*Socio-Economic Review*, 2020, Vol. 0, No. 0, 1–19
doi: 10.1093/ser/mwaa040
Presidential Address



Presidential Address

# Predicting the Future: Art and Algorithms

**Akos Rona-Tas***

Department of Sociology, University of California, San Diego, CA, USA

*Correspondence: aronatas@ucsd.edu

Predictive algorithms are replacing the art of human judgement in rapidly growing areas of social life. By offering pattern recognition as forecast, predictive algorithms mechanically project the past onto the future, embracing a peculiar notion of time where the future is different in no radical way from the past and present, and a peculiar world where human agency is absent. Yet, prediction is about agency, we predict the future to change it. At the individual level, the psychological literature has concluded that in the realm of predictions, human judgement is inferior to algorithmic methods. At the sociological level, however, human judgement is often preferred over algorthms. We show how human and algorithmic predictions work in three social contexts—consumer credit, college admissions and criminal justice—and why people have good reasons to rely on human judgement. We argue that mechanical and overly successful local predictions can result in self-fulfilling prophecies and, eventually, global polarization and chaos. Finally, we look at algorithmic prediction as a form of societal and political governance and discuss how it is currently being constructed as a wide net of control by market processes in the USA and by government fiat in China.

**Key words:** 5× consumers, public policy, social norms, social policy, technological change

**JEL classification:** 3× e.g. D63 Welfare Economics: Equity, Justice, Inequality, and Other Normative Criteria and Measurement, D81: Information, Knowledge, and Uncertainty: Criteria for Decision-Making under Risk and Uncertainty D84 Information, Knowledge, and Uncertainty: Expectations • Speculations

## 1. Introduction

The recent proliferation of predictive algorithms in everyday life is squeezing out more subjective forms of prediction, such as human judgement, expertise and imagination. It is not a friend but Amazon's algorithm that predicts what one wants to buy. In late 2013, Amazon patented 'anticipatory shipping' to ship items its individual customers have not yet ordered

**MPIfG Journal Article**
Akos Rona-Tas: Predicting the Future: Art and Algorithms. In: Socio-Economic Review 18(3), 893-911 (2020). Oxford University Press
The original publication is available at the publisher's web site: https://doi.org/10.1093/ser/mwaa040

The MPIfG Journal Articles series features articles by MPIfG researchers and visiting scholars published in peer-reviewed journals.
Max Planck Institute for the Study of Societies (MPIfG) Cologne | www.mpifg.de

but the company anticipates they will (U.S. Patent# 8615473).[1] The seeming success of algorithmic predictions is dazzling. HR departments use algorithms not seasoned professionals to predict who will do well on their job and therefore should be hired and promoted, and who will quit soon (King and Mrkonich, 2015; Kiviat, 2019; Kim 2018). In finance, algorithms are churning out predictions about future stock prices, bankruptcy, who will borrow, who will not pay their loans, and the amount that will be collected on delinquencies (MacKenzie, 2008; Rona-Tas and Hiss, 2010; Cavalcante *et al.*, 2016; Krippner, 2017; Guseva and Rona-Tas, 2019). In education, predictive technology is increasingly used to select students who will succeed once admitted or need special attention (Siu and Reiter, 2009; Marcus, 2014; Kurzweil and Wu, 2015). In the criminal justice system, computer-generated predictions are used in policing, bail setting, sentencing and parole decisions (Berk, 2012; Lum and Isaac, 2016; Ferguson, 2016; Brayne, 2017; Ensign, 2017; Kehl *et al.*, 2017; Kleinberg *et al.*, 2018; Popp, 2017; Sunstein, 2019; Werth, 2019). The novelty of these predictions is that they estimate not future behaviours of aggregates but of individual social actors. The danger of algorithmic anticipation of individual actions is that it can seriously limit human agency and can pre-emptively colonize the future.

This poses a special challenge for social scientists. Most explanations proffered by social science focus not on the future but on the past or present. Causal explanations turn our attention backward to the past and build understanding from events already happened. Structural explanations identify forces in the present that limit or enable what social actors can do. Yet, social action itself, to the extent to which it is intentional, is driven by some image of the future, some set of expectations about things yet to happen. Causes from the past and structural constraints in the present are all filtered through those future expectations.

Different disciplines have had different engagement with the problem of the future. Economics has always had a deep seated interest in integrating the future in its rational action model. Yet until recently, it assumed that people thinking about the future just used the discipline's own scientific methodology properly modelled by rational, mathematical calculations (Muth, 1961; Fama, 1965; Lucas and Sargent, 1981; Frederick *et al.*, 2002), a special case of what Bourdieu calls the scholastic fallacy (Bourdieu, 1990). Management science being closer to the messy world of actual decision making and being on call to provide useful tools for business strategy had elaborated prediction support from scenario planning and simulations to the Delphi method and prediction markets (e.g. Armstrong and Grohman, 1972; Godet and Roubelat, 1996; Amer *et al.*, 2013). Lately, psychology has seen a surge of research on this topic (Gilbert and Wilson, 2007; Seligman *et al.*, 2016; Oettingen *et al.*, 2018), and so has political science (Silver, 2012; Tetlock and Gardner, 2016; Tetlock, 2017) and sociology (Selin, 2008; Mische, 2009; Tavory and Eliasoph, 2013; Beckert, 2016; Gans, 2016).

Looking at social action through the prism of future expectations reveals a recent and important shift in the social world: expectations are increasingly being formed by highly formalized, complex predictive algorithms. Algorithms are a set of mechanical instructions about how to process some data input to get some output in the form of suggestion, advice, decision or direct action. Yet, they are also an explicit form of presenting and sharing knowledge. In this respect, algorithms are not unlike writing, in that they make the

1 http://patft1.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PALL&p=1&u=%2Fnetahtml%2FPTO%2Fsrchnum.htm&r=1&f=G&l=50&s1=8,615,473.PN.&OS=PN/8,615,473&RS=PN/8,615,473

recording, articulation and accumulation of knowledge easier. Today, predictive algorithmic models are statistical, written in computer code, although throughout history non-statistical algorithms have been in wide circulation. From tarot card reading to astrology, most esoteric predictions are built on hermetic algorithms that follow mechanical, and often quite elaborate instructions, to arrive at a prognosis of the future from some event or observation available in the present (Lewinsohn, 1961; Genuth, 1997; Martens and Trachet, 1998; Decker and Dummett, 2013). The word 'algorithm' highlights the central point: instead of relying on intuition, imagination, judgement, inspiration or epiphany, algorithmic predictions take some data, any data, from the past, the only place where data can be extracted from, and make a *mechanical* projection into the future.

