

SEMINAIRE « INTELLIGENCE ARTIFICIELLE, ALGORITHMES ET MONDE PUBLIC »  
« L'Intelligence artificielle va-t-elle superviser et orienter le travail des forces de sécurité » ?

Chaire Transformation de l'action publique  
Science Po Lyon  
3 mars 2021

# Predictive policing

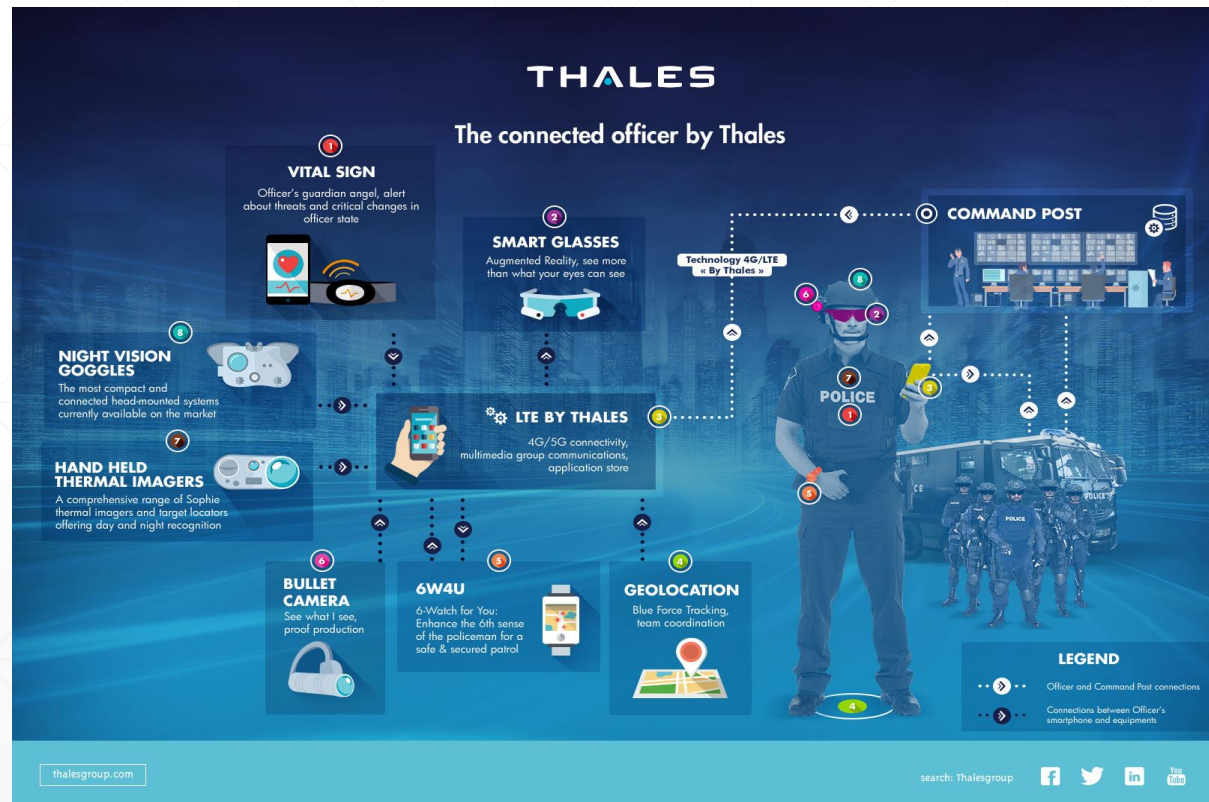
---

Imaginaire cybernétique, moralisation des mathématiques et mathématisation de la morale

# Plan de la présentation

- Imaginaire cybernétique : la sécurité dans un flux de données
  - La réalité gestionnaire : une police productiviste
  - Moralisation des mathématiques : critique des discriminations et interruption
  - Mathématisation de la morale : l'équité dans la machine
-

