UNIVERSITÀ DI PISA

XAI Models for Quality of Experience Prediction in Wireless Networks

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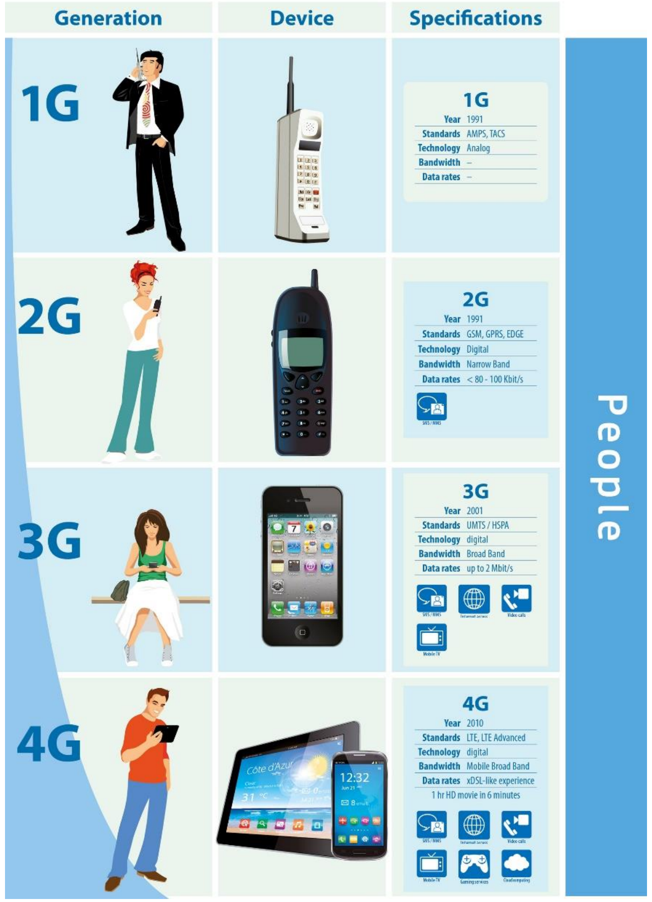
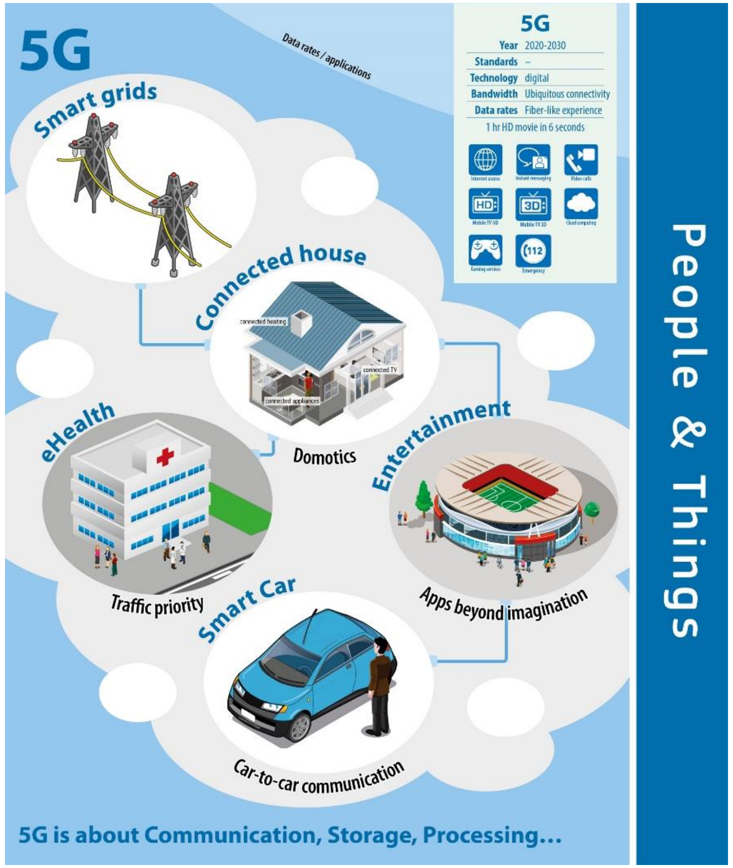
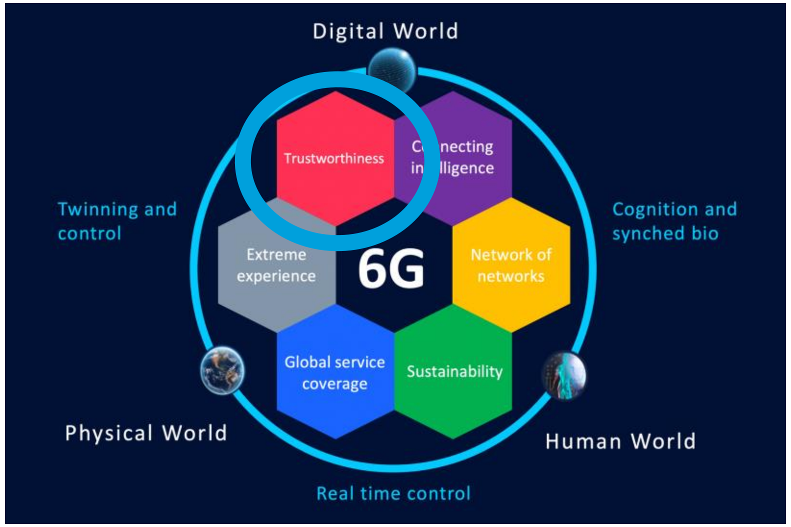
Introduction: AI and Wireless Networks