## 2. The statistical versus clinical prediction debate

The relative power of statistical algorithms in predicting future outcomes compared to the art of judgement by experts has been subject of a large torrent of research in cognitive psychology beginning with Paul Mehl's book Clinical versus Statistical Prediction (Meehl, 1954). The five decades that followed produced a large amount of evidence both experimental and quasi-experimental in and outside psychology addressing this issue (see Dawes *et al.*, 1989; Ægisdottir *et al.*, 2006). In 2000, a meta-analysis of 136 studies looking at the prediction of a wide variety of outcomes including academic performance, medical events, psychiatric symptoms, job performance, business success, criminal recidivism, marital satisfaction, coupon redemption and suicide, all set up as a prediction competition between statistical models and trained experts found that only 6% of the studies showed the experts winning. For the rest, statistical models triumphed hands down or did at least as well as the art of human judgement (Grove *et al.*, 2000). In 2002, an article in the Philosophy of Science with the not so subtle title: 50 Years of Successful Predictive Modeling Should Be Enough! insisted that it is time for those believing in the art of human, clinical judgement to concede defeat (Bishop and Trout, 2002). It argued that statistical predictions are more accurate as they are not vulnerable to cognitive fallacies and limitations. They are also more reliable as algorithms do not have bad days and do not get distracted. Finally, if an expert can articulate what she knows that the model does not, one can easily improve on the model by adding that variable to it as a predictor. The triumphant claim was not that algorithmic models are good, just that they are better than human predictions, an admittedly low bar to clear.

The statistical models deployed in this debate were drawn from the deductive hypothesis testing methodology of social statistics. The algorithms that defeated human experts were statistical tools such as analysis of variance, regression and discriminant analysis. In these models, a set of carefully chosen input variables predicted some well-measured outcome, each input acquiring a weight in the process showing its importance and the direction of its effect. These models then could be translated into a narrative, telling a causal story. To dramatize the contest as a competition between expert and machine, the researchers removed from sight the important fact that the creation of these statistical models—the choice of the predictors, their measurement, the functional form of the model, the handling of missing data, etc.—and their interpretation—causal direction, spuriousness, omitted variables, selection bias, etc.—require the art of clinical judgement and human expertise (Rona-Tas and Hiss, 2010).

If impure statistical models from the 20th century contaminated by fallible human judgement were already proving human judgment obsolete in predictions, the more powerful methods of machine learning should bury clinicians six-feet under.

## 3. Three main technological developments enabling algorithmic predictions

In recent decades, improvements in sensor and communication technology, data storage and processing capacities and new powerful algorithms have put algorithmic prediction on steroids. The switch from analytic modelling to the new paradigm of inductive machine learning and its new algorithms, like deep neural networks or support vector machines, made it possible to fit mathematical and statistical functions to data with unprecedented success predicting unknown information from known observations. Predictive technologies now can claim several spectacular achievements in areas including image recognition (LeCun *et al.*, 2015), natural language processing (Goldberg, 2016), self-driving cars[2] and complex games such as chess, go and shogi (Hosanagar, 2019). It seems that we are on the cusp of a new era, where the future can be forecast before it happens. Artificial intelligence (AI) will be able to lay out the future with increasing precision leaving an ever shrinking territory for surprise, novelty, uncertainty and imagination.

## 4. Pattern recognition versus prediction

Yet, if we take a closer look at the big successes of algorithmic prediction, we discover that 'prediction' (Agrawal *et al.*, 2018) is a misleading metaphor. Machine learning can be powerful to predict an outcome in a sample, taking a half of that sample to build the model (training set) and use that model to predict in the other half (test set). Yet, this kind of prediction is not 'prediction' in the strict sense of the word. We are not forecasting something yet to happen. We are looking for patterns in the (near) past. The test set is not in the future. It is in the same time block as the training set. We are not predicting change, we are predicting patterns or variation.

The difference is time. Predicting variation is prediction only in the sense that one tries to predict the correct answer to be *revealed* in the future. But it is not the outcome that is in the future; only its reveal. We predict past variation not change. The real prediction is not in the algorithmic calculation. It is in the unspoken assumption that the variation will remain the same. Take this puzzle from the commonly used IQ test, called the Raven Progressive Matrices, where one must 'predict' the missing, nineth piece from among the eight tiles below (Figure 1).

Predicting the last element in this two-dimensional progression is not a guess about the future. It is a guess about a pattern that is current and present, although we may find out only in the future if we guessed correctly. This is the kind of prediction, machine learning algorithms are very good at, and this is why IQ tests like this, will soon be considered obsolete along with the skills they test. These skills will not be our comparative advantage over machines and will go by the way of doing long divisions or catching typos. Also, consider

2 See Andrew Ng, *Autonomous Driving*, COURSERA. https://www.coursera.org/lecture/machine-learning/autonomous-driving-zYS8T.

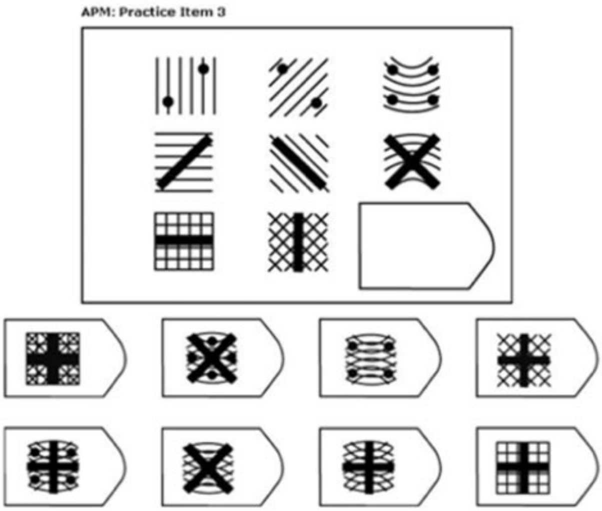


**Figure 1.** Example of an item from the Raven's Progressive Matrices Test.

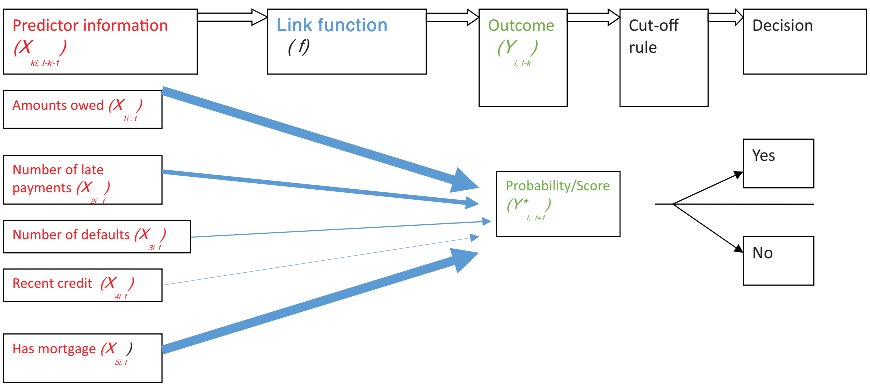


**Figure 2. The Algorithmic Process of Credit Scoring.**

the pattern in the Progressive Matrices test. Any eight tile would predict equally well the ninth one. But in no way do the eight we see cause the ninth one to be what it is. The explanation is not that the previous eight somehow caused the ninth. To explain why only THAT tile can be the ninth would entail pointing out the pattern and not producing a causal explanation.[3] Also notice, that the right answer to this puzzle has not changed since John Raven,

3 To find the correct answer—the third tile from the left in the bottom row—one could separate the repeated thin parallel lines in the background and the bold dots and lines in the front. One could point out that the pattern of the background varies top down while the dots and lines in the front vary left to right, both through the steps of transposition and then combination. This leaves only one correct tile from the eight offered.

the British psychologist, first invented it in the 1930s and will stay the same forever. The beauty of the problem is that it has no moving part that would change with time. When deep learning algorithms recognise that the picture is that of a Ford Escort, we are impressed. But no one would expect deep learning to predict what the Ford Escort will look like in 10 years, or indeed, if the model would exist at all by then.[4]

New predictive technology does not forecast. It finds patterns and when called to prognosticate it just mechanically projects them onto the future. Sometimes, the future is similar enough to the past that this projection is useful. However, the better these algorithms fit to the patterns of the past, the less wiggle room they have to bend to future changes. This is called the problem of overfitting the data. Overfitting the data is essentially mistaking noise for signal, randomness for pattern (Smith, 2018). It is essentially a math intensive cousin of tarot card reading, where the randomly appearing card is interpreted as a pattern revealing the future.