# Imaginaire cybernétique : la sécurité dans un flux de données



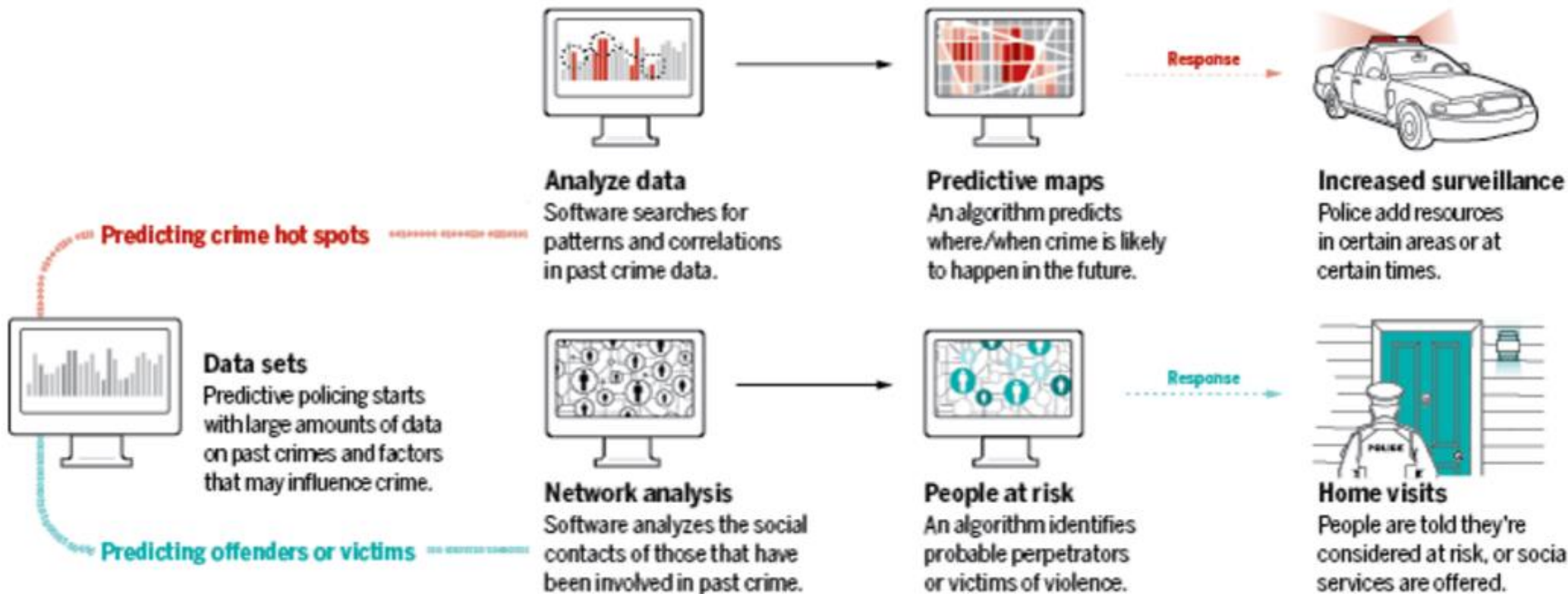


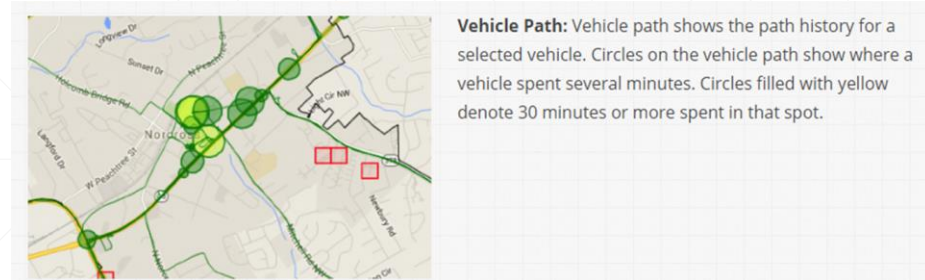
Diagram: G. Grullón/Science

# La réalité gestionnaire : une police productiviste

- Un « dosomètre »

- $ROI = \frac{Gains - Investment\ costs}{Investment\ costs}$

- Métriques d'équité

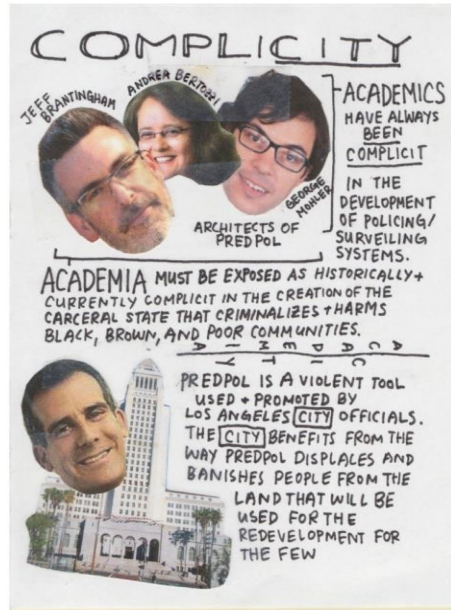




# Moralisation des mathématiques : critique des discriminations et interruption



stoplapdspyng 55 Follow including cookie policy.

