



Ethics Guidelines for Trustworthy AI

Course on Computer Ethics, prof. Viola Schiaffonati
Politecnico di Milano, 7 November 2019



Teresa Scantamburlo

European Centre for Living
Technology (ECLT)

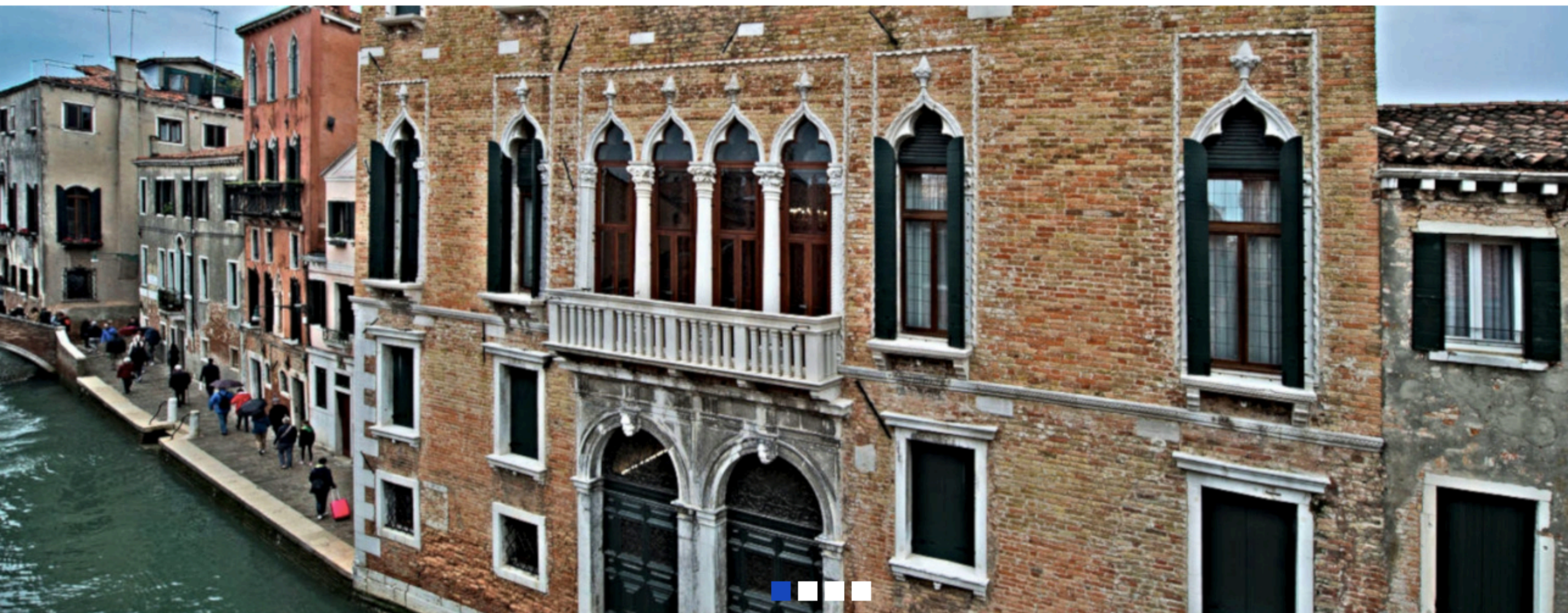
Ca' Foscari University of Venice



Ca' Foscari
University
of Venice

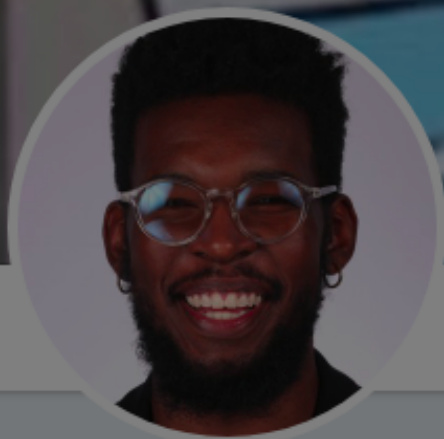
European Centre for Living Technology

[Home](#) [About us](#) [Research](#) [Activities](#) [News](#) [Location](#)





AI scandals



jackyalciné (he/him/his)

@jackyalcine

People-centric software consultant.