The statistical models, featured in the avalanche of research Meehl's book launched, do the same thing. They fit patterns to past observations, except, their fit is relatively poor and that leaves room for future uncertainty and human conversation and judgement. There is a clear tradeoff between prediction and explanation. There is also some evidence that simpler models that fit more poorly data from the past predict the future better (Gigerenzer, 2007).

## 5. Why one should be skeptical

If algorithmic predictions were hands down superior to human imagination, we would expect that when stakes of predicting are higher, people would choose algorithms over human judgement. Take three situations where we have to make individual predictions: credit where lenders have to predict the future of their loan, colleges that have to predict who will do well and therefore should be admitted or hired, and police that must anticipate where crime will occur and who will be involved to prevent it or be on time to catch the perpetrator.

Then why do banks use algorithms to issue consumer loans or credit cards of relatively modest amounts, but rely on decisions by committees that carefully discuss and deliberate when a large corporation wants a multimillion-dollar loan?

We see a similar tendency in college admissions. While most top American colleges use a complex system of human deliberation, many colleges in the USA and around the world fall back on simple algorithms when it comes to admitting undergraduate students. They take the applicants' high school or exit exam grade, add them together by some formula, depending on the country they may add or subtract points for certain factors, and arrive at an admission score. And as we will see, even these simple algorithms are under attack. But when it comes to admitting doctoral students, these rules are more flexible, and even more so when hiring professors, as colleges are unlikely to leave the decision to hire faculty to some mechanical device that counts publications, weights journals, assigns points for awards, etc. Increasing reliance on scientometric data notwithstanding, faculty is hired in most places after discussion and deliberation by faculty and administrators, because these decisions are far more consequential than admitting an undergraduate student.

4 The American production of the Ford Escort was discontinued in 2004 and the brand was resurrected in 2015 for the Chinese market.

Finally, why is it that in the criminal justice system, predictive algorithms can be deployed for robberies or burglaries resulting in the loss of a few tens of thousands of dollars at most, but not for white collar crimes, where the loss can be in the millions, or for serious police misconduct?

## 6. Credit

In the world of credit, the difference between lending paltry sums to consumers and princely fortunes to corporations cannot be more different but in a way that runs counter to Meehl's conclusion. The consumer credit bureau Experian extolling the virtues of statistical judgement explains why an individual must be put through their famous Fair, Isaac Co. (FICO) algorithm:

> Before credit scores, lenders physically looked over each applicant's credit report to determine whether to grant credit. A lender might deny credit based on a subjective judgment that a consumer already held too much debt, or had too many recent late payments. Not only was this time consuming, but ***also human judgment was prone to mistakes and bias***. Lenders used personal opinion to make a decision about an applicant that may have had little bearing on the applicant's ability to repay debt. Credit scores help lenders assess risk more fairly because they are ***consistent and objective*** (Emphasis added) Experian.[5]

Yet when it comes to corporate lending, the story changes. This is how large corporate loans are judged according to Standard and Poor's, one of the big three rating agencies:

> Credit ratings are ***opinions*** about credit risk. Our ratings express our opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time. Credit ratings ***can also speak to*** [notice the vagueness] the credit quality of an individual debt issue, such as a corporate or municipal bond, and the relative likelihood that the issue may default. Credit ratings ***are not absolute measure of default probability***. Since there are ***future events and developments that cannot be foreseen***, the assignment of credit ratings is ***not an exact science*** (Emphasis added) Standard and Poor's.[6]

All hinges on whether the future and the past are radically different. Fair, Isaac Co., the supplier of the consumer scores writes on its web site:

> Predictive models analyze past performance to 'predict' how likely a customer is to exhibit a specific behavior in the future.[7]

5 This is what Equifax says about the same thing: 'A credit score is the result of a ***mathematical formula*** that uses the information in your credit report, such as how well you have paid your bills ***in the past***, to help lenders and creditors assess how likely you are to pay your bills ***in the future'***. (Emphasis added) Equifax

6 And this is what Fitch, the smallest of the three, has to say: 'Ratings are the ***collective work*** product of Fitch, and no individual, or group of individuals, is solely responsible for a rating. Ratings are ***not facts*** and, therefore, ***cannot be described as being "accurate" or "inaccurate***."' (Emphasis added) Fitch

7 https://www.fico.com/blogs/what-are-types-predictive-analytics Fair, Isaac Co. also offers 'predictive analytics for businesses, but they carefully separate Business Intelligence (BI) from predictive analytics'. 'If BI tells you what's happened, predictive analytics tells you what to do'. Here

At the same time, any investment fund brochure would include a version of this sentence: 'Past performance is not an indicator of future outcomes'.

## 7. The science of scoring

To understand what is wrong with credit scores, we must see how they are created. Predictive algorithms connect an outcome at time $t-1$ with a set of input variables at $t-2$ with a mathematical function, that we call the link function. The link function in traditional statistical models assign weights to the input variables in a way that once combined, their weighted sum will best predict the outcome (Figure 2). The weights we can interpret as the net effect of the input variable but only if we do not use data mining or deep learning.

These models are not predicting the future. They are 'predicting' the more recent past from the distant past. In fact, the 'prediction' is made from a past where time is scrambled. The input values are rarely or never from the same time point for all cases, nor does the outcome happen at the same point in time. All we can be certain of is that the inputs preceded the outcome for each case. This allows for the possibility, that for certain cases, the output happens before the input for some other cases.

Most significantly, we have no data from the future. The real prediction then happens when the new applicant's input scores from the present ($t$) or past ($t-1$) are plugged into our equation and using the calculated weights, we predict her outcome in the future ($t+1$). So we assume that the way the distant past predicts the recent past, is exactly how the present data will predict the future.

Suppose, that the time-scale is short enough and we can reasonably assume that things may not change a lot in the short-run,[8] one still faces the following dilemma: Which link function to use? One answer is to build a theoretical argument upfront for, say, a logistic regression or discriminant analysis, carefully translating the mathematical assumptions of the algorithm to the problem at hand. However, this is not always possible because one cannot match mathematical operations with real-world processes. Another answer is to see which one predicts most precisely. Yet, we would still want to 'understand' how the model creates our prediction.

