relevance: error variation and covering $C(r)$

$$R(c) = \Delta E(c) C(r)$$

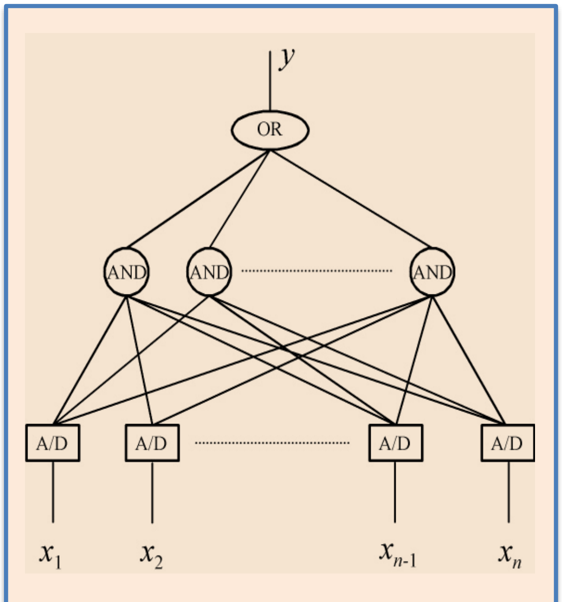
Relevance R_v of feature x_j

$$R_v(x_j) = 1 - \prod_k \left(1 - R(c_{kl})\right)$$

Rule of thumb: R_v<10%: marginal contribution; $C(r)$<20%: outliers

Logic Learning Machine (LLM)

Switching Neural Network (SNN)
(Muselli, 2006; Muselli & Ferrari, 2011)



R&D Team Impara Srl
Spin-off of CNR-IEIIT

Logic Learning Machine (LLM)
(Parodi et al., 2017; Skotko et al., 2017)

LLM Task from **Rulex®Analytics**

LLM is able to treat huge datasets and is therefore suited for Big Data Analytics.

The LLM model is currently used by several big companies in a wide variety of fields, among which supply chain, banking, insurance, industry, energy, water distribution, …

XAI example

XAI example slide

XAI example

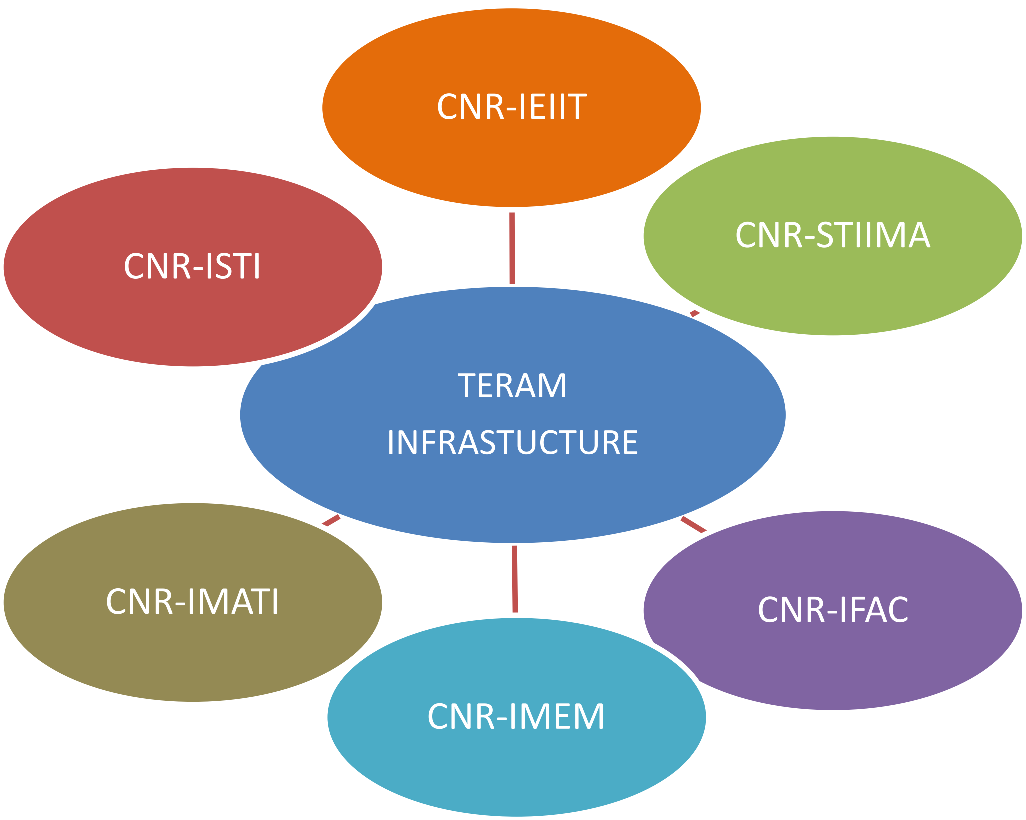
XAI example slide

Live demo in Rulex (www.rulex.ai)

