



Centre for  
Information  
Policy  
Leadership  
Hunton Andrews Kurth LLP

Centre for Information Policy Leadership Annual Executive Retreat

# **Accountable AI**

27 June 2018, San Francisco

- ❖ 8:30 AM Registration
- ❖ 9:00 AM **Opening Remarks**
- ❖ 9:15 AM **Introductory Keynotes on AI's Current and Future Role in Society**
- ❖ 10:20 AM Break
- ❖ 10:45 AM **Session I: Panel Discussion with Introductory Keynote Speakers**
- ❖ 12:00 PM Lunch
- ❖ 1:15 PM **Session II: The Challenges and Data Protection Risks of AI**
- ❖ 2:45 PM Break
- ❖ 3:15 PM **Session III: Elements of Accountable AI**
- ❖ 4:45 PM **Closing Remarks**
- ❖ 5:00 PM **End of Retreat and Cocktail Reception (hosted by Google)**



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# Opening Remarks

Bojana Bellamy, President, CIPL

Ben Smith, VP and Google Fellow, Google

BRIDGING REGIONS  
BRIDGING INDUSTRY & REGULATORS  
BRIDGING PRIVACY AND DATA DRIVEN INNOVATION

ACTIVE GLOBAL REACH

55+  
Member  
Companies

We **INFORM** through publications and events

We **NETWORK** with global industry and government leaders

5+  
Active Projects  
& Initiatives

We **SHAPE** privacy policy, law and practice

We **CREATE** and implement best practices

20+  
Events annually

15+  
Principals and  
Advisors

ABOUT US

- The Centre for Information Policy Leadership (CIPL) is a global privacy and security think tank
- Based in Washington, DC, Brussels and London
- Founded in 2001 by leading companies and Hunton Andrews Kurth LLP
- CIPL works with industry leaders, regulatory authorities and policy makers to develop global solutions and best practices for data privacy and responsible use of data to enable the modern information age



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2200 Pennsylvania Ave NW  
Washington, DC 20037



Park Atrium, Rue des Colonies 11  
1000 Brussels, Belgium



30 St Mary Axe  
London EC3A 8EP

**Mission – Developing global solutions for privacy and the responsible use of data to enable the fourth industrial revolution (4IR)**

## Corporate Digital Responsibility (Accountability Plus)

- Accountable AI/Machine Learning
- Applied Organisational Accountability workshops
- Incentivising Accountability
- Privacy and security

## Responsible Global Data Flows

- Participation in APEC meetings and Implementing APEC CBPR and PRP
- Interoperability between CBPR & GDPR Transfer Mechanisms
- Data Transfers Post GDPR
- Privacy Shield

**Vision – Global partner for business leaders, regulators and policymakers on privacy and information policy issues**

## Global Regulatory Engagement

- Socialise Regulating for Results paper
- Explore “Regulatory Sandbox”
- Regulator outreach
- Regional focus and working groups (Latin America, Asia, North America, India)

## EU Privacy Law Reform

- ePR papers and roundtables
- GDPR implementation
  - Cross-border transfer mechanisms
  - Profiling and ADM
  - Breach notification
  - Individual rights, complaints & consistency
  - Children’s data

# Challenges and Tensions Between AI Applications and Data Protection Principles

## Challenges associated with AI

•Fairness •Ethical Issues •Public Trust •Legal Compliance •Tensions

### Data Protection Requirements

Transparency

Legal basis for processing

Purpose specification & Use limitation

Retention limitation

Collection limitation / Data minimisation

Individual rights

Rules on ADM

### Tensions To Resolve

### Artificial Intelligence

Operates in a black box and may produce unexplainable outcomes

Insufficient/limited variety of legal bases may undermine full range of AI applications

Uses data for new and unforeseen purposes beyond original scope

Needs to retain data to function, find new purposes and for continuous improvement

Needs sufficient volumes of data for research, analysis, operation and training

Cannot always facilitate access, correction or explanation of the logic involved

Based on ADM & No human involvement



## **Introductory Keynotes: AI's Current and Future Role in Society**

- ❖ **Casimir Wierzynski, Senior Director of AI Research, Intel**
- ❖ **Maya Gupta, Principal Scientist, Google**
- ❖ **Rumman Chowdhury, Senior Principal, Artificial Intelligence, Accenture**
- ❖ **Rich Caruana, Principal Researcher, Microsoft**





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# **AI Systems: Applications, Trends and Futures**

Casimir Wierzynski

Senior Director of AI Research, Intel



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# Google AI Overview

Maya Gupta

Principal Scientist, Google



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# Accenture Fairness Tool

Rumman Chowdhury

Senior Principal, Artificial Intelligence, Accenture



# **FROM VIRTUE SIGNALING TO POSITIVE ACTION**

**Dr. Rumman Chowdhury, Responsible AI Lead, Accenture**

# WHY IS THIS UNFAIR?



**Vernon Prater**  
**3 Low Risk**



**Brisha Borden**  
**8 High Risk**

# WHAT IS FAIRNESS?

**“Whenever individuals are treated unequally on the basis of characteristics that are arbitrary and irrelevant, their fundamental human dignity is violated. Justice, then, is a central part of ethics and should be given due consideration in our moral lives.”**