black.af + koype.net; fmr @lob, @lyft,

@getclef jacky.wtf vegan

jacky.is@black.af

Joined June 2009



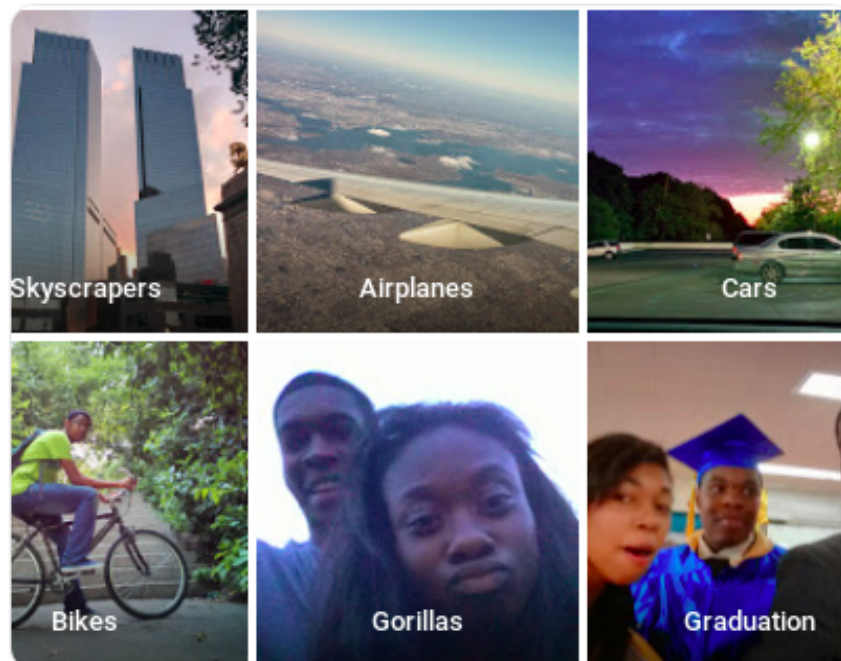
jackyalciné (he/him/his)

@jackyalcine

Follow



Google Photos, y'all fucked up. My friend's not a gorilla.



6:22 pm - 28 Jun 2015

3,261 Retweets 2,384 Likes

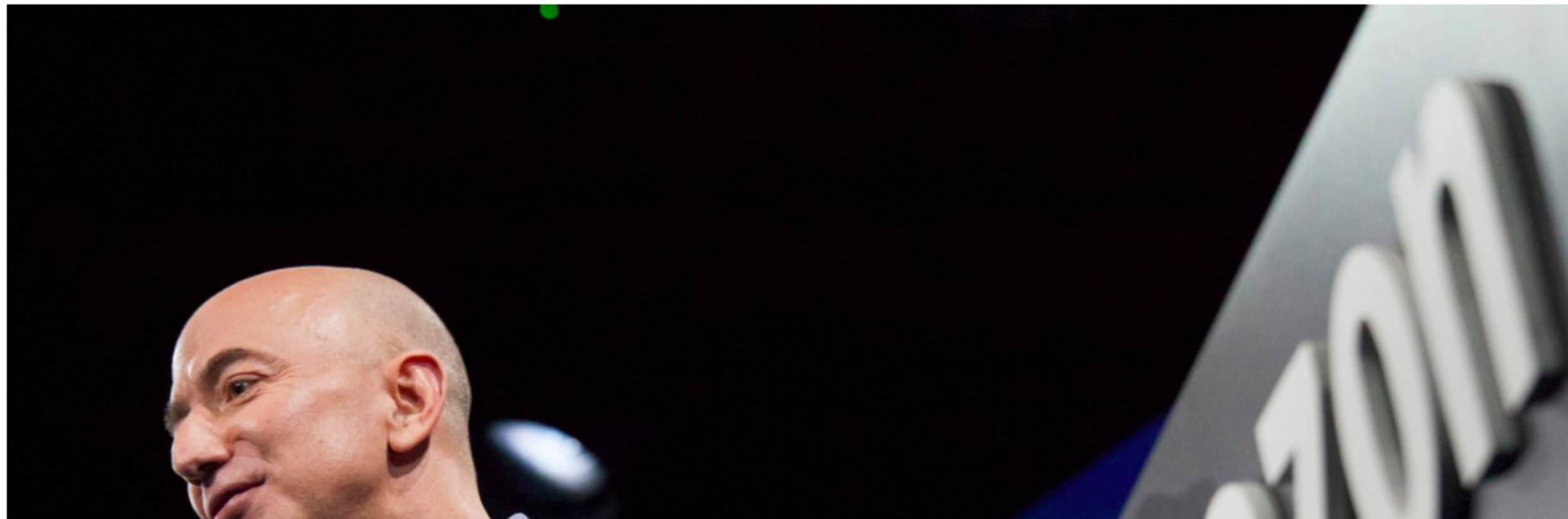


238 3.3K 2.4K



Amazon built an AI tool to hire people but had to shut it down because it was discriminating against women