Moreover, even the best models will predict with some error. Those will be of two types: false positives, people who look good to the model but are bad in reality and false negatives, good prospect classified as too risky. Banks that want to minimise losses may opt for a model that minimises false positives and choose a model that fits worse overall by racking up many false negatives ( Corbett-Davies *et al.*, 2017; Menon and Williamson, 2018). The bank may be happy but if the applicant is a good borrower and denied the loan she may be hurt simply by the choice of the link function.

If one makes these choices, in principle, one can interpret the outcome because human choices were based on some knowledge that got some support from getting a good fit. That is because there was a possibility of getting poor predictions, if the knowledge was wrong. But if it is the machine that makes the choices maximizing predictions, one's predictive

'prediction' doesn't promise to know what will happen. It only offers strategic advice. https://www.fico.com/blogs/how-does-predictive-analytics-differ-data-mining-and-business-intelligence

8 Most lenders find financial data older than 18 months useless.

success will rest on a mathematical operation that works equally well on meaningful and meaningless patterns.[9] Using the new tools of machine learning, one is likely to predict better, but at the cost of intelligibility.

## 8. Agency

Intelligibility is a problem of agency both for the predicted and the predictor. If the predicted does not understand why they are put into a certain category, why they were denied a loan or college admission, there is not much they can do to change their lot. This is especially dangerous for credit, since consumer lenders price loans according to risk calculated from the past—giving worse customers worse loans and better customers better loans—producing a positive feedback loop and a self-fulfilling prophecy. To break out of a downward spiral is hard, if one cannot find out how to improve her score.

But the predictor, here the lender, also loses agency. For the prediction algorithm to work, it needs a very specific outcome. Suppose the prediction is about default: failing to pay the debt on time.[10] Lenders also care about other things like profitability, market share, getting information about prospective clients and avoiding legal troubles. Those who pay their loans late can still be very profitable as they must pay penalties. Growing the customer base sweeps up many bad clients and that is not just unavoidable but also necessary because to know who is a good client there have to be some bad ones for comparison. Finally, no matter how well the algorithm predicts, having a system that one cannot reason about will result in legal challenges by those adversely affected. When these other objectives become more important, lenders can override the decisions of their algorithm.

The reason why banks use algorithms for consumer lending is that it is a cheap and fast way to make a rough guess on a large scale. Importantly, the cost of error is borne by the customers, the good ones who pay for the deadbeats, or with securitised loans sold to investors, it is the investors who are on the hook. The algorithm gives lenders legitimacy and legal protection. Their agency is not curtailed because they can suspend their reliance on the algorithm whenever it suits them, a choice not available to borrowers. At the same time, the algorithms in credit assessment remain proprietary secrets, further limiting the agency of borrowers, which lenders prefer. Algorithms are instruments of power.

Corporate lenders are in a different situation. Here, a rough guess is not enough, losses cannot be easily shifted to other clients. More importantly, the borrower here has more agency. As the famous saying goes, ‘if you borrow $10,000 from a bank you have a problem. If you borrow $100,000,000, the bank does’. Moreover, if the company borrows from a bank, it also can offer to buy other services. Their relationship is more interdependent and balanced. And if instead of

9 One can direct machine learning to worry about false positives more than about false negatives; howevwer, this will decrease the percentage of the correct predictions.

10 What exactly counts as default must be specified. Is it missing payments for 90 days? 120 days? Or 180 days? How would one count partial payment? If the payment is made late with interest and penalties, was there a default? What if the late payment was somehow the lender’s fault? These must be specified in detail for the algorithm. Credit scores usually punish late payment not necessarily the failure to pay.

going to banks, the company borrows through the financial markets and uses the rating agencies, those agencies are paid by the company, giving the corporate borrowers a certain leverage.[11]

## 9. College admission

In college admission, just as in credit decisions, one must evaluate the future performance of individuals and make a decision whether to grant them a service. In recent years, an increasing number of US universities moved away from standardised test scores and algorithmic formulas for admission and introduced 'holistic' methods, giving much more weight to human judgement (Syverson *et al.*, 2018). These include many of the top universities, such as the University of Chicago, that announced in 2018 that it no longer uses standardised tests in its highly competitive admissions process.[12] Instead, it will employ a holistic approach where a committee will judge applicants on a wide set of criteria, including essays responding to quirky prompts like this:

> Fans of the movie Sharknado say that they enjoy it because 'it's so bad, it's good'. Certain automobile owners prefer classic cars because they 'have more character'. And recently, vinyl record sales have skyrocketed because it is perceived that they have a warmer, fuller sound. Discuss something that you love not in spite of but rather due to its quirks or imperfections—*Inspired by Alex Serbanescu, Class of 2021.*[13]

College admissions are one of Meehl's strong cases for algorithmic decision making. So why do these colleges move towards clinical assessments?

Just as banks have multiple goals and algorithms are specific to only one of them, universities also must navigate multiple objectives. They want to get students with the greatest academic promise, but they are also keen on promoting social mobility, diversity, they want students who fit well with what the university can offer, and contribute to the college community.[14] Even if the standardized tests could help them meet one of the objectives, they may be useless or even counterproductive for others.

Standard scores do predict academic performance in college, but surprisingly poorly above a certain level (Geiser and Santelices, 2007; Atkinson and Geiser, 2009).[15] Chicago also pointed out that using standard scores directs the agency of the students in the wrong direction as students spend a lot of time and money on test preparation courses. The price of these courses puts poor students at a disadvantage and blocks social mobility. Predicting future promise using standardized tests will reproduce past inequalities.[16]

11 This puts the rating agencies in a situation of clear conflict of interest.

12 In May 2020, the University of California, a trendsetter in US higher education, decided to abandon standardized tests for admission. Because of the COVID-19, many universities made the same decision for the duration of the pandemic, conducting a de facto experiment.

13 https://collegeadmissions.uchicago.edu/apply/uchicago-supplemental-essay-questions

14 The Dean of Admissions at University of Chicago explained the change: 'It is about doing the RIGHT thing. Which is helping students and families of all backgrounds better understand and navigate this process and about bringing students with intellectual promise (no matter their background) to U Chicago (and making sure they succeed here too!)'. https://www.teenvogue.com/story/u-chicago-sat-act-requirement-dropped

15 Data for college outcome is available only for students who are enrolled in college. This means that normally we have no data for those whose scores are too low to be admitted. The same problem exist for credit applicants. This truncation of the data is known in the statistical literature as the sample selection bias (Winship and Mare, 1992).

16 Ironically, standardized tests were introduced in the 1930s to promote social mobility (Karabel, 2006; Lemann, 2000).

Most importantly, standardized tests valorize knowledge that can be standardized. They rely on problems with well-defined answers solvable with memory recall, fast processing and the application of rules (i.e. algorithms), skills that can be automated (Clark and Etzioni, 2016). Using algorithmic admission selects for the kind of knowledge that can be turned over to algorithms, for skills that are rapidly losing their value. Sticking to standardized admission tests, while it is a cheap form of selection, is based on the forward projection of past patterns connecting skills and future success, even though we already see these patterns on the wane.