***Velasquez, Manuel, et al. "Justice and fairness." Issues in Ethics (2015).***

**SO HOW CAN  
WE FIX IT?**

# **PROTOTYPING** **ALGORITHMIC** **FAIRNESS**

---

**The Alan Turing Institute** and those involved in the prototyping of this tool who joined the Data Study Group:

**Peter Byfield**, University of Warwick

**Paul-Marie Carfantan**, LSE

**Omar Costilla-Reyes**, University of Manchester

**Quang Vinh Dang**, INRIA, France

**Delia Fuhrmann**, University of Cambridge

**Jonas Glesaaen**, Swansea University

**Qi He**, UCL

**Andreas Kirsch**, Newspeak House

**Julie Lee**, UCL

**Mohammad Malekzadeh**, Queen Mary University of London

**Esben Sorig**, Goldsmiths University of London

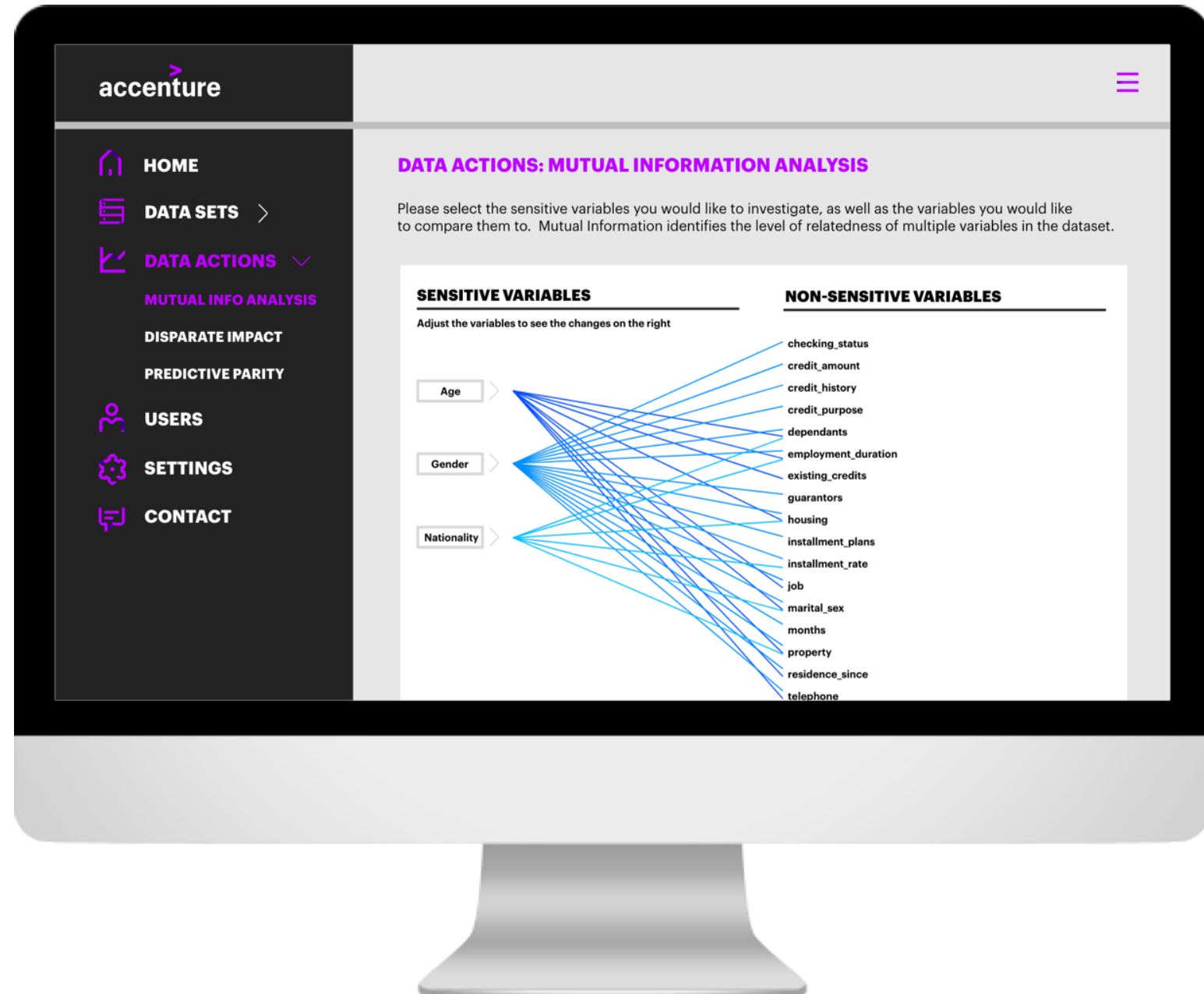
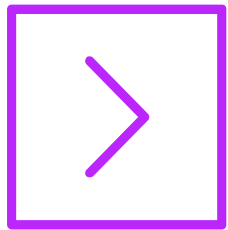
**Emily Turner**, University of Manchester



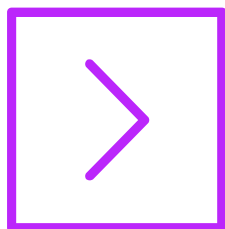
# THE DATA **FAIRNESS** TOOL

Based on the concept of **PREDICTIVE PARITY**  
<Algorithmic> justice and equality