Figures from https://digital-strategy.ec.europa.eu/en/library/1g-5g-infographic

Figure from Hexa-X Deliverable D1.2, “Expanded 6G vision, use cases and societal values”. Online: https://hexa-x.eu/wp-content/uploads/2021/05/Hexa-X_D1.2.pdf



Crucial role of **AI/ML** techniques

Introduction: Trustworthy AI

Trustworthy AI

- Human agency and oversight
- Technical robustness and safety
- Privacy and data governance
- Transparency
  - Traceability
  - Explainabilty
  - Communication
- Diversity non-discrimination and fairness
- Societal and environmental wellbeing
- Accountability

"AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned."

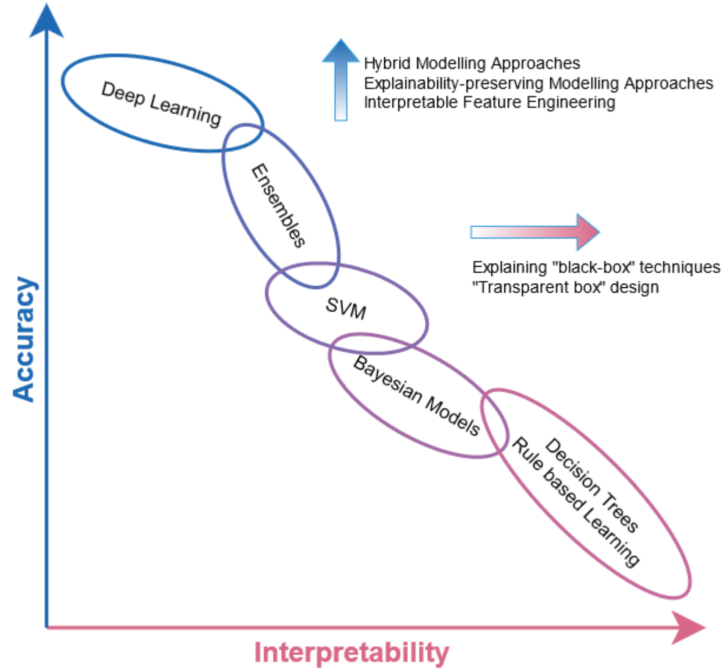
European Commission, *"Ethics guidelines for trustworthy AI"* Report, 2019

Introduction: Trustworthy AI (Cont’d)

Explainabilty

Design of **Inherently Interpretable** Models

***Post-hoc* Explainability** Techniques



Inspired to Arrieta et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." Information Fusion 58 (2020): 82-115.