## 10. Crime

### 10.1 Predictive policing

In the 2002 Steven Spielberg movie, *The Minority Report*, John Anderton played by Tom Cruise is the Chief of Precrime, a police unit, whose job is to prevent crime before it happens. Set in 2054, Anderton is aided by three precogs, mutated humans, who can previsualize crimes in their sleep, hours before they happen. Anderton's job is to swoop in, and arrest the would-be criminals when they are just about to commit their heinous act. The Precrime unit in the city of Chicago does not depend on mutants but on a computer generated hot list of likely perpetrators. The Strategic Subjects List (SSL) consists of over 400 people predicted to be at the highest risk of being involved in gun-related violence (Saunders *et al.*, 2016).[17] The algorithm considers not just one's criminal history but also his ties to other criminals.[18] This is defined as ego being arrested with alter. The ties that enter the model are first-degree and second-degree ties (ties to people one's co-arrestee was arrested with at another occasion). The original intent was to use the list to put criminals on notice, detain or arrest for minor violations and also to offer them help. The help part never materialized. The list showed little predictive accuracy but had the list worked perfectly, its predictions would have been overturned by the actions of the Chicago police: prediction in the service of prevention, if successful, always produces a self-frustrating prophecy. The policy question is whether the hot list decreased gun related crime. It did not. In fact, there was an uptick of gun related violence after its introduction. Yet predictive policing is spreading, and not just to US cities like Los Angeles and Kansas City. It is now piloted in Germany, in Karlsruhe and Stuttgart, focusing on burglaries, and also being tested in Denmark, Holland, the UK, as well as China.

The Chicago algorithm is based on a social theory of crime that emphasizes the role of social factors: crime comes from peer pressure. The German model, on the other hand, is based on learning theory using an earthquake analogy. As aftershocks follow quakes fairly predictably, burglars return to the same areas to rob because they invested in learning about the neighborhood and want to re-use their knowledge.[19] These are causal narratives that explain the prediction. Because the algorithm producing Chicago's SSL is a 'meaningful' one, we do see its flaws and strengths. One of its flaws is that it makes people 'responsible' for the people they associate with, and the people with whom their associates keep company.

17 Involvement includes both being a victim and a perpetrator.

18 The list generated by the computer algorithm was manually adjusted by top brass to produce the final list.

19 An evaluation of the German pilot by Gerstner (2018) found little effect.

This is unfair, but this may actually reduce crime, giving an incentive for people to shun criminal characters. The German model may force criminals to spread their burglaries over a larger territory which may make them more prone to mistakes leading to their apprehension.

Predictive policing is still in an early phase. Predictions may become better, and interventions may improve, yet it is based on a philosophical paradox. Predictive policing assumes that some people are destined to do wrong and have no agency to stop it but also assumes that those people choose to commit crime and can be held morally and legally responsible. This paradox of free will is at the center of The Minority Report.

It is also notable that algorithms are never used predicting who is likely to embezzle money or con others out of fortunes. That is because white collar perpetrators can better use their legal protections than the urban poor. Nor have algorithms been used to predict violence by police shielded by politicians and strong police unions. But algorithms are used elsewhere in the US criminal justice process: at setting bail,[20] sentencing[21] and parole. This is often referred to as Evidence-Based Decision Making. California next year will replace an entire industry with predictive AI. Unless a referendum stops it from happening, from 2020 once arrested, Californians will not have to post bail, but an algorithm will decide whether they can stay free while waiting trial, eliminating the bail bond industry.[22]

## 10.2 Lessons

Our examples of credit, college admission and criminal justice show that algorithmic predictions are instruments of action. They are not simply bets on how things beyond our control will turn out. In fact, the very reason for making predictions is to intervene and change the future. There is agency on both sides of these predictions. For the predictor—lender, college, criminal justice system—to be successful multiple objectives need be achieved, yet prediction works best when the outcome it forecasts is very specific.

20 Bail is set by a judge, deciding whether to put the arrested suspect in jail or let him stay free until the trial concludes posting an amount that he forfeits if he misbehaves (Kleinberg <i>et al</i>., 2018). The judge must decide how likely it is that the suspect will flee or commit another crime while in legal limbo. Judges usually use a bail schedule, a rule book that drives their decision. Since 2016, in San Francisco bail is set by computer algorithms, although judges often overrule the automated decision. https://qz.com/920196/criminal-court-judges-in-new-jersey-now-use-algorithms-to-guide-decisions-on-bail/

21 Unlike bail, sentencing is a much more complex decision. Judges must balance individual retribution, rehabilitation, deterrence and incapacitation (prevention of future crimes). Rehabilitation and incapacitation depend on future outcomes, but even good model predicting one or both of them would have to be negotiated against the other two objectives. Judges often consult the Level Service Inventory-Revised (LSI-R), an algorithm predicting recidivism that was used first by parole boards.

22 Parole boards often rely on the algorithm LSI-R to decide on early release. It has 54 items, and includes 10 subscales, some are within others outside the convict's control. The items the convict can change are giving them agency. Parole boards too must consider multiple goals beyond predicting recidivism. They worry about cost of keeping the prisoner, maintaining prison discipline, reducing overcrowding, giving incentives for rehabilitation, racial justice and 'sentence equalizing' (keeping to the same crime/same punishment principle).

The predicted—borrower, student applicant, suspect and criminal—also try to turn the prediction to their own advantage. Borrowers try to improve their FICO scores (and occasionally game the system). College students prep for the standardised tests and learn the tricks of test taking. Criminals avoid being arrested with other criminals not to get on the SSL.

While algorithmic predictions of the credit score or bail jumping could be preferable to the clinical predictions of biased loan officers or prejudiced judges, they also generate *historical inertia* and rigidity as they are mechanical projections of the past onto the future. Unless there is active intervention by those with power, its main effect will be to perpetuate past patterns and trap people and groups in divergent trajectories: making the poor poorer and the rich richer, children of the less educated flunk out and of the better educated get into good colleges, youth from crime infested neighborhoods go to jail and from affluent neighborhoods avoid the criminal justice system. While this is happening, the predictive power of the model is increasing, because it acts as self-fulfilling prophecy (Rona-Tas, 2017). The polarization goes on until the system becomes unsustainable. In a world where only the well-off get a mortgage, where only the educated can send their children to college, and where only people who can avoid in their youth to be arrested by the police can stay out of the criminal justice system, economic and political tensions will eventually boil over and result in unanticipated crises. Therefore, reasonably accurate predictions at the micro level are not just compatible with instability and chaos at the macro level, but the success of local predictions can be the very cause of unpredictability on a global scale.

So why did the overwhelming majority of psychology research find that algorithms are always better predictors than people? At least to some extent because the experimental situations favour algorithmic predictions. In a good experiment, outcomes must be well-defined, unambiguous and singular. Predictions are a one shot game, where at one time the expert and the algorithm predict and at another there is an outcome to be evaluated. In those carefully contrived experiments there are no self-fulfilling or self-frustrating prophecy effects as neither the predictor nor the predicted have any agency to interfere with the outcome. All of these factors would have confounded the experiments and would have incurred criticism from journal reviewers. To put it differently, psychologists sacrificed external validity for internal validity. Getting published requires designs that favor algorithms. Moreover, psychologists are interested in outcomes at the individual and not at the social level, and much of the problems with external validity come from the social and power relations surrounding individual decisions.