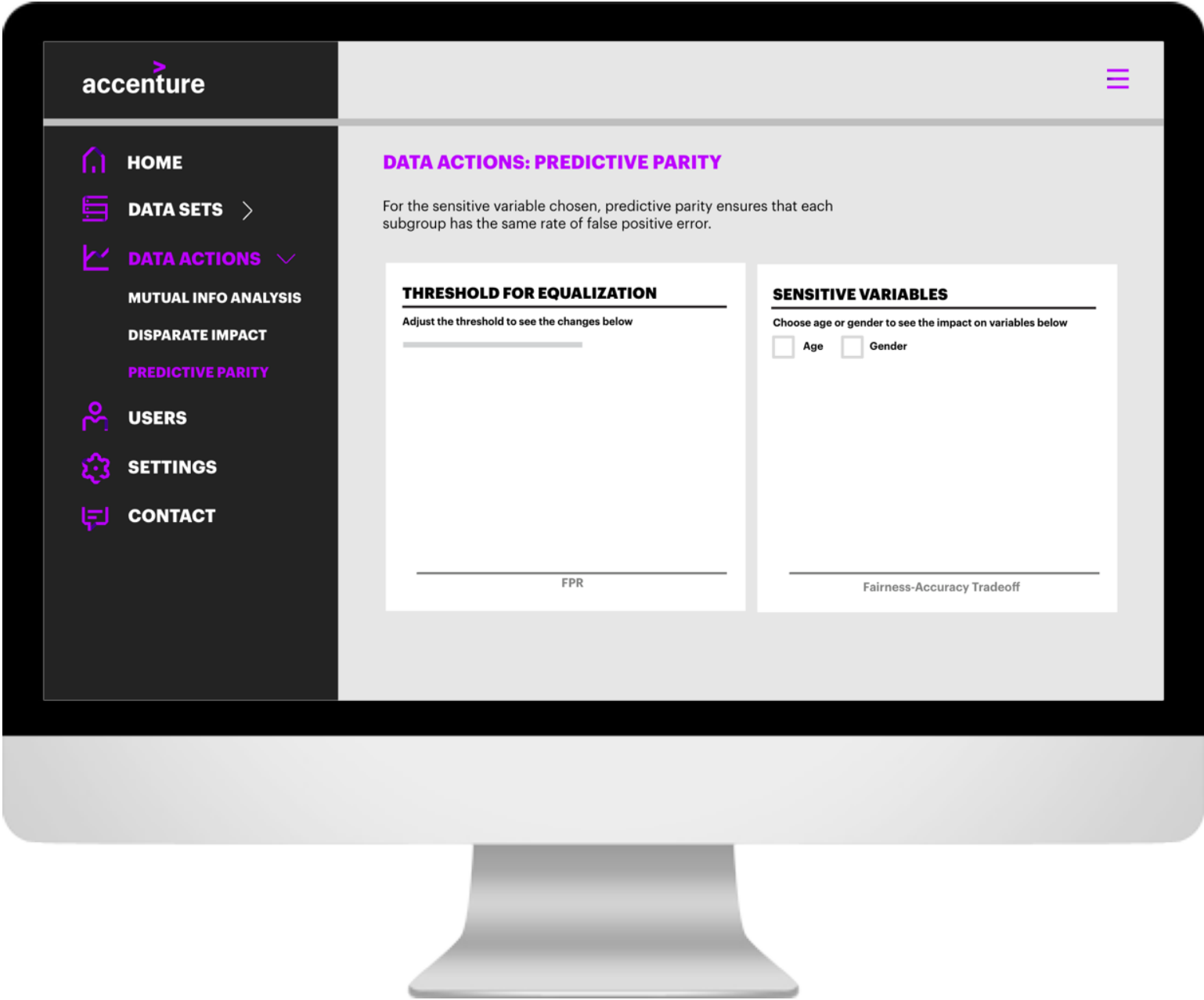
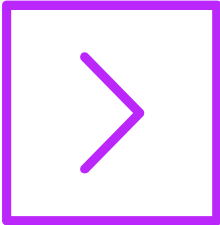
# MUTUAL INFO ANALYSIS



# DISPARATE IMPACT



# PREDICTIVE PARITY



# **LIMITATIONS**

**<A VERY NON-TECH THING TO DO>**

# AI LAUNCHPAD



## TECHNICAL

- Apply frameworks of explainable AI
- Design a user interface that is collaborative
- Provide a model maintenance plan

## BRAND

- AI focus groups
- How to guide media coverage and public perception
- Explainability/transparency
- Enabling trust

## GOVERNANCE

- Industry-specific ethics canvas
- Cross-cutting universal standards
- Internal ethics boards and how they can be relevant

## ORGANIZATIONAL

- Recruit and retain the right talent for long-term AI impact
- Revisiting organizational structure with an AI mindset

**THANK  
YOU**

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# **Friends Don't Let Friends Deploy Black-Box Models: The Importance of Transparency in Machine Learning**

Rich Caruana

Principal Researcher, Microsoft



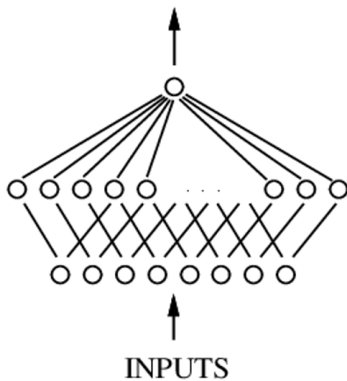
# The Importance of Intelligibility and Transparency in Artificial Intelligence and Machine Learning

Rich Caruana  
Microsoft

June 27, 2018

A surprising number of machine learning people believe that  
if you train a deep net on enough data and it looks  
accurate on the test set, it's safe to deploy.

Sometimes this is correct,  
but sometimes it is very wrong.





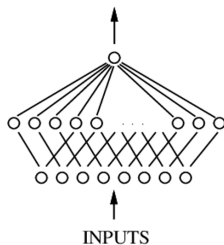
Friends Shouldn't Let Friends Deploy Black-Box Models!

# Motivation: Predicting Pneumonia Risk (Probability of Death)

- **LOW Risk:** outpatient: antibiotics, call if not feeling better
- **HIGH Risk:** admit to hospital ( $\approx 10\%$  of pneumonia patients die)

# Motivation: Predicting Pneumonia Risk (Probability of Death)

- **LOW Risk:** outpatient: antibiotics, call if not feeling better
- **HIGH Risk:** admit to hospital ( $\approx 10\%$  of pneumonia patients die)
- Most accurate model: **neural net**



# Despite High Accuracy, Afraid to Use Neural Net on Real Patients

- Rule Learned from Data: **HasAsthma(x) => LessRisk(x) (!)**
- True pattern in data:
  - asthmatics presenting with pneumonia considered very high risk
  - history of asthma means they notice symptoms and go to healthcare sooner
  - receive aggressive treatment and sometimes admitted to ICU
  - rapid treatment lowers risk of death compared to general population
- If Rules learned asthma is good for you, NN probably did, too
  - if we use NN for treatment decisions, could hurt asthmatics
- Key to discovering **HasAsthma(x)**... was intelligibility of rules
  - even if we can remove asthma problem from neural net, what other "bad patterns" might be in the neural net that RBL missed?