Fuzzy Models

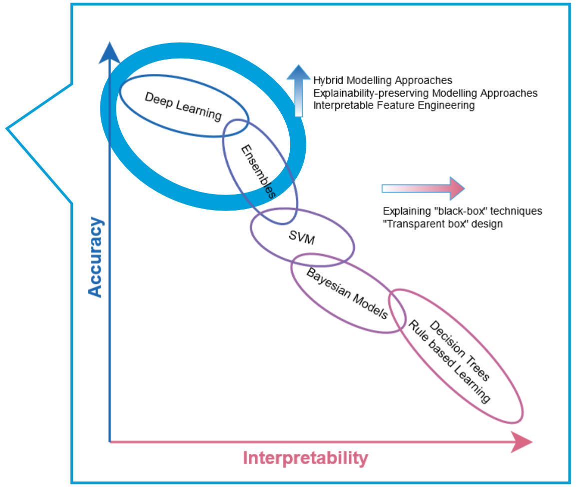
Linguistic representation enhances *semantic* interpretability

Motivation and goals

- Relevant **case study**:
  - Next Generation Networks will have stringent requirements in terms of:
    - Quality of Service (offered by the network)
    - Quality of Experience (user-perceived, tailored on the application)
- Vast majority of **current thrusts** for the adoption of AI for wireless networks are based on **“black-box” models**
- Increasing attention for **Trustworthy AI**

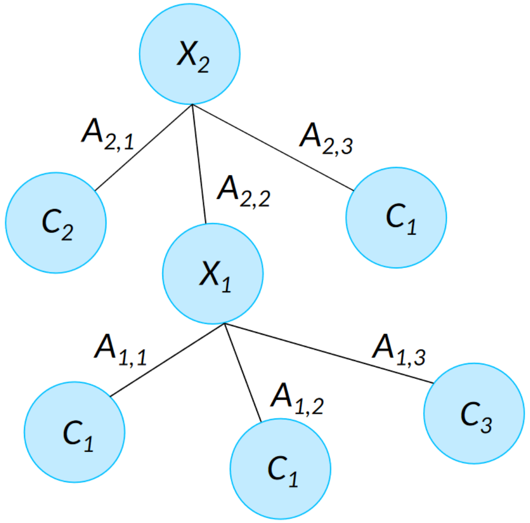
Goals:

- Adoption of **XAI models (Fuzzy Decision Trees)** in wireless networks for **Quality of Experience prediction**
- Experimental comparison: investigate the **explainability/accuracy trade-off** in the context of **tree-based models**

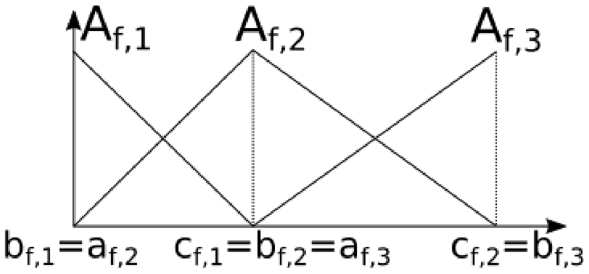


Background: Fuzzy Decision Tree (FDT)

- Directed acyclic graph
- Generated in a top–down way by performing **recursive partitions of the attribute space**.
- Typically, requires a **fuzzy partition defined upon each continuous attribute**.