Isobel Asher Hamilton Oct. 10, 2018, 5:47 AM

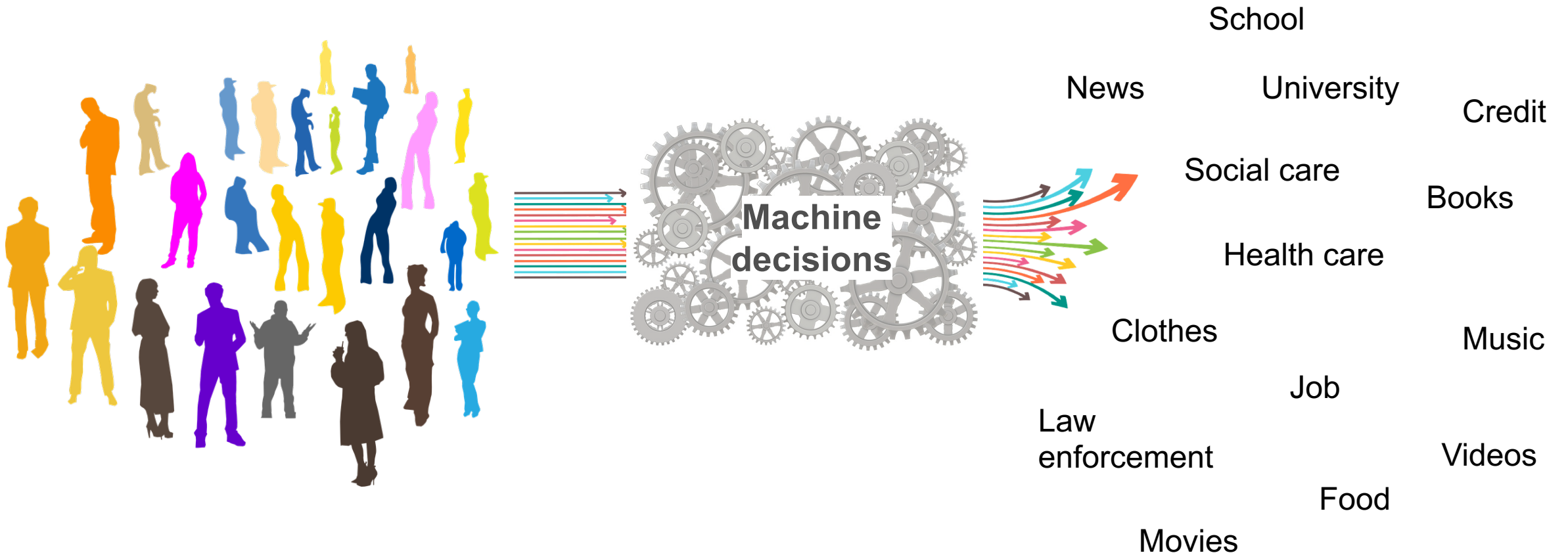


YouTube's Product Chief on Online Radicalization and Algorithmic Rabbit Holes

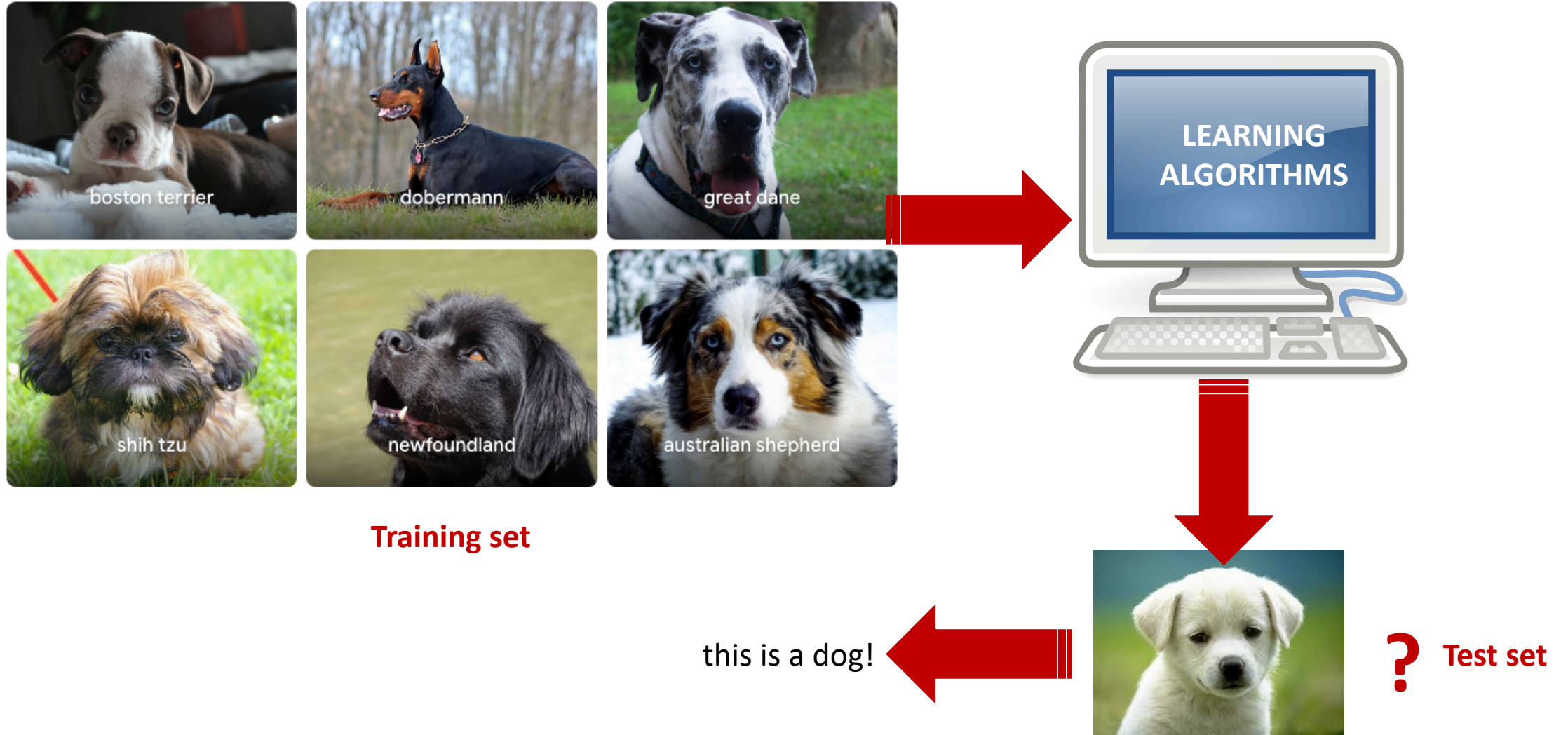
Neal Mohan discusses the streaming site's recommendation engine, which has become a growing liability amid accusations that it steers users to increasingly extreme content.



Algorithms as new gatekeepers



Machine Learning & diagnostic decisions





Can we trust AI
decisions?



Outline

AI & ethics in Europe:

- **Case study** in law enforcement
- European commitment to **Human-centred AI**
- **Ethics Guidelines** for Trustworthy AI by the High-level Expert Group on AI
- Concluding remarks

HART: Harm Assessment Risk Tool

BBC

Sign in

News

Sport

Reel

Worklife

Travel

Future

NEWS

Home

Video

World

UK

Business

Tech

Science

Stories

Entertainment & Arts

Technology

Durham Police AI to help with custody decisions

By Chris Baraniuk
Technology reporter

🕒 10 May 2017 | 📄



🔗 Share



What is HART?

- HART = Harm Risk Assessment Tool
- It is a Risk Assessment Tool (RAT) that is used to predict the **likelihood of reoffending** after a follow-up period (i.e. 2 years after arrest)
- RATs are usually based on **statistics** or **machine learning**
- They can be introduced at several steps of the justice process, e.g. pre-trial hearing, early release from prison (parole), sentencing, etc.
- There are several RATs in use both in US and Europe, e.g.:
 - USA: COMPAS, Public Safety Assessment Tool, Ohio Risk Assessment System... (for a list see: <https://epic.org/algorithmic-transparency/crim-justice/>)
 - Europe: HART (England), OGRS (England and Wales), StatRec (Netherlands), Static99 (just for sexual offenders, Netherlands)

Our sources

- The analysis of HART is based on the following sources:
 - Urwin S (2016) *Algorithmic Forecasting of Offender Dangerousness for Police Custody Officers: An Assessment of Accuracy for the Durham Constabulary*. Master Degree Thesis, Cambridge University, UK
 - Oswald M, Grace J, Urwin S and Barnes GC (2018) Algorithmic risk assessment policing models: lessons from the Durham HART model and ‘Experimental’ proportionality, *Information & Communications Technology Law*, 27(2): 223-250
 - Barnes G, and Hyatt J (2012) , *Classifying Adult Probationers by Forecasting, Future Offending*, Tech report
- Extensive media coverage
 - BBC: <https://www.bbc.com/news/technology-39857645>