## 11. The world of algorithmic governance

Algorithmic governance means the replacement of social institutions and processes with algorithmic decision making. There are areas where this should be welcome: the algorithmic coordination of traffic lights surely beats policemen standing at the intersections with batons directing traffic. When the process is well-targeted, well-intentioned and low-stakes, we are usually happy to hand it over to algorithms if they do their jobs well. Now, however, we are entering a world where algorithms are taking over in high-stakes and wide areas of social life.

### 11.1 The market-led solution: expansion of credit score in the USA

In the USA, credit scores designed to predict loan payments are now used off-label, for other purposes, widening their jurisdiction. Job applications often require submitting credit scores, car insurance premiums are calculated on the basis of these numbers and landlords demand to see them to decide whether to rent and with what conditions (Kiviat, 2019; Rona-Tas, 2017). Credit scores are now predicting if one will be a good employee, a safe driver or a good tenant. One result of this general use of one's credit score is that error in the score (this is common because the underlying data are error prone) will have vast consequences. Another, more important one is that by linking various predictions a bad score will lead not just to worse loans but to failing to get a job and paying more for insurance, which in turn will lead to a vortex of more credit trouble, lower scores and so on.

There is a second development changing credit scores. Here not the use but the base on which the score is calculated became broader. Traditionally, FICO scores are derived strictly from credit records. Credit information companies are now widening the scope of the predictors as they purchase other companies that have accumulated data (Guseva and Rona-Tas, 2019; Hurley and Adebayo, 2016). For instance, Equifax purchased a payroll outsourcing company, getting hold of over 150 million employee records. Credit score providers also bought other companies collecting tax and wealth data. Now their scores are calculated on a wider base, creating new opportunities for self-reinforcing processes. For instance, combining payroll and credit data means that if someone loses her job her score will go down, just when she lost her income and may need a loan. The credit score itself creates a polarizing up and down spiral, but the widening use and base make this much worse. In addition, these models allow even less understanding of how one can break the spiral. One new company,[23] for example, uses thousands of variables to assess creditworthiness, including whether one types with all uppercase, lowercase or correct case letters filling out the application form, or whether one gives the exact legal name of one's employer. The latter counts, counterintuitively, as a minus.

The bigger concern, however, is not random noise masquerading as signal, but actual yet spurious correlations that will discriminate against protected and unprotected groups. A growing literature on algorithmic fairness points out that one of the main sources of algorithmic bias is in the data itself. Past discrimination, injustice, prejudice or adverse circumstances generate the very patterns that algorithms are so apt to pick up and then forecast as essential facts of the future (Barocas and Selbst, 2016; Caliskan *et al.*, 2017; Cook *et al.*, 2019).

### 11.2 The state-led solution: China's emerging social credit system

The statist version of algorithmic governance is pioneered in China. Since 2014, the state is overseeing the construction of the national 'social credit system', which takes an expansive view of individual creditworthiness defining it as personal credibility, trustworthiness or character (Liu, 2019). Payment information is complemented by data on legal compliance and violations, and by social and moral history. While many of the details are still unclear, the social credit system is supposed to be a tool to increase 'sincerity' and trust.[24]

23 ZestFinance, founded by a former CIO of Google in 2009.

24 The social credit score is supposed to increase sincerity and trust in government—by keeping tabs on the behavior of civil servants, in commercial relations—by improving honesty in commercial

Currently, the new social credit system is only a patchwork of various pilot projects, but it is scheduled for nation-wide launch in 2020, a deadline that is unlikely to be met. In 2015, eight companies were licensed by the Central Bank to create their own rating systems. Those efforts were to be consolidated into a single company in 2019. The largest and most successful company project is called Sesame (zhima ) Credit by Ant Financial (formerly Alipay, a subsidiary of the giant online merchant Alibaba).[25] As payment is migrating from cards to smart phones, it works by vacuuming up a wealth of information from the phone ranging from data on items bought and searches to online chats and financial transactions.[26] Its algorithm includes five broad categories: (i) payment history; (ii) behaviour: some quite specific, like hours of videogames one plays and the kind of things one buys; (iii) ability to pay: such as money in one's bank account and education; (iv) connections: the score of one's friends, and, finally; (v) other characteristics: like age, place of residence, etc. The data are processed into a single number from 300 to 950 modeled on the U.S. FICO score. High scores (over 650) result in perks including no-deposit bicycle and car rental or hotel reservation. A low credit score can result in denial of a loan or access to certain purchases. Sesame Credit currently has over 200 million users who voluntarily opted into this service.

At the same time, municipalities are setting up their own scoring systems for general behaviour. Points are gained or lost for unpaid court fees, jay walking and even for neglecting one's elderly parents. The plan is to integrate these systems into the government's social credit database that will also add official files at various government agencies and data from surveillance cameras in public places analysed with face recognition software. Prediction is on its way of being transformed into a pervasive system of surveillance and control. The system is supposed to predict trustworthy behaviour, but it is unclear how that is measured.

So far what we see is that certain violations become the focus of the system. For Sesame Credit, it started with loan payment behaviour. Yet a lot of people don't borrow, so Zhima was allowed to include the black list of people who failed to pay court fees and judgements. Those people saw their credit score adjusted downwards. It is important to see that this has little to do with predictions anymore. The adjustment is not done according to some predictive algorithm that would show how much more likely it is that the people who did not pay their legal fees will default on their loans. The algorithm—which is secret—simply deducts points determined by some managers of Sesame Credit. The same is true for the municipal initiatives. There the algorithm is based on the moral intuition of local officials. Municipal scoring is backward looking, it is a system of reactive sanctions more than estimated likelihoods of future behaviour, even if the intention is to avoid future bad conduct. However, once those social scores are created for some citizens, an algorithm can generate a predicted social credit score for everyone based on any available input variable that is correlated with

credit, and in social relations—by making people more virtuous in a wide variety of areas from healthcare, birth control and hygiene to energy saving and online behavior. Last but not least, the system is intended to record judicial probity to advance integrity in legal and criminal matters. See State Council Notice concerning Issuance of the Planning Outline for the Construction of a Social Credit System (2014–2020). The original and the translation by Rogier Creemers can be found at https://chinacopyrightandmedia.wordpress.com/2014/06/14/planning-outline-for-the-construction-of-a-social-credit-system-2014-2020/.

25 The other bigger one is by WeChat Pay, owned by TenCent, the large internet service company and one of China's leaders in developing artificial intelligence.

26 Although Ant claims they don't look at chat content.

the score. Moreover, the scores themselves can be used as predictors to forecast different future outcomes. Scores seek to measure general trustworthiness and can be used algorithmically to predict specific future behaviours.

This then runs up against a fundamental problem: if the entire point of scoring is to change behaviour, machine learning will not work well because the authorities would not be able to communicate what the citizen must do to improve their scores. But there is also the opposite danger: transparency gives people agency not just to mend their ways but also to fix their scores without necessarily becoming better citizens—that is, to game the system. Currently, Sesame Credit is very popular in China because, while it itself lacks transparency, it is a tool that makes other people's behaviour more transparent and predictable, two qualities that many in China felt were sorely missing. During the last decades of rapid social change, the country was flooded with *piànzi* (swindlers). Social institutions did not protect people well from fraud; algorithms, to some extent, do that. Sesame's success, however, is not in its magical capacity to foresee what people will be doing but in its very real ability to put pressure on them to behave in a more desirable and predictable way.