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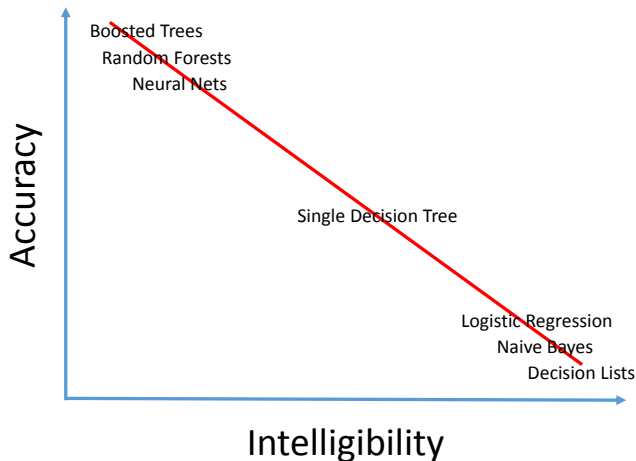
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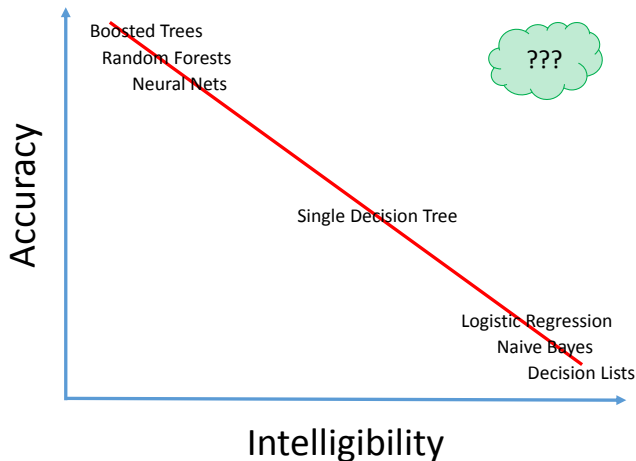
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All we need is a model as accurate as a neural net,  
but as intelligible as linear regression

# Problem: The Accuracy vs. Intelligibility Tradeoff



# Problem: The Accuracy vs. Intelligibility Tradeoff



# What New Intelligible/Transparent Models Learn About Pneumonia

- Has\_Asthma => lower risk
- Patients > 85 not treated as well as patients < 85
- Patients > 100 treated better than Patients < 100
- History of chest pain => lower risk
- History of heart disease => lower risk
- Good we didn't deploy the black-box neural net
- Can understand, edit and safely deploy new intelligible/transparent models
- **Important:** Must keep potentially offending features in model!



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# FAT/ML: ProPublica COMPAS Recidivism Data

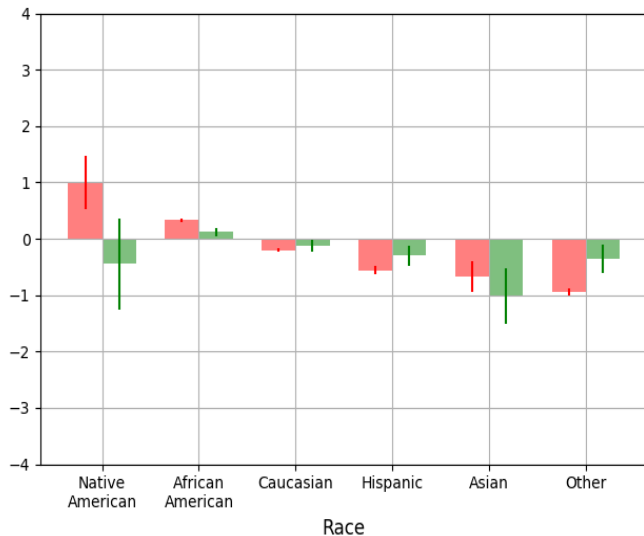
- COMPAS is a black-box model used to predict future criminal behavior
  - model is black-box because IP is protected, not complexity
  - criminal justice officials use risk prediction to inform bail, sentencing and parole decisions
- Is COMPAS model biased?



# Using Intelligible Models to "Open Up" COMPAS Black-Box

- As reported by others, COMPAS appears to be racially biased
  - appears to be more racially biased than the training data
- Most important variable to COMPAS appears to be number of prior convictions
- COMPAS appears to not model age and gender as well as it could
- COMPAS appears to be a very simple model (too simple?)
  - NorthPointe revealed recently that the COMPAS only uses 6/150+ variables
- We now have techniques for "opening" black-box models like deep nets and COMPAS

# Using Intelligible Models to "Open Up" COMPAS Black-Box



# Summary

- All datasets are biased
- Must be able to understand AI and ML models trained on data
- Now have methods for training intelligible/transparent models
- Methods can be used to understand and correct what is in black-box models
- Discover problems you did not anticipate in advance
- Important to keep protected variables in model so bias is localized



# Thank You

## Session I

# Panel Discussion with Introductory Keynote Speakers

- ❖ **Moderator: Fred Cate, Global Policy Advisor, CIPL**
- ❖ **Casimir Wierzynski, Senior Director of AI Research, Intel**
- ❖ **Maya Gupta, Principal Scientist, Google**
- ❖ **Rumman Chowdhury, Senior Principal, Artificial Intelligence, Accenture**
- ❖ **Rich Caruana, Principal Researcher, Microsoft**

## Session II

# The Challenges and Data Protection Risks of AI

- ❖ Moderator: Fred Cate, Global Policy Advisor, CIPL
- ❖ Elizabeth Denham, Information Commissioner, UK Information Commissioner's Office
- ❖ Shuhei Ohshima, Specialist Commissioner, Japan Personal Information Protection Commission
- ❖ Zee Kin Yeong, Deputy Commissioner, Singapore Personal Data Protection Commission
- ❖ Raina Yeung, Assistant Commissioner, Office of the Privacy Commissioner for Personal Data, Hong Kong
- ❖ Norberto Andrade, Privacy and Public Policy Manager, Facebook
- ❖ Julie Brill, Corporate Vice President and Deputy General Counsel, Microsoft
- ❖ Michelle Dennedy, Vice President and Chief Privacy Officer, Cisco
- ❖ Riccardo Masucci, Global Director of Privacy Policy, Intel