A brief sketch

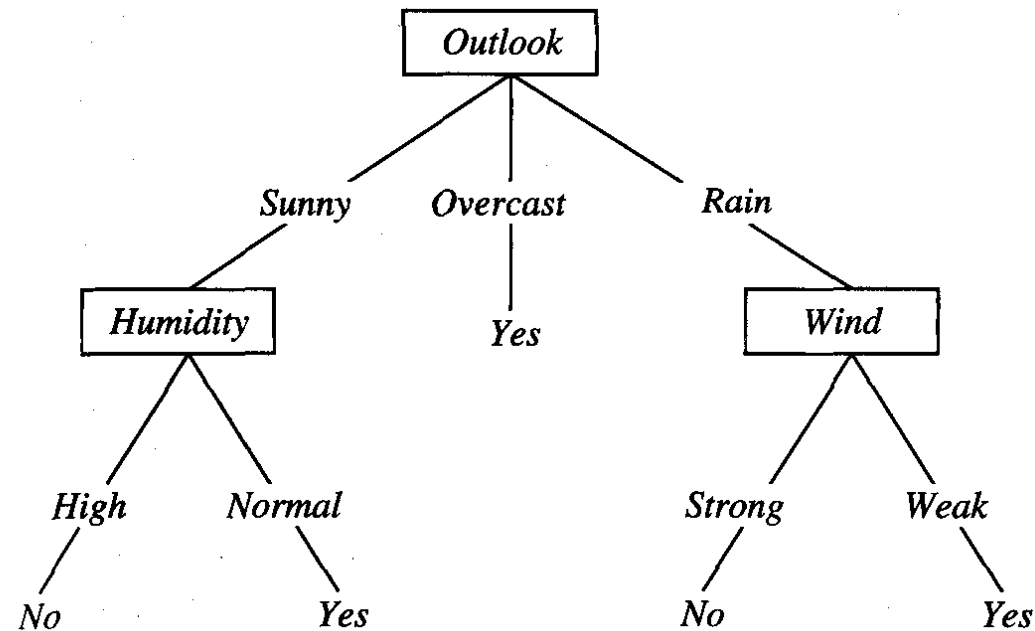
- Launched in May 2017
- Developed by Durham Police in collaboration with Cambridge University
- **Objective**: to support custody decision = “decision taken by the custody officer following arrest at the end of the first custody period” (Urwin, 2016)
- Model’s **output**: “high-risk” – “moderate-risk” – “low-risk”
- Context: “checkpoint programme” that aims at providing “moderate-risk offender” with an alternative to prosecution (<https://www.durham.police.uk/Information-and-advice/Pages/Checkpoint.aspx>)

HART's training set

- 104,000 custody events within a period between Jan 2008 and Dec 2012
- 34 features such as:
 - Age at custody event
 - Gender
 - Count of any past offences
 - Instant violence offence (Y/N)
 - Custody Outward **Postcode** (3-4 first characters)
 - (Experian) **Mosaic Code** (socio-geo demographic)
 - Age at first offence
 - ...
- Categorical labels:
 - **High-risk** = a new serious offence within the next 2 years
 - **Moderate-risk** = a non-serious offence within the next 2 years
 - **Low-risk** = no offence within the next 2 years

Decision tree

- A **decision tree** is a popular classification technique that tests an attribute at each node and assign instances to the descending branches based on the value taken by instances for that attribute

