The age of secrecy and unfairness in recidivism prediction

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In our current society, secret algorithms make important decisions about individuals. There has been substantial discussion about whether these algorithms are unfair to groups of individuals. While noble, this pursuit is complex and ultimately stagnating because there is no clear definition of fairness and competing definitions are largely incompatible. We argue that the focus on the question of fairness is misplaced, as these algorithms fail to meet a more important and yet readily obtainable goal: transparency. As a result, creators of secret algorithms can provide incomplete or misleading descriptions about how their models work, and various other kinds of errors can easily go unnoticed. By partially reverse engineering the COMPAS algorithm — a recidivism-risk scoring algorithm used throughout the criminal justice system — we show that it does not seem to depend linearly on the defendant’s age, despite statements to the contrary by the algorithm’s creator. This observation has not been made before despite many recently published papers on this algorithm. Furthermore, by subtracting from COMPAS its (hypothesized) nonlinear age component, we show that COMPAS does not necessarily depend on race, contradicting ProPublica’s analysis, which assumed linearity in age. In other words, faulty assumptions about a proprietary algorithm lead to faulty conclusions that go unchecked without careful reverse engineering.

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Were the algorithm transparent in the first place, this would likely not have occurred. We demonstrate other issues with definitions of fairness and lack of transparency in the context of COMPAS, including that a simple model based entirely on a defendant’s age is just as ‘unfair’ as COMPAS by ProPublica’s chosen definition. The most important result in this work is that we find that there are many defendants with low risk score but long criminal histories, suggesting that data inconsistencies occur frequently in criminal justice databases. We argue that transparency satisfies a different notion of procedural fairness by providing both the defendants and the public with the opportunity to scrutinize the methodology and calculations behind risk scores for recidivism.

1 Introduction

Secret algorithms control important decisions about individuals, such as judicial bail, parole, sentencing, lending decisions, credit scoring, marketing, and access to social services. These algorithms may not do what we think they do, and they may not do what we want.

There have been numerous debates about fairness in the literature, mainly stemming from a flawed analysis by the ProPublica group (1, 2) of data from Broward County FL, claiming that the proprietary prediction model COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) (3) is racially biased. COMPAS is used throughout the criminal justice system in the U.S., and its predictions have serious consequences in the lives of many people (4–14). The bottom line from these debates is that there is not a single correct definition of fairness. Unfortunately, it might be difficult for a layperson to understand the intricacies of these definitions, or the fact that multiple types of fairness are incompatible. We put aside typical fairness considerations for a moment to focus on more pressing issues.

One issue with COMPAS is that it is complicated. It is based on 137 variables (15) that are collected from a questionnaire. This is a serious problem because typographical or data entry errors, data integration errors, missing data, and other types of errors are abound when relying on manually-entered data. Individuals with long criminal histories are sometimes given low COMPAS scores (which labels them as low risk), and vice versa. In the past, there have been documented cases where individuals have received incorrect COMPAS scores based on incorrect criminal history data (16, 17) and have had no mechanism to correct it after a decision was
made based on that incorrect score. This problem has inadvertently occurred with other (even transparent) scoring systems, at least in one case leading to the release of a dangerous individual who committed a murder while on bail \((18,19)\). An error in a complicated model is much harder to find than an error in a simple model, and it not clear how many times typographical errors in complicated models have led to inappropriate releases that resulted in crimes, after decades of widespread use of these models. The question of whether calculation errors occur often in these models is of central importance to the present work.

A separate issue with COMPAS is that it is proprietary, which means its calculations cannot be double-checked for individual cases, and its methodology cannot be verified. Furthermore, it is unclear how the data COMPAS collects contribute to its automated assessments. For instance, while some of the questions on the COMPAS questionnaire are the same as those in almost every risk score — age, and number of past crimes committed — other questions seem to be direct proxies for socioeconomic status, such as “How hard is it for you to find a job ABOVE minimum wage compared to others?” It is not clear that such data should be collected or permitted for the purposes in which these risk scores are used.

Though creators of proprietary algorithms often provide descriptions of how their models work, by nature, it is difficult for third-parties to verify these descriptions. This may allow errors in documentation to propagate unchecked for years. By partially reverse engineering COMPAS in Broward County, we show in Section 2.2 that COMPAS depends nonlinearly on age, contradicting its stated methodology. As a result, ProPublica’s conclusion that being African-American leads to a higher COMPAS score, even controlling for criminal history and sex, based on a logistic regression is invalid because the linearity assumption is violated.

While COMPAS depends heavily on age, we show in Sections 2.3 through 2.6 that it does not seem to depend in such a strong way on either criminal history or proxies for race. We discuss several possible reasons, but it is possible that COMPAS depends less on criminal history than we might expect. This leads to the possibility that COMPAS depends heavily on variables that we may not want it to depend on.

Using our partially reverse-engineered model, in Section 3 we pinpoint many individuals whose COMPAS scores seem unusually low given their criminal histories. Since COMPAS is proprietary, we cannot fully determine whether these low scores are due to errors in calculation or methodology, but we present evidence that some of them may be due to errors in calculation.