# AI Governance Initiatives

Presentation by Yeong Zee Kin, Deputy Commissioner  
Centre for Information Policy Leadership – Accountable AI Workshop  
27 June 2018

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# AGENDA

1. Overview of AI Governance Structure
2. Discussion Paper on Fostering Responsible AI
3. Proposed Reference AI Governance Framework
4. Advisory Council on the Ethical Use of AI and Data
5. Research Programme on Governance of AI and Data Use

# 1. OVERVIEW OF AI GOVERNANCE STRUCTURE

## Advisory Council on the Ethical Use of AI and Data

### Composition

- Industry-led
- Private sector thought leaders
- Consumer advocates

**Roles:** Advise and support Government, including:

- Identifying **regulatory, legal, policy, ethical and governance issues** relating to the commercial deployment of data-driven technologies e.g., AI in the private sector
- Providing **insights and recommendations** to Government on issues that may require policy consideration and/or regulatory/legislative intervention
- Developing ethics standards and reference governance frameworks and publish advisory guidelines, practical guidance, and/or codes of practice for the voluntary adoption by the industry
- Providing insight and guidance to the Research Programme

Provide industry  
& consumer  
perspectives

Provide  
regulators'  
perspectives

## Research Programme on Governance of AI and Data Use

Executive Committee  
(National Research Foundation, AI  
SG, IMDA, Singapore Management  
University - SMU)

Management Team  
(SMU)

[RESTRICTED]

## Public Sector AI Governance Roundtable

### Composition

- Sector regulators and public agencies (e.g. legal services, health, monetary authority, competition, manpower, info-comm, national development)

### Roles

- **Community of Practice** for public agencies
- Establish **common AI governance principles and framework** across sectors
- **Co-ordinated, principled and outcome-focused sectoral regulations** where necessary

## 2. DISCUSSION PAPER ON FOSTERING RESPONSIBLE AI

Personal Data Protection Commission (PDPC) published a discussion paper on 5<sup>th</sup> June 2018 intended to trigger public discussion on responsible AI and data governance. The paper arose from input provided by the *Public Sector AI Governance Roundtable* and closed consultations with private sector companies. It consists of two main parts:

1. Broad articulation of the principles for responsible AI; and
2. A proposed governance framework that sets out practical ways that organisations using AI can translate the principles into processes.

The two parts aim to promote **Public Understanding** and **Trust** in AI technologies.

### Strategic Considerations

Promote

- Development & adoption of AI
- Innovation, competition & consumer choice
- Consistency in decisions affecting consumers

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### Principles for Responsible AI



DECISIONS MADE BY AI  
SHOULD BE

**EXPLAINABLE,  
TRANSPARENT  
AND FAIR**



AI SYSTEMS, ROBOTS AND  
DECISIONS SHOULD BE  
**HUMAN-CENTRIC**

# 3. PROPOSED REFERENCE AI GOVERNANCE FRAMEWORK



## OBJECTIVES

- Explaining how AI systems work and verifying that they work consistently
- Building in good data accountability practices
- Creating open and transparent communication between stakeholders



## ORGANISATIONAL GOVERNANCE MEASURES

### GOVERNANCE

- Putting in place internal corporate governance and oversight processes
- Taking measures to identify and mitigate risks or harm
- Reviewing how and where AI is deployed within the company periodically

### OPERATIONS MANAGEMENT AND SYSTEMS DESIGN

- Having good practices in managing data
- Ensuring AI performs consistently
- Understanding what data was used to make algorithmic decisions
- Training and maintenance of AI models



## CONSUMER RELATIONSHIP MANAGEMENT

### TRANSPARENCY

- Policy for disclosure
- Policy for explanation

### COMMUNICATION

- Establishing a feedback channel
- Reviewing decisions made by AI

### INTERACTION

- Reviewing human-machine interactions for user friendliness
- Providing an option to opt-out



## DECISION MAKING AND RISK ASSESSMENT

- Determining the appropriate decision-making approach to maximise benefits and minimise risk of harm.
- **“Human-in-the-loop”** involves a human who relies on intelligent systems but ultimately makes the final decision
- **“Human-over-the-loop”** involves a human who has made a choice but relies on intelligent systems to suggest options to perform an action
- **“Human-out-of-the-loop”** involves automated decisions by intelligent systems based only on a pre-determined set of scenarios



## 4. ADVISORY COUNCIL ON THE ETHICAL USE OF AI & DATA

- Need to address **ethical, regulatory and governance issues** arising from commercial deployment of AI and other data-driven technologies.
- June 5<sup>th</sup> 2018, the Advisory Council was established to:
  - Provide private sector insights and recommendations to the Government relating to commercial deployment of data-driven technologies, and issues that may require policy consideration and/or legislative intervention; and
  - Support Government in developing voluntary ethics standards and governance frameworks for businesses in Singapore and publishing discussion papers, voluntary advisory guidelines, practical guidance, and/or codes of practice
- Advisory Council is chaired by former Attorney General V.K. Rajah and comprises private sector thought leaders in AI and Big Data from local and international companies; academia; and consumer advocates

## 5. RESEARCH PROGRAMME ON GOVERNANCE OF AI & DATA USE

- IMDA-National Research Foundation (NRF) have set-up a ***Research Programme on Governance of AI & Data Use*** through a grant call for proposal.
- The Singapore Management University School of Law was awarded a S\$4.5 million dollar grant to run the programme for 5 years.
- The Research Programme aims to:
  - Promote cutting edge thinking and practices in AI and data policies/regulations;
  - Inform AI and data policy and regulation formulation in Singapore through research publications and stakeholder engagement; and
  - Position Singapore as a global thought leader in AI and data policies/regulations