Multi-way FDT



Strong Fuzzy Partition

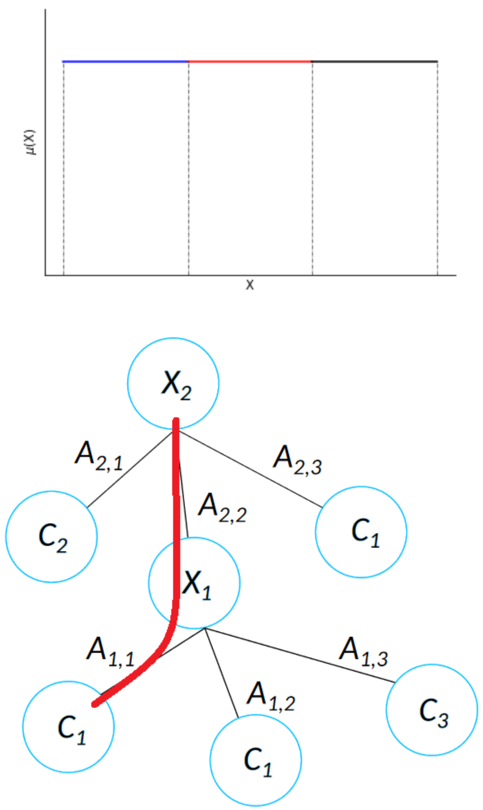
Segatori, Armando, Francesco Marcelloni, and Witold Pedrycz. "On distributed fuzzy decision trees for big data." IEEE Transactions on Fuzzy Systems 26.1 (2017): 174-192.

Background: Fuzzy Decision Tree

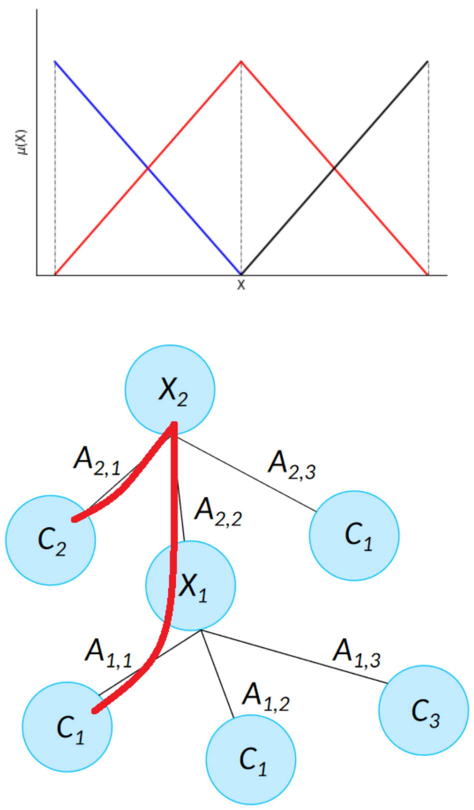
Main factors that affect **explainability** of FDTs

- Structural complexity
  - Numbers of nodes/leaves
- Inference process
  - Maximum *association degree*
- Linguistic fuzzy partition
  - Semantic interpretability
  - *Strong* triangular fuzzy partition

Crisp Decision Tree



Fuzzy Decision Tree



Experimental Setup: *QoS-QoE* Dataset

- Around 69000 **streaming video sessions**
- Goal: to derive a mapping between **QoS metrics** and **QoE factors** (multi-class classification problem)
- Simulated in a fully controllable simulation environment at both *network* and *streaming* levels

29 input variables

TABLE I
INPUT ATTRIBUTES: QOS METRICS AND THEIR DESCRIPTION.

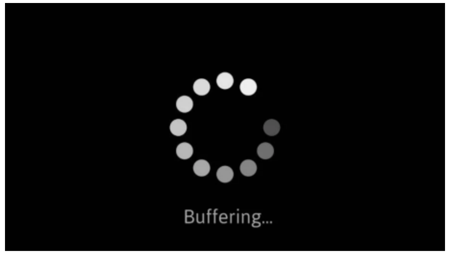
Name	Description
TCP[Output/Input]Packet	Number of TCP packets (In and Out)
TCP[Output/Input]Delay	Avg. delay of TCP packets (In and Out)
TCP[Output/Input]Jitter	Avg. jitter of TCP packets (In and Out)
TCP[Output/Input]Ploss	Loss rate of TCP packets (In and Out)
TCPInputRetrans	Packet retransmissions of TCP
StdNetworkRate	Standard deviation of the network rate
[x]_InputRateVariation; x in {0,5,10,25,50,75,90,95,100}	x^{th} quantile for the network rate (measured in intervals of 2s)
StdInterATimesReq	Std. dev. of inter-arrival times of segment requests
[x]_InterATimesReq; x in {0,5,10,25,50,75,90,95,100}	x^{th} quantile for the inter-arrival times of segment requests

$f(\cdot)$

NoStall [51155: ~74%]

MildStall [17180: ~25%]

SevereStall [794: ~1%]



Vasilev, Vladislav, et al. "Predicting QoE factors with machine learning." 2018 IEEE International Conference on Communications (ICC). IEEE, 2018.