## 12. Conclusion

'Prediction is very difficult, especially if it's about the future', said famously the Danish physicist, Niels Bohr. The future is a different country. Algorithms are good at finding patterns in past data. When they 'predict' they project those patterns mechanically onto the future. This works so long as the future is similar to the past. The human imagination is not constrained this way. Moreover, the art of human judgment is, in principle, open to contestation and deliberation. Algorithms with their scientific authority are often deployed precisely to avoid both.

One of the fundamental paradoxes of predicting the future is that we predict because we want to change the future, but we can predict only to the extent to which the future is unchangeable. If we thought the future were fully predictable there would be no point in peeking forward except, possibly, to ease our anxieties. In fact the future is changing in unforeseeable ways, and our prediction can be a force of shaping it. Self-fulfilling and self-frustrating prophecies are everywhere. Self-fulfilling prophecies can lead to social polarization as they reinforce and amplify past inequalities.

Prediction is a claim *about* and claim *on* what lies ahead. It is capturing and colonizing the future by attempting to cement certain futures and make them appear inevitable.

## References

Ægisdóttir, S. White, M. J., Spengler, P. M., Maugherman, A. S., Anderson, L. A., Cook, R. S., Nichols, C.N., Lampropoulos, G.K., Walker, B.S., Cohen, G. and Rush, J. D. (2006) 'The Meta-analysis of Clinical Judgment Project: Fifty-six Years of Accumulated Research on Clinical Versus Statistical Prediction', *The Counseling Psychologist*, **34**, 341–382.

Agrawal, A., Gans, J., and Goldberg, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*, Boston, MA, Harvard Business Review Press

Amer, M., Daim, T. U., and Jetter, A. (2013) 'A Review of Scenario Planning', *Futures*, **46**, pp. 23–40.

Armstrong, J. S., and Grohman, M. C. (1972) 'A Comparative Study of Methods for Long-range Market Forecasting', *Management Science*, **19**, 211–221.

Atkinson, R. C., and Geiser, S. (2009) 'Reflections on a Century of College Admissions Tests', *Educational Researcher*, **38**, 665–676.

Beckert, J. (2016). *Imagined Futures*, Cambridge, MA, Harvard University Press.

Barocas, S., and Selbst, A. D. (2016) 'Big Data's Disparate Impact', *California Law Review*, **104**, 671.

Berk, R. (2012). *Criminal Justice Forecasts of Risk: A Machine Learning Approach*, New York, Springer Science & Business Media.

Bishop, M. A., and Trout, J. D. (2002) '50 Years of Successful Predictive Modeling should be Enough: Lessons for Philosophy of Science', *Philosophy of Science*, **69**, S197–S208.

Brayne, S. (2017) 'Big Data Surveillance: the Case of Policing', *American Sociological Review*, **82**, 977–1008.

Bourdieu, P. (1990) 'The Scholastic Point of View', *Cultural Anthropology*, **5**, 380–391.

Caliskan, A., Bryson, J. J., and Narayanan, A. (2017) 'Semantics Derived Automatically From Language Corpora Contain Human-like Biases', *Science*, **356**, 183–186.

Cavalcante, R. C. Brasileiro, R. C., Souza, V. L., Nobrega, J. P. and Oliveira, A. L. (2016) 'Computational Intelligence and Financial Markets: A Survey and Future Directions', *Expert Systems with Applications*, **55**, 194–211.

Clark, P., and Etzioni, O. (2016) 'My Computer is an Honor Student—but How Intelligent is it? Standardized Tests as a Measure of AI', *AI Magazine*, **37**, 5–12.

Cook, C. M. Howard, J. J., Sirotin, Y. B., Tipton, J. L. and Vemury, A. R. (2019) 'Demographic Effects in Facial Recognition and Their Dependence on Image Acquisition: An Evaluation of Eleven Commercial Systems', *IEEE Transactions on Biometrics, Behavior, and Identity Science*, **1**, 32–41.

Corbett-Davies S. Pierson E. Feller A. Goel S. and Huq A. (2017). Algorithmic decision making and the cost of fairness. In. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 797–806.

Dawes, R. M., Faust, D., and Meehl, P. E. (1989) 'Clinical Versus Actuarial Judgment', *Science*, **243**, 1668–1674.

Decker, R., and Dummett, M. (2013). *The History of the Occult Tarot*, Prelude Books, New York.

Ensign, D. Friedler, S. A., Neville, S., Scheidegger, C. and Venkatasubramanian, S. (2017). Runaway Feedback Loops in Predictive Policing. In Conference on Fairness, Accountability and Transparency, pp. 160-171.

Fama, E. F. (1965) 'The Behavior of Stock-market Prices', *The Journal of Business*, **38**, 34–105.

Ferguson, A. G. (2016) 'Policing Predictive Policing', *Washington University Law Review*, **94**, 1109.

Frederick, S., Loewenstein, G., and O'donoghue, T. (2002) 'Time Discounting and Time Preference: a Critical Review', *Journal of Economic Literature*, **40**, 351–401.

Gans, H. (2016). *For and Empirical Sociology of the Future. Items: Insights from the Social Sciences, SSRC*, accessed at https://items.ssrc.org/insights/for-an-empirical-sociology-of-the-future/ on August 15, 2020.

Geiser, S., and Santelices, M. V. (2007). *Validity of High-school Grades in Predicting Student Success Beyond the Freshman Year: High-school Record vs. Standardized Tests as Indicators of Four-year College Outcomes*, accessed at https://escholarship.org/uc/item/7306z0zf on August 15, 2020.

Genuth, S. S. (1997). *Comets, Popular Culture, and the Birth of Modern Cosmology*, Princeton, NJ, Princeton University Press.

Gerstner, D. (2018). 'Using Predictive Policing to Prevent Residential Burglary: Findings from the Pilot Project P4 in Baden-Württemberg, Germany'. In *European Law Enforcement Research Bulletin–Special Conference Edition Nr. 4*. European Union Agency for Law Enforcement Training (CEPOL), pp. 1–11.

Gigerenzer, G. (2007). *Gut Feelings: The Intelligence of the Unconscious*, Penguin, New York. [Database]

Godet, M., and Roubelat, F. (1996) 'Creating the Future: the Use and Misuse of Scenarios', *Long Range Planning*, **29**, 164–171.

Gilbert, D. T., and Wilson, T. D. (2007) 'Prospection: Experiencing the Future', *Science*, **317**, 1351–1354.

Goldberg, Y. (2016) 'A Primer on Neural Network Models for Natural Language Processing', *Journal of Artificial Intelligence Research*, **57**, 345–420.

Graefe, A., Luckner, S., and Weinhardt, C. (2010) 'Prediction Markets for Foresight', *Futures*, **42**, 394–404.

Grove, W. M. Zald, D. H., Lebow, B. S., Snitz, B. E. and Nelson, C. (2000) 'Clinical versus Mechanical Prediction: A Meta-Analysis', *Psychological Assessment*, **12**, 19–30.