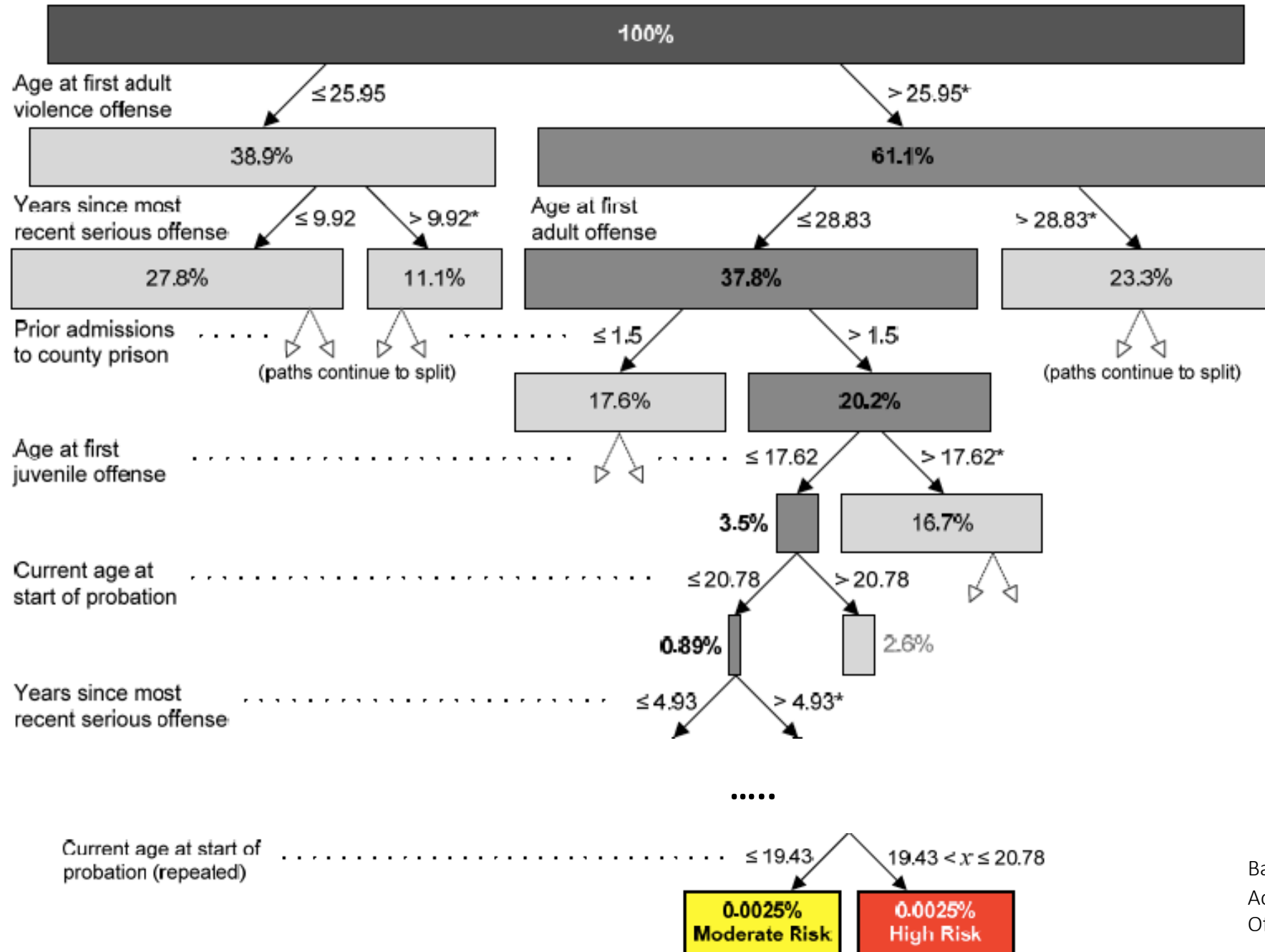


Simple example of a decision tree from Mitchell T, *Machine Learning*, 1997

HART's model

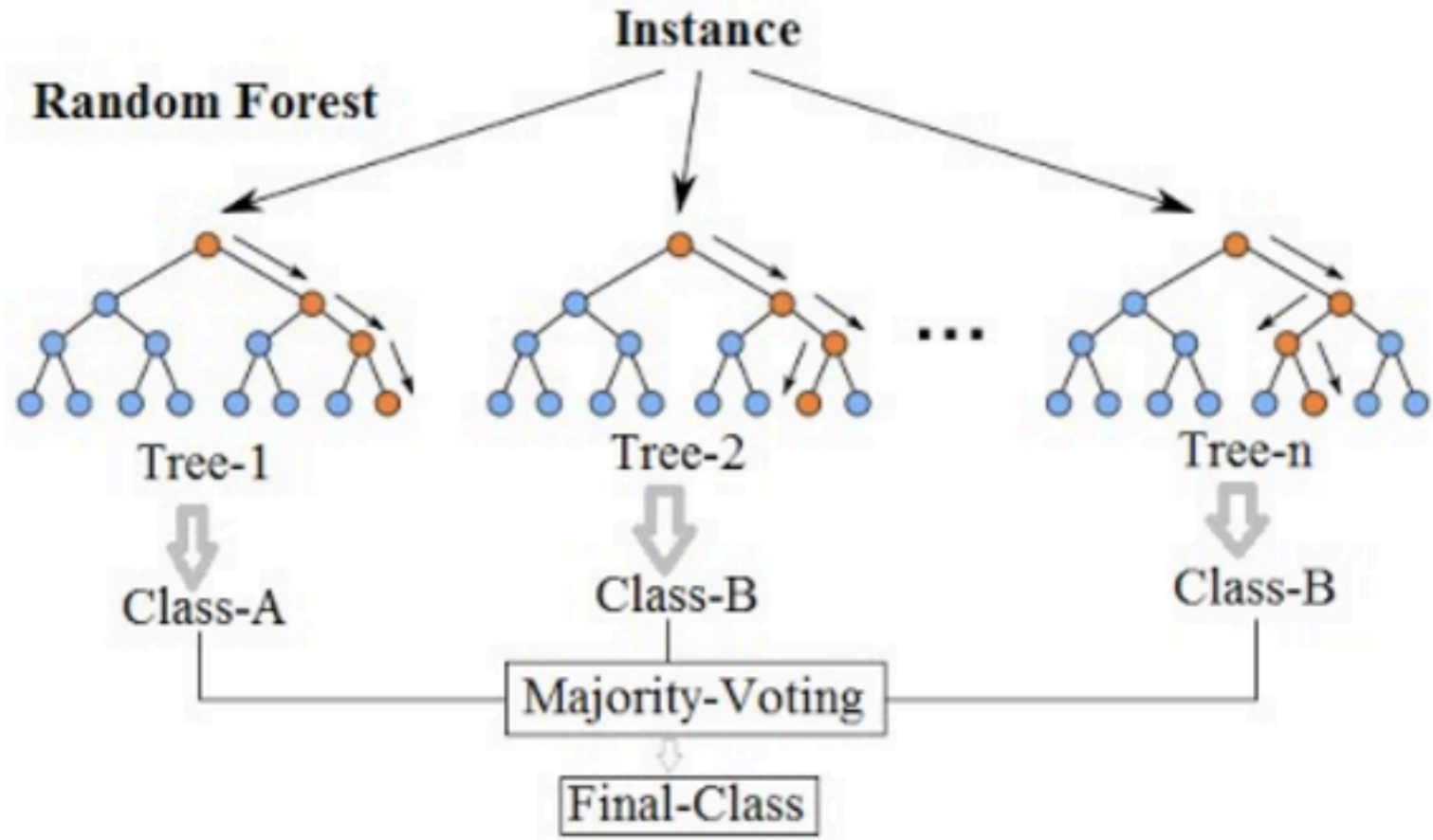
- HART is based on **Random Forest**, a ML method that results from the combination of a multitude of decision trees
- Each decision tree is trained on a **random subsamples** of the training set and using a **random subset** of **features**
- HART uses **509 decision trees**, each producing a prediction. The output corresponds to the output that receives the most votes