Model evaluation via 5-fold stratified CV

- Model complexity (number of nodes, leaves)
- Evaluation metrics: Precision, Recall, F1-measure per class

Experimental Setup: Classification Models

Model	Multiway Fuzzy Decision Tree	Binary Decision Tree	Random forest (RF)
Implementation	Segatori et al. (2018)	CART scikit-learn	scikit-learn
Depth	**{3,4}** –> {MFDT-3, MFDT-4}	**{6, 11}** –> {BDT-6, BDT-11}	*default*
Splitting criterion	Fuzzy infogain	Infogain	*default*
Partitioning	Fuzzy - *a priori* - supervised	During tree construction	During trees construction
Max fuzzy sets	5	-	-

Experimental Results: Original Dataset

RESULTS ON THE ORIGINAL DATASET. AVERAGE VALUES.

	F1-measure Training	Test
MFDT-3	0.8443	0.8422
MFDT-4	0.8493	0.8472
BDT-6	0.8764	0.8678
BDT-11	**0.9158**	**0.8737**
RF	***0.9999***	***0.8953***

(a) micro-average F1

	Model Complexity Leaves	Nodes
MFDT-3	88.8	***115.2***
MFDT-4	331.6	438.6
BDT-6	***60.2***	119.4
BDT-11	740.0	1479.0
RF	337601.0	675102.0

(b) Model Complexity

	No Stall			Mild Stall			Severe Stall		
	F1	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall
MFDT-3	0.9008	0.8881	0.9149	0.6785	0.7017	0.6639	0.0279	0.1846	0.0151
MFDT-4	0.9032	0.9025	0.9045	0.7015	0.6923	**0.7149**	0.0257	0.1833	0.0138
BDT-6	0.9173	0.9021	**0.9335**	0.7228	0.7588	0.6938	0.5207	**0.7599**	0.3994
BDT-11	**0.9209**	**0.9103**	0.9320	**0.7378**	**0.7658**	0.7142	**0.6068**	0.6548	***0.5681***
RF	***0.9348***	***0.9166***	***0.9539***	***0.7777***	***0.8241***	***0.7376***	***0.6536***	***0.8670***	0.5291

(c) Precision and Recall by class on test set.

- **BDTs** slightly outperform **MFDTs** in terms of micro-average F1-score on the test set
- **RF** achieves highest overall performance but with huge global complexity (and low interpretability)
- *Moderately* low performance on the intermediate class (**Mild Stall**)
- *Considerably* low performance on the minority class (**Severe Stall**)

⇒ **Dataset re-balancing**

Experimental Results: Dataset re-balancing

No Stall: 2000

Mild Stall: 2000

Severe Stall 695

RESULTS AFTER RE-BALANCING THROUGH RANDOM UNDERSAMPLING. AVERAGE VALUES.

	F1-measure	
	Training	Test
MFDT-3	0.7859	0.8119
MFDT-4	0.8167	**0.8335**
BDT-6	0.8508	0.8112
BDT-11	**0.9447**	0.8026
RF	*1.0*	*0.8575*

(a) micro-average F1

	Model Complexity	
	Leaves	Nodes
MFDT-3	115.0	143.6
MFDT-4	396.0	500.8
BDT-6	***55.0***	***109.0***
BDT-11	278.4	555.8
RF	43911.2	87722.4