Guseva, A., and Rona-Tas, A. (2019) 'Consumer Credit Surveillance', In Wherry, F. F. and Woodward, I. (eds) *The Oxford Handbook of Consumption*, Oxford, Oxford University Press, pp. **343-357**.

Hosanagar, K. (2019). *A Human's Guide to Machine Intelligence: How Algorithms Are Shaping Our Lives and How We Can Stay in Control*. Viking, New York.

Hurley, M. and Adebayo, J. (2016) 'Credit Scoring in the Era of Big Data', *Yale Journal of Law and Technology*, **18**, 148.

Karabel, J. (2006). *The Chosen: The Hidden History of Admission and Exclusion at Harvard, Yale, and Princeton*, Boston, MA, Houghton Mifflin Harcourt.

Kehl, D. L., Guo, P., and Kessler, S. A. (2017). *Algorithms in the Criminal Justice System: Assessing the Use of Risk Assessments in Sentencing, accessed at* https://dash.harvard.edu/bitstream/handle/1/33746041/2017-07_responsivecommunities_2.pdf? sequence=1 on August 15, 2020.

Kim, P. T. (2018) 'Big Data and Artificial Intelligence: New Challenges for Workplace Equality', *University of Louisville Law Review*, **57**, 313.

King, A. G., and Mrkonich, M. J. (2015) 'Big Data and the Risk of Employment Discrimination', *Oklahoma Law Review*, **68**, 555.

Kiviat, B. (2019) 'The Art of Deciding with Data: Evidence from How Employers Translate Credit Reports into Hiring Decisions', *Socio-Economic Review,* **17**, 283–309.

Kleinberg, J. Lakkaraju, H., Leskovec, J., Ludwig, J. and Mullainathan, S. (2018). 'Human Decisions and Machine Predictions', *The Quarterly Journal of Economics*, **133**, 237–293.

Krippner, G. R. (2017) 'Democracy of Credit: Ownership and the Politics of Credit Access in Late Twentieth-century America', *American Journal of Sociology*, **123**, 1–47.

Kurzweil, M., and Wu, D. D. (2015). Building a path to student success at Georgia State University. *Ithaka S+ R*, April, 23.

LeCun, Y., Bengio, Y., and Hinton, G. (2015) 'Deep Learning', *Nature*, **521**, 436–444.

Lemann, N. (2000). *The Big Test: The Secret History of the American Meritocracy*, New York, Macmillan.

Lewinsohn, R. (1961). *Science, Prophecy, and Prediction: Man's Efforts to Foretell the Future, from Babylon to Wall Street*, Palatine, IL, Harper.

Liu, C. (2019) 'Multiple Social Credit Systems in China', *Economic Sociology: The European Electronic Newsletter*, **21**, 22–32.

Lucas, R. E., and Sargent, T. J. (eds) (1981). *Rational Expectations and Econometric Practice*, Vol. **2**, Minneapolis, MN, University of Minnesota Press.

Lum, K., and Isaac, W. (2016) 'To Predict and Serve?', *Significance*, **13**, 14–19.

MacKenzie, D. (2008). *An Engine, Not a Camera: How Financial Models Shape Markets*, Cambridge, MA, MIT Press.

Marcus, J. (2014) ‘Like retailers tracking trends, colleges use data to predict grades, graduations’, *The Hechinger Report*. December 10, accessed at http://hechingerreport.org/like-retailers-tracking-trends-colleges-use-data-predict-grades-graduations/ on August 15, 2020.

Martens, R., and Trachet, T. (1998). *Making Sense of Astrology*, Buffalo, NY, Prometheus Books.

Meehl, P. E. (1954). *Clinical Versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence*, Minneapolis, MN, University of Minnesota Press.

Mische, A. (2009). ‘Projects and Possibilities: Researching Futures in Action’, In *Sociological Forum*, Vol. **24**, No. 3, Oxford, UK, Blackwell Publishing Ltd, pp. 694–704.

Muth, J. F. (1961) ‘Rational Expectations and the Theory of Price Movements’, *Econometrica*, **29**, 315–335.

Oettingen, G., Sevincer, A. T., and Gollwitzer, P. M. (eds) (2018). *The Psychology of Thinking about the Future*, New York, Guilford Publications.

Popp, T. (2017). Black Box Justice. *The Pennsylvania Gazette*, August 28, accessed at https://thepenngazette.com/black-box-justice/ on August 15, 2020.

Rona-Tas, A. (2017) ‘The Off-label use of Consumer Credit Ratings’, *Historical Social Research/Historische Sozialforschung*, **42**, 52–76.

Rona-Tas, A., and Hiss, S. (2010). ‘The Role of Ratings in the Subprime Mortgage Crisis: the Art of Corporate and the Science of Consumer Credit Rating’. In Michael, L. and Paul M. H. (eds) *Markets on Trial: The Economic Sociology of the US Financial Crisis: Part A*. Emerald Group Publishing Limited, pp. 115–155.

Saunders, J., Hunt, P., and Hollywood, J. S. (2016) ‘Predictions Put into Practice: a Quasi-Experimental Evaluation of Chicago’s Predictive Policing Pilot’, *Journal of Experimental Criminology*, **12**, 347–371.

Seligman, M. E. Railton, P., Baumeister, R. F. and Sripada, C. (2016). *Homo Prospectus*, Oxford, UK, Oxford University Press.

Selin, C. (2008) ‘The Sociology of the Future: Tracing Stories of Technology and Time’, *Sociology Compass*, **2**, 1878–1895.

Silver, N. (2012). *The Signal and the Noise: Why so Many Predictions Fail–but Some Don’t*, Penguin, New York.

Siu, E., and Reiter, H. I. (2009) ‘Overview: What’s Worked and What Hasn’t as a Guide Towards Predictive Admissions Tool Development’, *Advances in Health Sciences Education*, **14**, 759–775.

Smith, G. (2018). *The AI Delusion*, Oxford, UK, Oxford University Press.

Sunstein, C. R. (2019) ‘Algorithms, Correcting Biases’, *Social Research: An International Quarterly*, **86**, 499–511.

Syverson, S., Franks, V., and Hiss, W. (2018). Defining Access: How Test-optional Works, accessed at https://www.nacacnet.org/globalassets/documents/publications/research/defining-access-report-2018.pdf on August 15, 2020.

Tavory, I., and Eliasoph, N. (2013) ‘Coordinating futures: toward a theory of anticipation’, *American Journal of Sociology*, **118**, 908–942.

Tetlock, P. E. (2017). *Expert Political Judgment: How Good is It?, How Can We Know?-New Edition*, Princeton, NJ, Princeton University Press.

Tetlock, P. E., and Gardner, D. (2016). *Superforecasting: The Art and Science of Prediction*, New York, Random House.

Werth, R. (2019) ‘Risk and Punishment: the Recent History and Uncertain Future of Actuarial, Algorithmic, and “Evidence-Based” Penal Techniques’, *Sociology Compass*, **13**, e12659.

Winship, C., and Mare, R. D. (1992) ‘Models for Sample Selection Bias’, *Annual Review of Sociology*, **18**, 327–350.