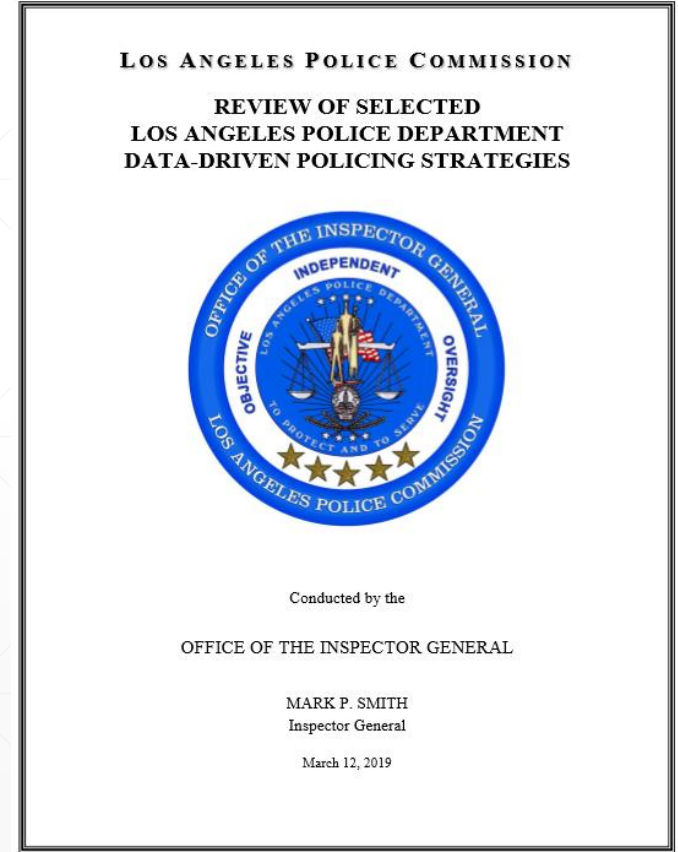


## Over 450 academics reject Predpol

stoplapdspyng Oct 9, 2019 · 12 min read

Over 400 academics, faculty and students, from universities across the United States and abroad join 65 UCLA faculty and students rejecting the merits and ethics of UCLA Professor Jeff Brantingham’s research behind Predpol and

other algorithm and location-based policing, calling it “troubling legacies of anthropology and the social sciences.”



NEWS · 19 JUNE 2020

# Mathematicians urge colleagues to boycott police work in wake of killings

More than 1,400 researchers have signed a letter calling on the discipline to stop working on predictive-policing algorithms and other models.

Daide Castelvechi



RELATED ARTICLES

What the data say about police brutality and racial bias – and which reforms might work



Reform predictive policing



# Mathématisation de la morale

“Corbett-Davies et Goel (2018) proposent trois définitions formelles de l'équité, à savoir:

- « anticlassification »,
- « parité de classification »
- « calibration ».

L'anti-classification fait référence aux algorithmes qui ne prennent pas en compte les attributs protégés dans les méthodes de classification ou de prédiction; la probabilité d'un résultat est égale pour tous les individus, indépendamment de leur appartenance à un groupe.

Une autre classe d'algorithmes est appelée parité de classification, ou parité démographique; la probabilité d'un résultat est égale pour tous les individus appartenant à un même groupe.

Enfin, la troisième définition est connue sous le nom de calibration. Elle requiert que les résultats soient indépendants des attributs protégés après un contrôle du risque estimé. Par exemple, parmi les demandeurs de crédit qui ont 10% de chances de ne pas rembourser le crédit demandé, la méthode de calibration requiert que les taux de défaut de paiement soient les mêmes à travers plusieurs groupes”.

Patrice Bertail, D. Bounie, Stéphan Cléménçon, Patrick Waelbroeck. Algorithmes : Biais, Discrimination et Équité. 2019. [{hal-02077745}](#)

Name	Closest relative	Note
Statistical parity	Independence	Equivalent
Group fairness	Independence	Equivalent
Demographic parity	Independence	Equivalent
Conditional statistical parity	Independence	Relaxation
Equal opportunity	Separation	Relaxation
Equalized odds	Separation	Equivalent
Conditional procedure accuracy equality	Separation	Equivalent
Disparate mistreatment	Separation	Equivalent
Balance for positive class	Separation	Relaxation
Balance for negative class	Separation	Relaxation
Predictive equality	Separation	Relaxation
Conditional use accuracy equality	Sufficiency	Equivalence
Predictive parity	Sufficiency	Relaxation
Calibration	Sufficiency	Equivalence

Solon Barocas; Moritz Hardt; Arvind Narayanan, [Fairness and Machine Learning](#). Retrieved 15 December 2019.