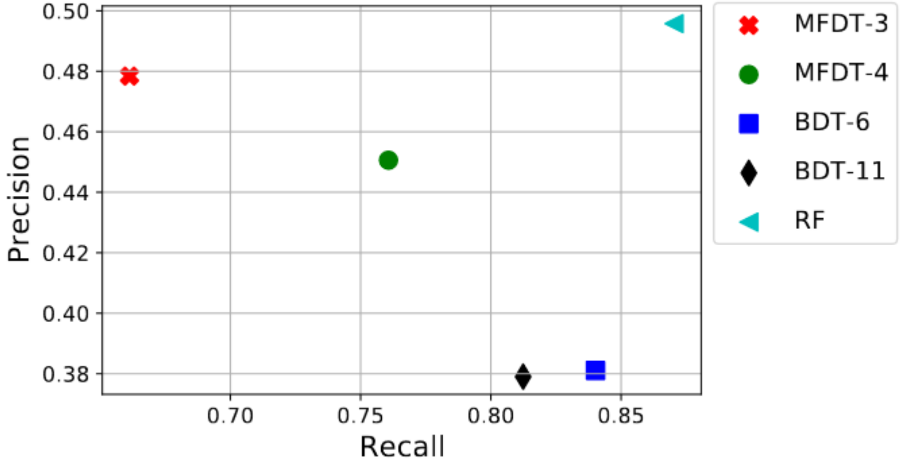
(b) Model Complexity

	No Stall			Mild Stall			Severe Stall		
	F1	Prec.	Recall	F1	Prec.	Recall	F1	Prec.	Recall
MFDT-3	0.8712	0.9396	0.8125	0.6856	0.5916	0.8171	0.5546	**0.4784**	0.6613
MFDT-4	**0.8907**	0.9415	**0.8451**	**0.7071**	**0.6323**	0.8024	**0.5590**	0.4506	0.7607
BDT-6	0.8731	**0.9504**	0.8082	0.6862	0.5920	**0.8189**	0.5235	0.3811	**0.8402**
BDT-11	0.8689	0.9311	0.8146	0.6611	0.5817	0.7665	0.5152	0.3790	0.8124
RF	*0.9070*	*0.9537*	*0.8649*	*0.7452*	*0.6740*	*0.8349*	*0.6291*	*0.4958*	*0.8703*

(c) Precision and Recall by class on test set.

- All models improve their **recall** on **Mild Stall** and **Severe Stall** classes
- **MFDTs** comparable or slightly better than **BDTs** in terms of micro-average F1-score
- **RF** achieves highest overall performance but with huge global complexity (and low interpretability)

Experimental Results: Explainability



(b) Results on class 2: *SevereStall*

$$R_{MFDT-4}: \textbf{IF } \textit{100\_InterATimesReq} \textbf{ is } \textit{VeryHigh}$$
$$\textbf{AND } \textit{25\_InterATimesReq} \textbf{ is } \textit{VeryHigh}$$
$$\textbf{AND } \textit{TCPInputPloss} \textbf{ is } \textit{VeryLow}$$
$$\textbf{THEN } \textit{StallLabel is SevereStall}$$

$$R_{BDT-6}: \textbf{IF } \textit{StdInterATimesReq} > 1.30$$
$$\textbf{AND } \textit{25\_InterATimesReq} > 0.86$$
$$\textbf{AND } \textit{StdInterATimesReq} > 1.59$$
$$\textbf{AND } \textit{25\_InputRateVariation} > 186749.00$$
$$\textbf{AND } \textit{TCPOutputJitter} > 0.00$$
$$\textbf{AND } \textit{90\_InputRateVariation} > 473853.50$$
$$\textbf{THEN } \textit{StallLabel is SevereStall}$$

- BDTs and MFDTs achieve different trade-offs between precision and recall
- BDT-6 outperforms BDT-11 with respect to all objectives

Conclusions

- Adoption of **fuzzy models** for addressing the task of **Quality of Experience classification**
- **Experimental comparison** between tree-based models on a recently proposed **QoS-QoE dataset,** characterized by a severe **class imbalance**
  - **Multiway Fuzzy Decision trees** achieves competitive performance in capturing *stall events,* in terms of precision, recall, micro-avg F1-measure.
  - **Multiway Fuzzy Decision trees** feature higher semantic interpretability than Binary Decision Trees
  - Random Forest outperforms all other models but does not feature inherent interpretability

What's next:

- QoS-QoE as a **time-series prediction** problem
- **Multi-objective evolutionary algorithms** for concurrently optimizing accuracy and complexity of FDTs

Thank you for your attention