**Thank You**

**CIPL Workshop  
“Accountable AI”  
27 June 2018 | San Francisco**

# **The Challenges and Data Protection Risks of AI**

**Raina YEUNG**

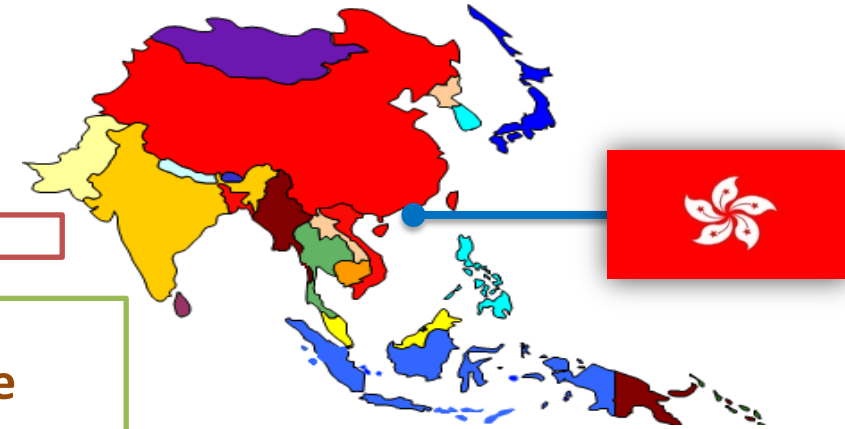
**Assistant Privacy Commissioner for Personal Data (Legal, Policy & Research)  
Office of the Privacy Commissioner for Personal Data, Hong Kong, China**

# The Personal Data (Privacy) Ordinance

Referenced to OECD Privacy Guidelines 1980 & Data Protection Directive 95/46/EC

## Principle based & technology neutral

- **Data collection**: Informed, necessary, adequate but not excessive
- **Retention**: Not longer than necessary
- **Accuracy**: Shall not use if believed to be inaccurate
- **Use**: Express and voluntary consent for change of use
- **Security**: Safeguard data from unauthorised or accidental access, processing, erasure, loss or use
- **Transparency**: Clear policies and practices made known to individuals



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# Challenges of AI

## Data Privacy Issues



- Massive and ubiquitous data collection from multiple sources
- Low transparency
- No meaningful notice and consent
- Unexpected and unpredictable data use
- Doubtful inferences: Coincidence, correlation, or causal relation?
- Re-identification and revelation of sensitive information

# Challenges of AI



## Ethical Issues

- Unfair or discriminatory predictions
- Incomprehensible and “black box” algorithms: Difficult for individuals to dispute automated decisions

# Hong Kong PCPD Way Forward and Strategic Focus





# Data Ethics



спасибо  
danke 謝謝  
ngiyabonga  
teşekkür ederim  
dank je  
gracias  
tapadh leat  
moichchakkeram  
go raibh maith agat  
arigatō  
dakujem  
merci  
ευχαριστώ  
kop khun krap  
sukriya  
sagolun  
hvala  
maururu  
dziękuje  
bedankt  
obrigado  
terima kasih  
감사합니다

# Contact Us



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248 Queen's Road East,  
Wanchai, HK

## Session III

### Elements of Accountable AI

- ❖ **Moderator: Bojana Bellamy, President, CIPL**
- ❖ **Caroline Louveaux, EVP/Chief Privacy Officer, Mastercard**
- ❖ **Alison Howard, Assistant General Counsel, Microsoft**
- ❖ **Charina Chou, Public Policy Manager, Google**
- ❖ **Deborah Santiago, Managing Director of Legal Services, Digital & Strategic Offerings, Accenture**
- ❖ **Scott Goss, Vice President & Privacy Counsel, Qualcomm**



# Privacy Challenges in Machine Learning

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**Scott Goss**

VP, Privacy Counsel

Qualcomm Incorporated

June 2018

[sgoss@qualcomm.com](mailto:sgoss@qualcomm.com)