# The effect of differential victim crime reporting on predictive policing systems

Nil-Jana Akpınar  
nakpinar@stat.cmu.edu  
Department of Statistics and Data  
Science & Machine Learning  
Department  
Carnegie Mellon University

Maria De-Arteaga  
Information, Risk, and Operations  
Management Department  
McCombs School of Business  
University of Texas at Austin

Alexandra Chouldechova  
Heinz College & Department of  
Statistics and Data Science  
Carnegie Mellon University

## ABSTRACT

Police departments around the world have been experimenting with forms of place-based data-driven proactive policing for over two decades. Modern incarnations of such systems are commonly known as hot spot predictive policing. These systems predict where future crime is likely to concentrate such that police can allocate patrols to these areas and deter crime before it occurs. Previous research on fairness in predictive policing has concentrated on the models are trained on discov-  
lications for models trained demonstrate how differential geographical areas can lead to ie hot spot prediction models. 1 patterned after district-level vey data for Bogotá, Colombia. rime reporting rates can lead otots from high crime but low ime and high reporting areas. i in the form of over-policing

I Alexandra Chouldechova. 2021. *orting on predictive policing sys- ability, and Transparency (FAcCT ada*. ACM, New York, NY, USA, 3445877

modern incarnations of predictive policing date back to 2008, when the Los Angeles Police Department (LAPD) began its explorations

of these systems, followe New York Police Depart including Azavea, KeySt: US-centric phenomenon, Europe, the UK, and Chit

More recently, predic scrutiny due to their lael they may lead to further by virtue of being train: Critics commonly point produce dangerous feedb recent arrests is used to neighbourhoods where tl and conduct even more [33] and Ensign et al. [19 theoretically how such fe

Proponents and devel have argued that such an policing that do not acc inputs to such systems, n dict. The analysis of Lum demonstrates how using inputs to a self-exciting pr in PredPol would result in and ethnic minority neig they do not use data on c in generating their predic

ld have been experimenting

2018 IEEE International Conference on Systems, Man, and Cybernetics

## A penalized likelihood method for balancing accuracy and fairness in predictive policing

George Mohler, Rajeev Raje  
Department of Computer and Information Science  
Indiana University - Purdue University Indianapolis  
{gmohler, rraje}@iupui.edu

Matthew Valasik  
Department of Sociology  
Louisiana State University  
mvalasik@lsu.edu

Jeremy Carter  
School of Public and Environmental Affairs  
Indiana University - Purdue University Indianapolis  
carterjg@iupui.edu

P Jeffrey Brantingham  
Department of Anthropology  
University of California Los Angeles  
pjb@anthro.ucla.edu

**Abstract**—Racial bias of predictive policing algorithms has been the focus of recent research and, in the case of Hawkes processes, feedback loops are possible where biased arrests are amplified through self-excitation, leading to hotspot formation and further arrests of minority populations. In this article we develop a penalized likelihood approach for introducing demographic parity into point process models of crime. In particular, we add a penalty term to the likelihood function that encourages the amount of police patrol received by each of several demographic groups to be proportional to the representation of that group in the total population. We apply our model to historical crime incident data in Indianapolis and measure the fairness and accuracy of the two approaches across several crime categories. We show that fairness can be introduced into point process models of crime so that patrol levels proportionally match demographics, though at a cost of reduced accuracy of the algorithms.

**Index Terms**—Predictive Policing, Fairness, Hawkes Process, Maximum Penalized Likelihood Estimation, Demographic Parity

### I. INTRODUCTION

Crime events cluster in space and time forming “hotspots” where 25-50% of crime may be captured in only a few percent of the land area of a city [1]–[3]. Spatial-temporal predictive policing algorithms [4], [5] attempt to capture the space-time dynamics associated with hotspot formation and direct police patrols in response, which can then lead to crime rate reductions [4]. The predictive policing data cycle is shown in Figure 1, where input may be generated from victim reports or police initiated arrests (for example). This data enters the police database and is then used by a predictive algorithm to inform police activity and patrol. That activity may then influence future suspects and victims in the areas the algorithm selects for patrol, as well as in those areas that do not receive police attention.

algorithm leading to hotspot formation and further arrests of minority populations (see Figure 1). A similar concern is raised by Ferguson [11], who notes that arrests in a prediction area ‘memorializes’ that location as ‘hot’, which guarantees that it will show up again as a prediction area producing further arrests.