@CNR

AEROSPACE @ CNR-DIITET: NEW SHARED INFRASTRUCTURE

TERAM: Advanced manufacturing and testing of mm-wave and sub-THz components & systems



LAB for RF testing of components @ mm-wave and sub-THz

LAB for advanced manufacturing:

- Micro-machining
- Additive manufacturing
- Non-destructive testing

AEROSPACE @ CNR-IEIIT: KNOW-HOW

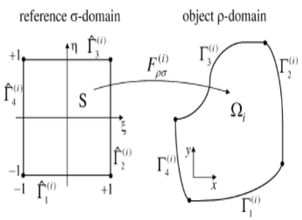
TECHNOLOGICAL DOMAINS

TECHNOLOGICAL SUB-DOMAINS

TD 6 - RF Systems, Payloads and Technologies

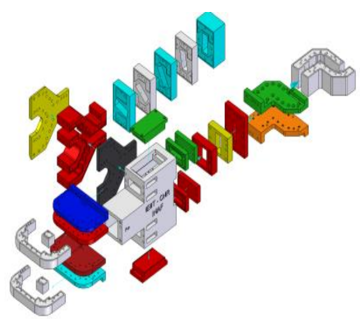
TD 7 - Electromagnetic Technologies and Techniques

Electromagnetic Modelling



$$\iint_{\Omega_i} \nabla_t\phi^{(i)}\nabla_t v^{(i)}\mathrm{d}\Omega_i - k_t^2 \iint_{\Omega_i} \phi^{(i)} v^{(i)}\mathrm{d}\Omega_i = \sum_{k=1}^{N_{\mathrm{ports}}^{(i)}} \int_{\Gamma_{\mathrm{wg}}^{(k)}} \frac{\partial\phi_{\mathrm{wg}}^{(k)}}{\partial n_{\mathrm{wg}}^{(k)}} v^{(i)}\mathrm{d}\Gamma_{\mathrm{wg}}^{(k)} \quad \forall v^{(i)} \in X_v^{(i)}$$

Electromagnetic and Mechanical Design



MAIT

Electromagnetic Testing

AEROSPACE @ CNR-IEIIT: ON-GOING ACTIVITIES

APPLICATION DOMAINS

PROJECTS

Astrophysics/ Radio-Astronomy

International Square-Kilometer-Array Programme

(2010 -)

ASI Mission

Large Scale Polarization Explorer

(2011 - 2022)

Satellite Telecommunication

ARTES ESA Programme

- Pre-aligned non-intrusive Ku-band direct-to-home antenna using advanced manufacturing (2018 -2021)
- On-board feed chain for combined Q, V-band feeder and Ka-band user LInks (2020 - 2022)
- Radio-Frequency (RF) feeds with integrated RF, mechanical and thermal functions (2020 - 2022)

Earth Observation

Copernicus EC Programme

- Phase A/B1 of passive Microwave Imaging Mission (CIMR) (2018 - 2020)
- Copernicus HPCM -CIMR - Phases B2, C/D and E1 (2020-2023)

MetOp-SG ESA Programme

MWI Microwave Imager

(2018 - 2021)

TRANSVERSAL TO APPLICATION DOMAINS

GSTP ESA Programme

Evaluation and consolidation of Additive Manufacturing processes and materials for the manufacturing of RF hardware (2019-2022)