119,988 New Probation Case Starts, 2002-2007



Barnes G, and Hyatt J (2012) , Classifying Adult Probationers by Forecasting, Future Offending, Tech report

Random Forest Simplified



Confusion matrix

2013 Validation	Actual High	Actual Moderate	Actual Low	Total
Forecast High	6.26%	10.01%	2.23%	18.49%
Forecast Moderate	4.88%	32.53%	13.55%	50.95%
Forecast Low	0.73%	5.81%	24.02%	30.55%
Total	11.86%	48.35%	39.79%	100% = 14,882 custody events

Confusion Matrix for the test set (see table 8 in Urwin, 2016: 54)

Technical assessment

- Out-of-bag error = when a random sample is drawn to grow a decision tree a small amount is held out and used as a test set to estimate the generalization error during training
- Weighting different types of errors:
 - **Dangerous errors**: misclassifying a serious offender as a low-risk
 - **Cautious errors**: misclassifying a non-serious offender as a high-risk
- Policy decision: HART weights more dangerous error (i.e. it applies a lower cost-ratio)

Performance measures

Comparison with the accuracy of a **random baseline**:

$$[P(Y = \text{“high”}) * P(\hat{Y} = \text{“high”})] + [P(Y = \text{“moderate”}) * P(\hat{Y} = \text{“moderate”})] + [P(Y = \text{“low”}) * P(\hat{Y} = \text{“low”})] =$$

$$[0.1186 * 0.1186] + [0.4835 * 0.4835] + [0.3979 * 0.3979] = 0.406 = \mathbf{41\%}$$

	OOB construction data	2013 validation data	
Overall accuracy : what is the estimated probability of a correct classification?	68.50%	62.80%	
Sensitivity / recall: what is the true positive rate for each class label?	72.60%	52.75%	HIGH
	70.20%	67.28%	MODERATE
	65.30%	60.35%	LOW
Precision: what is the rate of relevant instance for each class label?	48.50%	33.83%	HIGH
	70.20%	63.84%	MODERATE
	75.60%	78.60%	LOW
Very dangerous errors : of those predicted low risk, the percent that was actually high risk (subset of the false omission rate)	2.40%	2.38%	
Very cautious errors: of those predicted high risk, the percent that was actually low risk (subset of the false discovery rate)	10.80%	12.06%	

From accuracy to trust

- Being accurate is not enough
 - What performance measures are used?
 - What sample is used for validation?
- Can results be reproduced?
- How are decisions made?
- What model has been used? What features?
- Can we explain the logics behind the algorithm to the interested subject? (GDPR)
- Is the algorithm fair? Or does it discriminate?
- How does the user (police officer / judges / doctors..) approach machine learning predictions?
- ...

What is
Europe
doing?



