

Criminal Machine Learning

Automated Inference on Criminality using Face Images

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Abstract

We study, for the first time, automated inference on criminality based solely on still face images, which is free of any biases of subjective judgments of human observers. Via supervised machine learning, we build four classifiers (logistic regression, KNN, SVM, CNN) using facial images of 1856 real persons controlled for race, gender, age and facial expressions, nearly half of whom were convicted criminals, for discriminating between criminals and non-criminals. All four classifiers perform consistently well and empirically establish the validity of automated face-induced inference on criminality, despite the historical controversy surrounding this line of enquiry. Also, some discriminating structural features for predicting criminality have been found by machine learning. Above all, the most important discovery of this research is that criminal and non-criminal face images populate two quite distinctive manifolds. The variation among criminal faces is significantly greater than that of the non-criminal faces. The two manifolds consisting of criminal and non-criminal faces appear to be concentric, with the non-criminal manifold lying in the kernel with a smaller span, exhibiting a law of "normality" for faces of non-criminals. In other words, the faces of general law-biding public have a greater degree of resemblance compared with the faces of criminals, or criminals have a higher degree of dissimilarity in facial appearance than non-criminals.

management science, criminology, etc.

In all cultures and all periods of recorded human history, people share the belief that the face alone suffices to reveal innate traits of a person. Aristotle in his famous work *Prior Analytics* asserted, "It is possible to infer character from features, if it is granted that the body and the soul are changed together by the natural affections". Psychologists have known, for as long as a millennium, the human tendency of inferring innate traits and social attributes (e.g., the trustworthiness, dominance) of a person from his/her facial appearance, and a robust consensus of individuals' inferences. These are the facts found through numerous studies [3, 39, 5, 6, 10, 26, 27, 34, 32].

Independent of the validity of pedestrian belief in the (pseudo)science of physiognomy, a tantalizing question naturally arises: what facial features influence average Joes' impulsive and yet consensual judgments on social attributes of a non-acquaintance member of their own specie? Attempting to answer the question, Todorov and Oosterhof proposed a data-driven statistical modeling method to find visual determinants of social attributes by asking human subjects to score four percepts: dominance, attractiveness, trustworthiness, and extroversion, based on first impression of static face images [33]. This method can synthesize a representative (average) face image for a set of input face images scored closely on any of the four aforementioned social percepts. The ranking of these synthesized face images by subjective scores (e.g., from least to most trustwor-

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Responses to Critiques on Machine Learning of Criminality Perceptions (Addendum of arXiv:1611.04135)

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In November 2016 we submitted to arXiv our paper “Automated Inference on Criminality Using Face Images”. It generated a great deal of discussions in the Internet and some media outlets. Our work is only intended for pure academic discussions; how it has become a media consumption is a total surprise to us.

Although in agreement with our critics on the need and importance of policing AI research for the general good of the society, we are deeply baffled by the ways some of them misrepresented our work, in particular the motive and objective of our research.

1. Name calling

It should be abundantly clear, for anyone who reads our paper with a neutral mind setting, that our only motive is to know if machine learning has the potential of acquiring humanlike social perceptions of faces, despite the complexity and subtlety of such perceptions that are functions of both the observed and the observer. Our inquiry is to push the envelope and extend the research on automated face recognition from the biometric dimension (e.g., determining the race, gender, age, facial expression, etc.) to the sociopsychological dimension. We are merely interested in the distinct possibility of teaching machines to pass the Turing test on the task of duplicating humans in their first impressions (e.g., personality traits, mannerism, demeanor, etc.) of a stranger. The face perception of criminality was expediently (unfortunately to us in hindsight) chosen as an easy test case, at least in our intuition as explained in our paper:

“For validating the hypothesis on the correlations between the innate traits and social behaviors of a person and the physical characteristics of that persons face, it would be hard pushed to find a more convincing experiment than examining the success rates of discriminating between criminals and non-criminals with modern automatic classifiers. These two populations should be among the easiest to differentiate, if social

attributes and facial features are correlated, because being a criminal requires a host of abnormal (outlier) personal traits. If the classification rate turns out low, then the validity of face-induced social inference can be safely negated.”

By a magical stretch of imagination, few of our critics intertwine the above passage into some of our honest observations and morph them into the following deduction of, they insist, ours:

“Those with more curved upper lips and eyes closer together are of a lower social order, prone to (as Wu and Zhang put it) “a host of abnormal (outlier) personal traits” ultimately leading to a legal diagnosis of “criminality” with high probability.”

We agree that the pungent word criminality should be put in quotation marks; a caveat about the possible biases in the input data should be issued. Taking a court conviction at its face value, i.e., as the “ground truth” for machine learning, was indeed a serious oversight on our part. However, throughout our paper we maintain a sober neutrality on whatever we might find; in the introduction, we declare

“In this paper we intend not to nor are we qualified to discuss or debate on societal stereotypes, rather we want to satisfy our curiosity in the accuracy of fully automated inference on criminality. At the onset of this study our gut feeling is that modern tools of machine learning and computer vision will refute the validity of physiognomy, although the outcomes turn out otherwise.”

Nowhere in our paper advocated the use of our method as a tool of law enforcement, nor did our discussions advance from correlation to causality. But still we got interpreted copiously by some with an insinuation of racism. This is not the way of academic exchanges we are used to.

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Business / Banking & Finance

Explainer | How an avalanche of rules buried Ant Group's US\$39.5 billion stock sale and looks set to reshape China's fintech landscape

- Ant Group will need months at least to assess the fallout from the regulatory shift, make the business compliant with new rules and update potential investors
- We lay out a timeline of the key events leading up to China halting Ant's IPO in Shanghai and Hong Kong at the eleventh hour



Alison Tudor-Ackroyd

Published: 8:00am, 7 Nov, 2020 ▾

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Elon Musk: Tesla Gigafactory Shanghai





MOBILITY IN CHINA

THE SHARED ECONOMY FOR CARS IS BOOMING

CAR OWNERSHIP IS RARE



CHINA

China has only 1 car for every 7 people



USA

1 car per 1.25 people



WESTERN EUROPE

1 car per 2 people



About

150,000,000

Chinese have a driver's license
but don't own a car

RENTING IS STILL UNCOMMON

China has just

0.4 rental cars per 1,000 people

(compared to approx. 3.5 in Western Europe)

SHARING IN GENERAL IS HUGE

Sharing apps for just about everything – strollers, umbrellas, battery packs, books and even folding chairs! – are flourishing

Roughly 10% of the Chinese vehicle fleet is "shared" in the form of taxis, rental cars, ride hailing etc.

(compared to approx. 1% in Western markets)



TAXI AND LIMOUSINE USE IS WIDESPREAD

China has about
12 times as many
taxis as the USA

(adjusted for the ratio
of taxis to the total car parc)



USA

CHINA



Since their launch, ride hailing services have exploded. Didi China has around **8 times** more rides per day than Uber worldwide

UBER



DIDI

Taxi rides in Beijing and Shanghai cost about half what they do in New York (adjusted for purchasing power)

CAR SHARING COULD BE EVEN BIGGER!

Vast potential for car sharing business (hourly-based car rental) through both organic growth and conversion from other mobility segments

Time spent traveling
(thousands of journeys
per day)

x40

1,600

40

2015

2020e