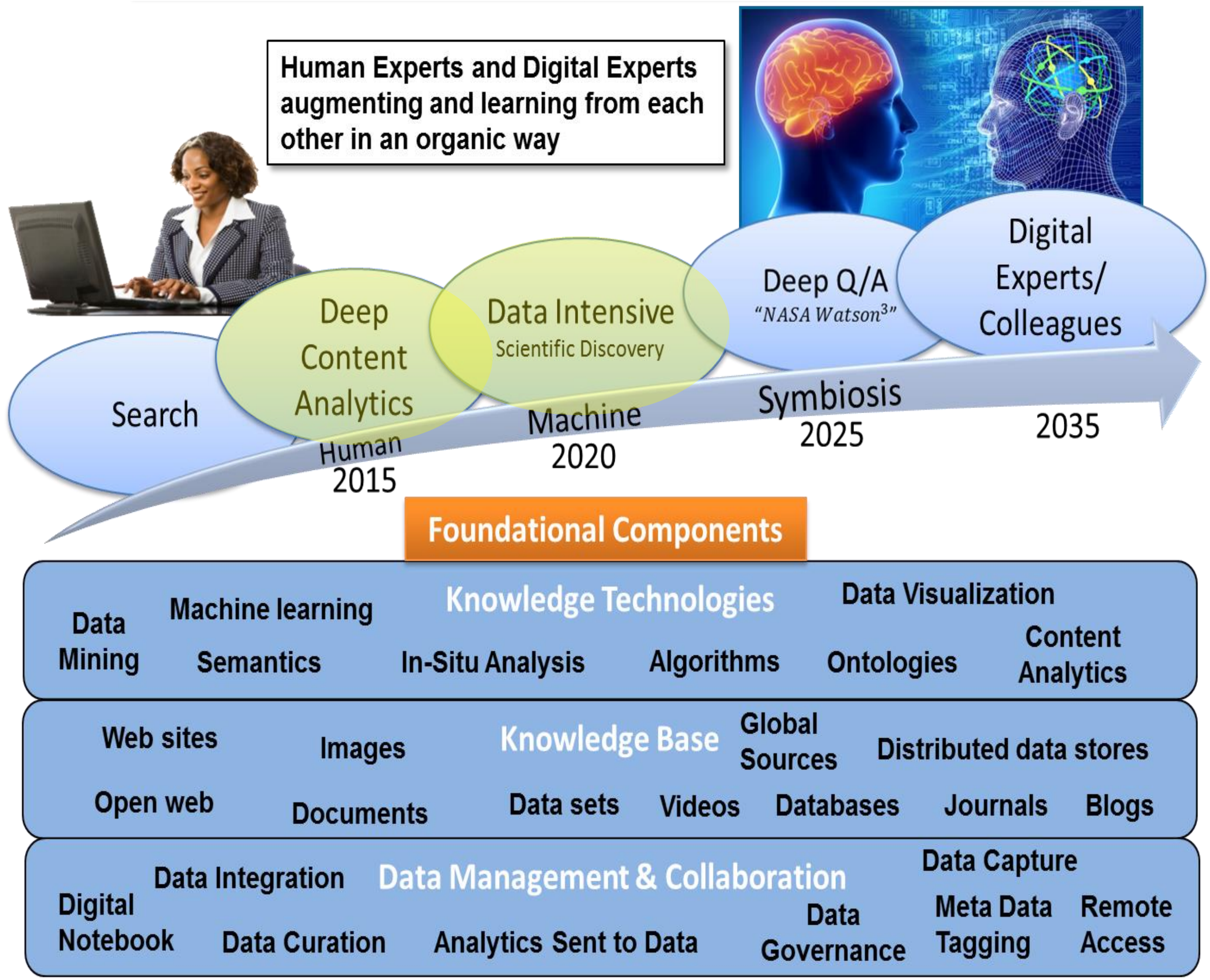
ITI ESA Programme

3D screen printing of high frequency components (2018 - 2020)

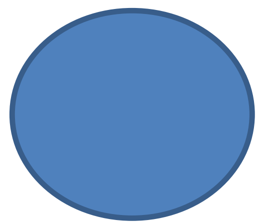
Conclusions

Conclusions: view into the future

Enable NASA employees to achieve greater scientific discoveries and systems innovations



THANK YOU:… Q&A



Titolo

Bla bla

Logic Learning Machines vs Decision Trees

Logic Learning Machine

- Training is fast and parallelizable
- Models rules are independent from each other
- Relevance measures for variables and values are automatically generated
- Accuracy is generally higher
- Specificity and sensitivity can be controlled
- Usually models are less complex with simpler rules

Decision Trees

- Training is fast but not efficiently parallelizable
- Model rules are disjoint but conditions are strictly dependent
- Relevance measures for variables and values are not directly available
- Accuracy is generally poorer
- Specificity and sensitivity cannot be controlled
- Usually models are more complex with longer rules

Rule generation

A.1)

Discretization → *Cut-offs* applied to continuos variables. Optimal placement of the cut-offs.