In this article we develop a penalized likelihood approach for introducing demographic parity into point process models of crime. Our goal is similar to the one developed in [12] where police patrols should match the “true” crime rate in an area, rather than crime rates that result from biased arrests. To achieve this goal, we add a penalty term to the likelihood function that encourages the amount of police patrol received by each of  $1, \dots, M$  demographic groups to be proportional to the representation of that group in the total population.

We note upfront that the introduction of a fairness penalty may lead to its own form of bias. Whereas biased arrests may result from interactions between police and suspects, bias may also adversely affect victims of crime [13]. Such bias may arise, for example, if an officer taking a report downgrades a burglary to a lesser crime as a result of the officer’s implicit bias towards the victim’s race/ethnicity. Fairness algorithms have the potential to operate in a similar manner. Consider the scenario for the predictive policing flow chart in Figure 1 characterized by a fairness algorithm being applied to crime reported by minority victims, leading to reduced hotspots in minority areas and less patrols, which then might lead to further crime rate increases in those areas.

In this paper we do not attempt, given a particular dataset and crime type, to distinguish between these forms of bias that may affect suspects or victims of crime differently. Instead, we explore the accuracy-fairness tradeoff when applying a fairness penalty to maximum likelihood estimation of point process



ACM FAccT is the new acronym for the ACM Conference on Fairness, Accountability, and Transparency!

ACM FAccT will be held online March 3-10, 2021. More information on this year’s conference is posted on the [2021 ACM FAccT webpage](#).

Visit the [ACM FAccT Registration Webpage](#) to Register Now

Algorithmic systems are being adopted in a growing number of contexts, fueled by big data. These systems filter, sort, score, recommend, personalize, and otherwise shape human experience, increasingly making or informing decisions with major impact on access to, e.g., credit, insurance, healthcare, parole, social security, and immigration. Although these systems may bring myriad benefits, they also contain inherent risks, such as codifying and entrenching biases; reducing accountability, and hindering due process; they also increase the information asymmetry between individuals whose data feed into these systems and big players capable of inferring potentially relevant information.

## Des standards en préparation...



### **IEEE P7003™, Standard for Algorithmic Bias Considerations Working Group**

IEEE Computer Society/Software & Systems  
Engineering Standards Committee (C/S2ESC)

---

# ...pour des enjeux de certification.

The screenshot shows the IEEE Standards Association website. At the top left is the logo "IEEE STANDARDS ASSOCIATION". To the right is a search bar with the text "Search" and a magnifying glass icon. Below the logo is a navigation menu with the items "Standards", "Products & Services", "Technologies & Initiatives", and "Participate". On the right side of the navigation bar are two buttons: "MAC ADDRESS" and "BUY STANDARDS". The main content area has a blue header with the title "The Ethics Certification Program for Autonomous and Intelligent Systems (ECPAIS)" and a subtitle "Developing metrics and processes towards the implementation of a certification methodology addressing transparency, accountability and algorithmic bias". Below this is a section titled "< Industry Connections" with a sub-header "The Ethics Certification Program for Autonomous and Intelligent Systems". To the right of this text is an image of a hand holding a glowing scale of justice. Further right is an "About" section with the text: "The goal of The Ethics Certification Program for Autonomous and Intelligent Systems (ECPAIS) is to create specifications for certification and marking processes that advance transparency, accountability and reduction in algorithmic bias in Autonomous and Intelligent Systems (A/IS)."

IEEE STANDARDS ASSOCIATION

Search

Standards Products & Services Technologies & Initiatives Participate

MAC ADDRESS BUY STANDARDS

## The Ethics Certification Program for Autonomous and Intelligent Systems (ECPAIS)

Developing metrics and processes towards the implementation of a certification methodology addressing transparency, accountability and algorithmic bias

< Industry Connections

The Ethics Certification Program for Autonomous and Intelligent Systems



### About

The goal of The Ethics Certification Program for Autonomous and Intelligent Systems (ECPAIS) is to create specifications for certification and marking processes that advance transparency, accountability and reduction in algorithmic bias in Autonomous and Intelligent Systems (A/IS).