# Qualcomm invents core mobile technologies

We are engineers, scientists and researchers



# Evolution of connected devices



Yesterday



Today

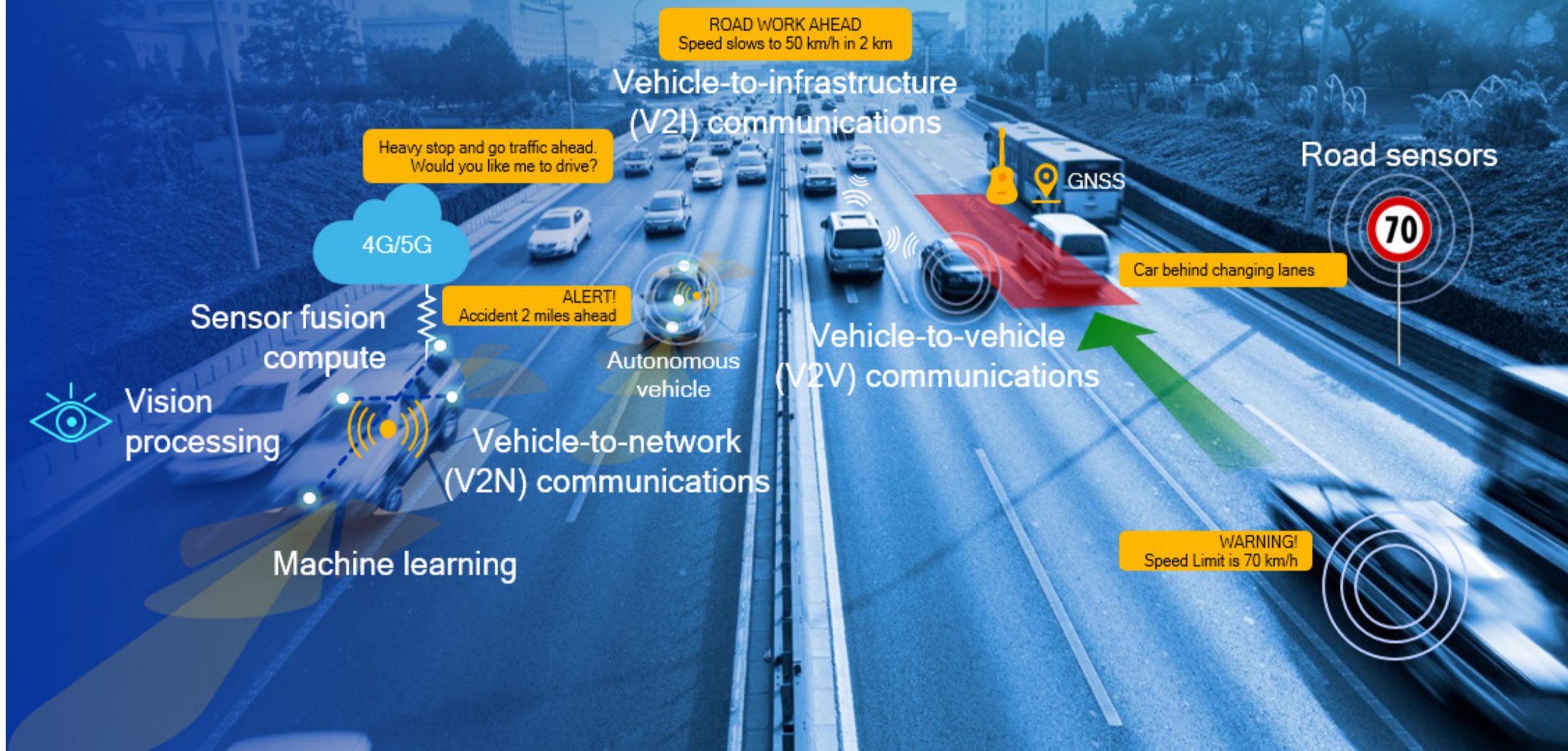


Tomorrow



# Powering connected and automated vehicles

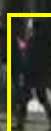
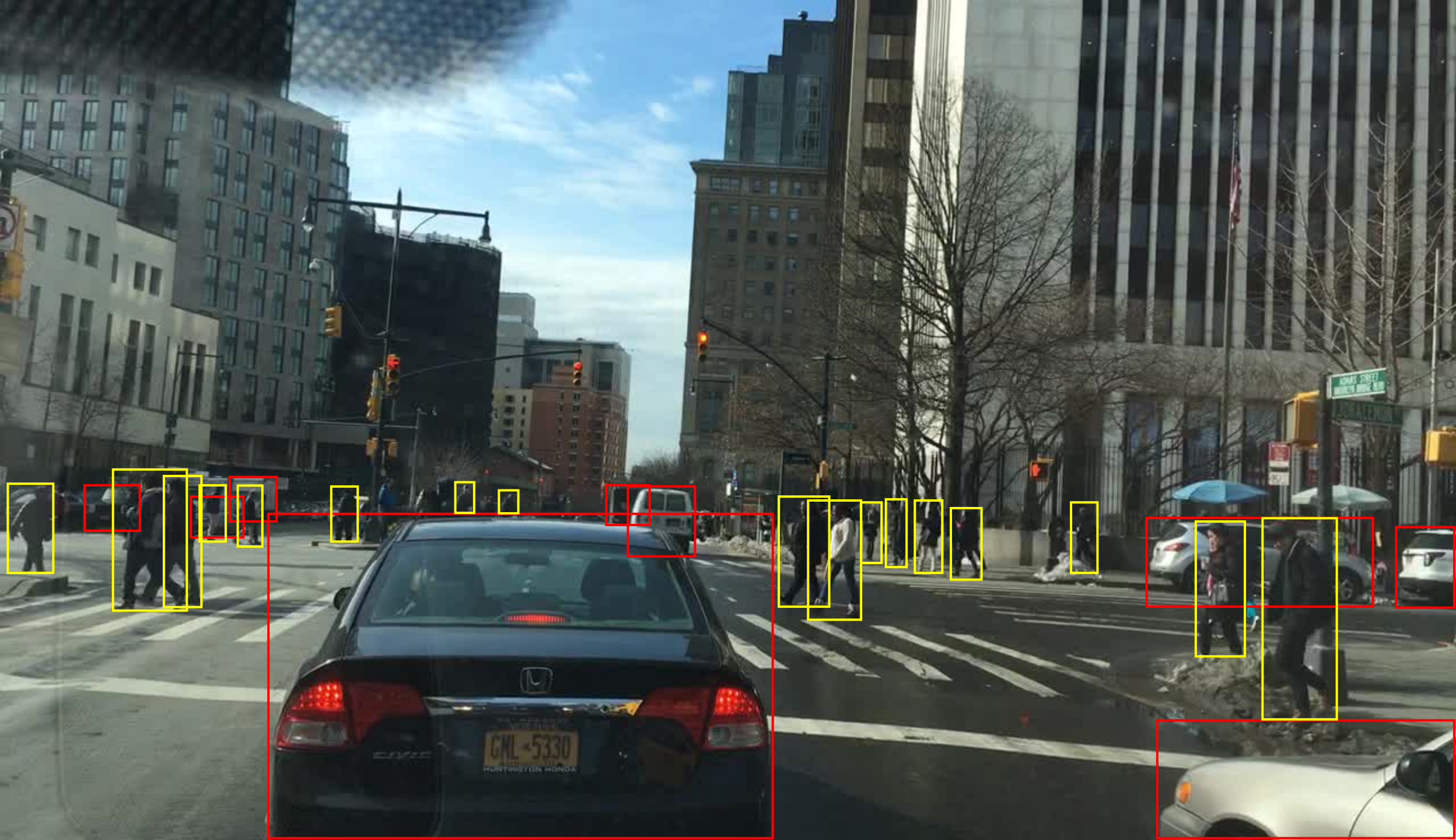
## Enabling safer, greener and more efficient transport