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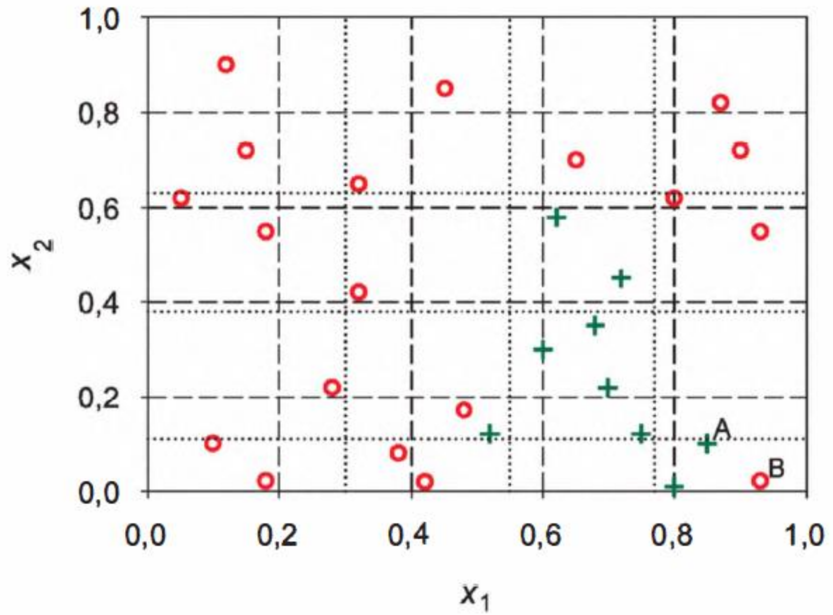
Discretization → *Cut-offs* applied to continuos variables. Optimal placement of the cut-offs.



A simple bidimensional problem: the points of the two classes are represented by circles and crosses, respectively.

E. Ferrari and M. Muselli. Maximizing pattern separation in discretizing continuous features for classication purposes. In The 2010 International Joint Conference on Neural Networks (IJCNN), pages 1{8, July 2010. doi: 10.1109/IJCNN.2010.5596838.

A)

Discretization & Latticization

- Inverse *only-one coding*

$$\left.\begin{array}{l}[x_1,\dots,x_n] \rightarrow [0,1]^n \\ [y_1,\dots,y_k] \rightarrow [0,1]^k\end{array}\right\} \rightarrow [0,1]^{n+k}$$

Class	x_1	$Bin(x_1)$	x_2	$Bin(x_2)$	Final string
B	8	011	0	01	01101
A	12	101	1	10	10110
A	22	110	1	10	11010

Latticization: for continous variables, as x_1, binary values correspond to cut-offs between adjacent values (e.g.: 10 and 20)

A)

Discretization & Latticization

- Inverse *only-one coding*

$[x_1, \ldots, x_n] \rightarrow [0,1]^n$

$[y_1, \ldots, y_k] \rightarrow [0,1]^k$

$\rightarrow [0,1]^{n+k}$

Class	x_1	$Bin(x_1)$	x_2	$Bin(x_2)$	Final string
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A	22	110	1	10	11010

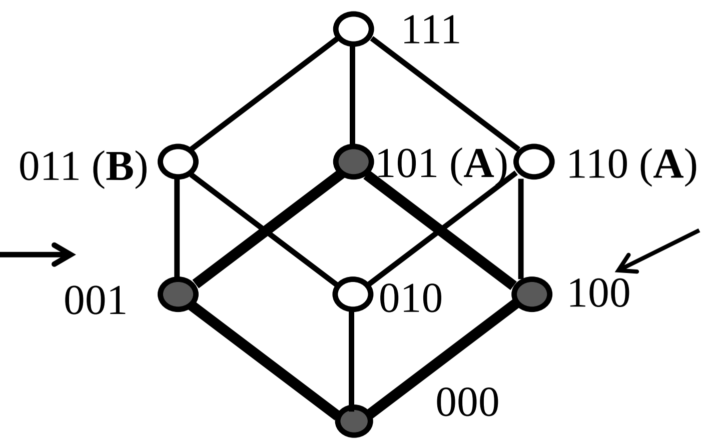
For continous variables, as x_1, binary values correspond to cut-offs between adjacent values (e.g.: 10 and 20)

B)