European approach to AI

“Artificial Intelligence for Europe” COM(2018) 237, 25 April 2018

The European initiative aims to:

- “Boost the EU's technological and industrial capacity and AI uptake across the economy”
- “Prepare for socio-economic changes brought about by AI”
- “Ensure an **appropriate ethical and legal framework**, based on the Union's values and in line with the Charter of Fundamental Rights of the EU”

“Coordinated Plan on Artificial Intelligence” COM(2018) 795, 7 December 2018

“Overall, the ambition is for Europe to become the world-leading region for developing and deploying cutting-edge, **ethical and secure AI**, promoting a **human-centric approach** in the global context.”

Human-centric AI

In short human-centric AI implies:

- People can **trust** AI systems (trustworthy AI)
- Individuals and the society can **benefit from** the use of **AI**
- AI systems are based on **ethical** and **societal values**, in particular, the European **Charter** of Fundamental Rights

In more concrete terms:

- ethical and secure by design
- clear ethics guidelines and standards
- legal framework



INDEPENDENT
**HIGH-LEVEL EXPERT GROUP ON
ARTIFICIAL INTELLIGENCE**
SET UP BY THE EUROPEAN COMMISSION



**ETHICS GUIDELINES
FOR TRUSTWORTHY AI**

Ethics guidelines

High-level Expert Group on Artificial Intelligence (AI HLEG)

AI HLEG's main deliverables:

- AI Ethics guidelines delivered
- Policy and investment Recommendations

AI HLEG's ethics guidelines:

- first draft December 2018
- public consultation
- official delivery in April 2019
- **piloting process** with the support of AI4EU (June-December 2019)

Website: <https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai>

Trustworthy AI

“AI systems need to be **human-centric**, resting on a commitment to their use in the service of humanity and the common good, with the goal of improving human welfare and freedom.”

Trustworthy AI (instead of ethical AI)

- being demonstrably worthy of trust (concrete pathways)
- it refers to the **socio-technical system** in which AI technology is embedded (holistic approach)
- Trustworthy AI to promote “responsible competitiveness”
- Addressed to AI stakeholders, e.g. companies, civil society organisations, individuals, ...

Some remarks:

- Trustworthy AI is a contribution to elaborate “a normative vision of an AI-immersed future”
- need of an **ethical culture** through public debate, education and practical learning

Trustworthy AI

Lawful AI

(not dealt with in this document)

Ethical AI

Robust AI

Foundations of Trustworthy AI

Adhere to ethical principles based on fundamental rights

4 Ethical Principles

Acknowledge and address tensions between them

- Respect for human autonomy
- Prevention of harm
- Fairness
- Explicability

Realisation of Trustworthy AI

Implement the key requirements

7 Key Requirements

Evaluate and address these continuously throughout the AI system's life cycle

via

Technical
Methods

Non-Technical
Methods

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

Assessment of Trustworthy AI

Operationalise the key requirements

Trustworthy AI Assessment List

Tailor this to the specific AI application

Framework

AI HLEG, *Ethics Guidelines for Trustworthy AI* (2019, p 8)

Addressing requirements

They can help the implementation of trustworthy AI

1. human agency and oversight
2. technical robustness and safety
3. privacy and data governance
4. transparency
5. diversity, non-discrimination and fairness
6. societal and environmental well-being
7. accountability



value-by-design methodology
fairness metrics
explainable AI methods
multiple performance measures
adversarial testing
testing performed by diverse groups
regulation (e.g. GDPR)
codes of conduct
"bug bounties"
accountability via governance frameworks
education
stakeholder participation
diversity and inclusive design teams

Trustworthy assessment list

Brief sketch:

- list of **questions** structured around the 7 requirements
- goal = to operationalise the key requirements
- primarily addressed to developers and deployers of AI systems
- compliance with this list is **not evidence of legal compliance**
- piloting process (qualitative and quantitative assessment)

Assessment List: https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=60440

Towards trustworthy AI

Some **insights**:

- holistic approach, being open to changes (business models)
- diversity and inclusion (design, validation, deployment)
- disseminate results and communication to the public (realistic expectations, open questions)
- long term solutions, gradual and dynamic process (ethical culture)

Some **weaknesses**:

- being demonstrably trustworthy is hard
- some methods for implementing requirements are too abstract
- assessment list include too many questions
- risks of applying requirements/assessment list in a mechanical way

Main references

- Scantamburlo T., Charlesworth A. and Cristianini N. (2019). “Machine decisions and human consequences”. In K. Yeung & M. Lodge (eds) *Algorithmic Regulation*, Oxford: Oxford University Press (the draft accepted for publication is available on arXiv)
- High-Level Expert Group on Artificial Intelligence (2019), Ethics Guidelines for Trustworthy AI, <https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai>

Thanks for your attention

Feedbacks, comments or requests are welcome

teresa.scantamburlo@unive.it