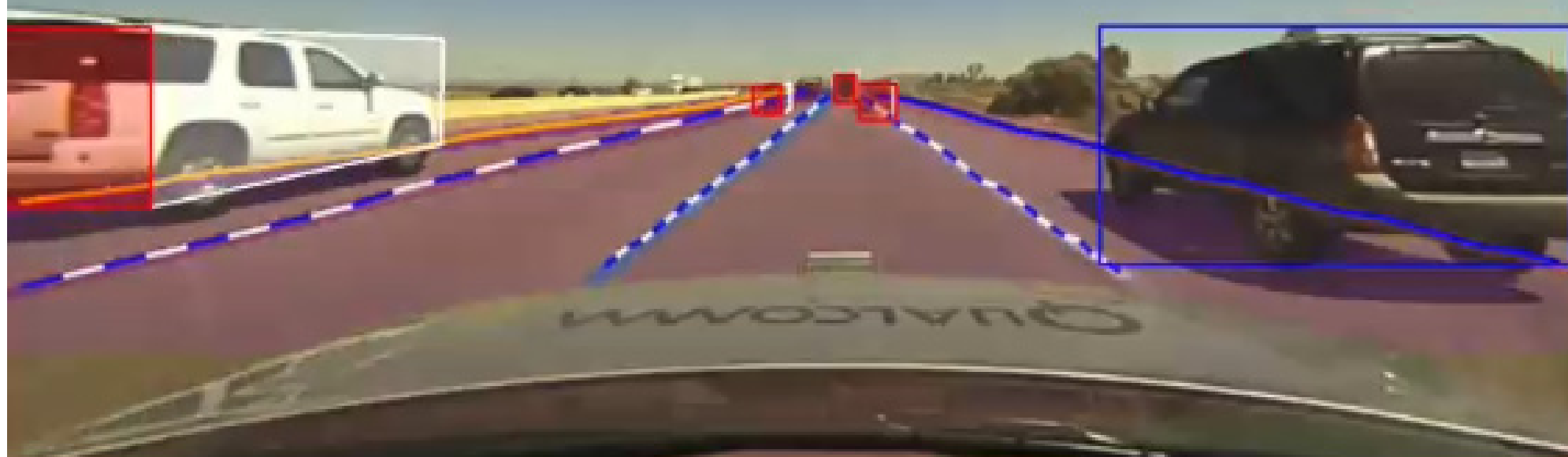








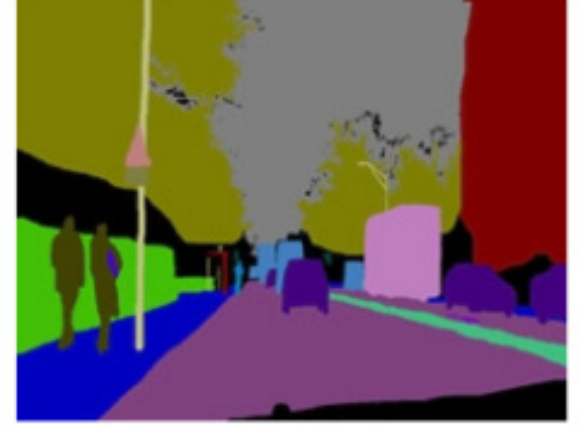
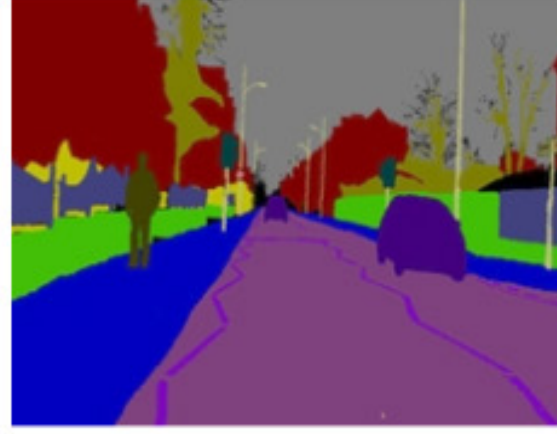
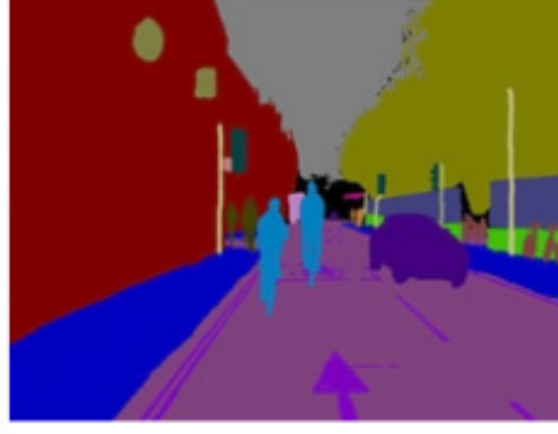
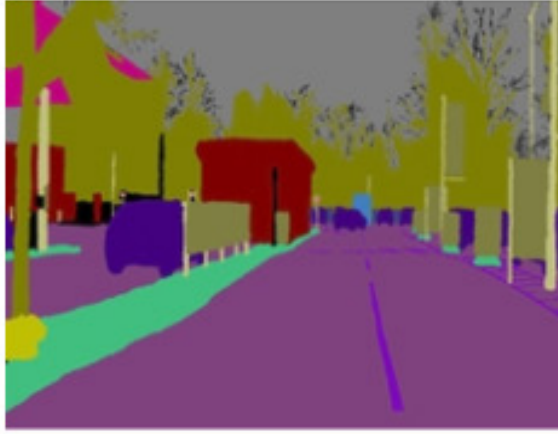
FOV 150



Input



Output





# Privacy Challenges in Machine Learning

- Identifiable faces and license plates
- US law: public places; no expectation of privacy
- ROW data protection law challenges:
  - Transparency
  - Legal basis
  - Data subject rights
  - Transfer restrictions
- Solutions?
  - Only US data? No.
  - Collect all the data ourselves? No.
  - Controls for self-collected; Legal review of all 3<sup>rd</sup> party licensed

# Thank you

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# Closing Remarks

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