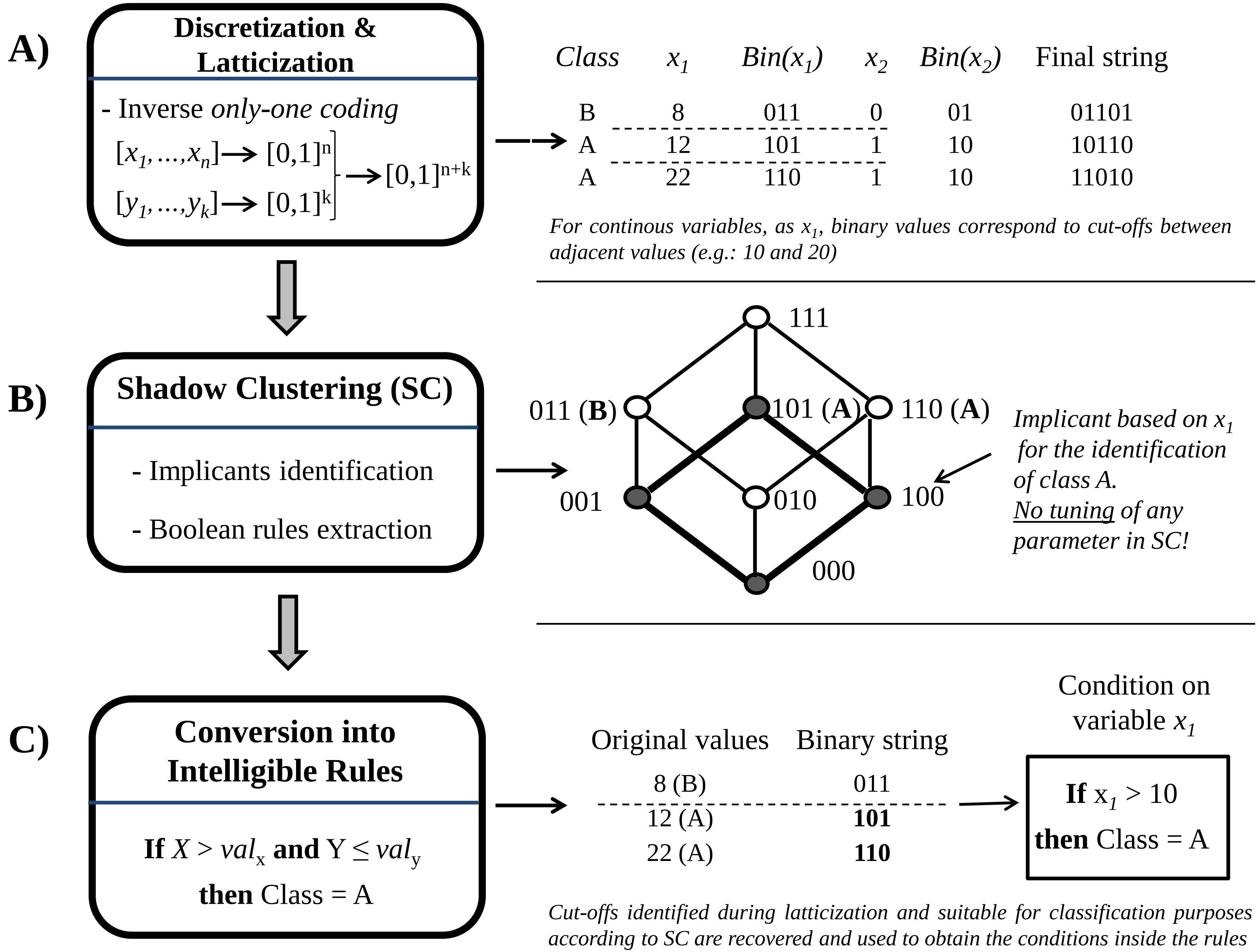
Shadow Clustering (SC)

- Implicants identification

- Boolean rules extraction



Implicant based on x_1 for the identification of class A.
No tuning of any parameter in SC!


A)
Discretization & Latticization
- Inverse only-one coding
[x1,…,xn] → [0,1]n
[y1,…,yk] → [0,1]k
→ [0,1]n+k
Class x1 Bin(x1) x2 Bin(x2) Final string
B 8 011 0 01 01101
A 12 101 1 10 10110
A 22 110 1 10 11010
For continous variables, as x1, binary values correspond to cut-offs between adjacent values (e.g.: 10 and 20)
B)
Shadow Clustering (SC)
- Implicants identification
- Boolean rules extraction
111
011 (B)
101 (A)
110 (A)
001
010
100
000
Implicant based on x1 for the identification of class A.
No tuning of any parameter in SC!
C)
Conversion into Intelligible Rules
If X > valx and Y ≤ valy then Class = A
Original values
Binary string
8 (B) 011
12 (A) 101
22 (A) 110
Condition on variable x1
If x1 > 10 then Class = A
Cut-offs identified during latticization and suitable for classification purposes according to SC are recovered and used to obtain the conditions inside the rules