Work in machine learning has shown that complicated, black-box, proprietary models are not necessary for recidivism risk assessment. Researchers have shown (on several datasets,
including the data from Broward County) that interpretable models are just as accurate as black models for predicting recidivism (20–23). These simple models involve age and counts of past crimes, and indicate that younger people, and those with longer criminal histories, are more likely to reoffend. A judge could easily memorize the models within these works, and compute the risk assessments without even a calculator (22, 23). Despite this knowledge, complicated models are still being used.

Given that we do not need proprietary models, why we should allow proprietary models at all? The answer is the same as it is in any other application: by protecting intellectual property, we incentivize companies to perform research and development. Since COMPAS has been at the forefront of the fairness debate about modern machine learning methods, it is easy to forget that COMPAS is not one of these methods. It is a product of years of painstaking theoretical and empirical sociological study. For a company like Northpointe to invest the time and effort into creating such a model, it seems reasonable to afford the company intellectual property protections. However, as we discussed, machine learning methods — either standard black-box or, better yet, recently-developed interpretable ones — can predict equally well or better than bespoke models like COMPAS (20–23). For important applications like criminal justice, academics have always been willing to devote their time and energy. High-performing predictive models can therefore be created with no cost to the criminal justice system. Allowing proprietary models to incentivize model development is not necessary in the first place.

Neglecting to use transparent models has consequences. We provide two arguments for why transparency should be prioritized over other forms of fairness. First, no matter which technical definition of fairness one chooses, \textit{it is easier to debate the fairness of a transparent model than a proprietary model}. Transparent algorithms provide defendants and the public with imperative information about tools used for safety and justice, allowing a wider audience to participate in the discussion of fairness. Second, \textit{transparency constitutes its own type of procedural fairness} that should be seriously considered (see (24) for a discussion). We argue that it is not fair that life-changing decisions are made with an error-prone system, without entitlement to a clear, verifiable, explanation.

In Section[2] we partially reverse-engineer COMPAS for Broward County and show how it is inconsistent with its official documentation; in Section[3] we identify a number of individuals with long criminal histories but low risk scores; and in Section[4] we describe transparency as a form of fairness. We consider the most transparent non-trivial predictive model we could find: age. Younger people tend to be at higher risk of recidivism. Our goal in this section is to modify
the discussion of fairness to be through the lens of transparency.

2 Reverse Engineering COMPAS

Even with our limited data, we may have been able to partially reverse-engineer parts of the COMPAS model as it is implemented in Broward County. Let us describe these attempts.

2.1 COMPAS as described by its creator

There are two COMPAS recidivism risk assessments of interest: the general score and the violent score. These scores assess the risk that a defendant will commit a general or violent crime within the next two years. Each score is given as an integer between 1 and 10 but is based on a raw score that can take any value. Higher scores indicate higher risk. The raw score is computed by a formula and the final integer score is normalized based on a local population. We will therefore attempt to reverse engineer the raw scores.

To compute the COMPAS raw scores, Northpointe collects 137 variables from a questionnaire, computes a variety of subscales, and finally linearly combines the subscales and two age variables — the defendant’s age at the time of the current offense and age at the time of the first offense — to compute the raw risk scores. For example, using the equation exactly as written in the COMPAS documentation, the violent recidivism raw score is given by:

\[
\text{Violent Recidivism Risk Score} = (age \times -w) + (age-at-first-arrest \times -w) + (\text{history of violence} \times w) + (\text{vocation education} \times w) + (\text{history of noncompliance} \times w),
\]

where the variables not related to age are subscales and the weights “w” may be different for each variable. The notation “age \times -w” would commonly indicate “age times the negative of w.”

We have little knowledge of how the subscales depend on the questionnaire, the documentation states only which questionnaire items are used for which subscales. Table 1 shows for each subscale the recidivism score(s) to which it relates and the number of underlying questionnaire items we can compute using our data. We use the data made available by ProPublica as (25) notes, the Propublica dataset is missing features needed to compute the COMPAS score, and so we supplement this dataset with probation data from the Broward Clerk’s Office. However,

\[2\text{https://github.com/propublica/compas-analysis}\]
there remain missing items often related to subjective survey questions that cannot be computed without access to Northpointe’s data, which are not publicly available. Notes on our data processing can be found in the appendix.

Table 1: COMPAS subcales are inputs to the recidivism scores. We have some but not all of the questionnaire features that determine each subscale. For one of the History of Noncompliance features, “Was this person on probation or parole at the time of the current offense?”, we can compute only if the person was on probation or not.

| Subscale                          | # Features we have / Total | Relevant Recidivism Score |
|-----------------------------------|----------------------------|---------------------------|
| Criminal Involvement              | 4/4                        | General                   |
| History of Noncompliance          | 3/5                        | Violent                   |
| History of Violence               | 8/9                        | Violent                   |
| Vocational/Educational            | 0/12                       | Both                      |
| Substance Abuse                   | 0/10                       | General                   |

### 2.2 COMPAS depends nonlinearly on age, contradicting its documentation

We know that COMPAS, if it is like other scoring systems, should depend heavily on age in order to predict well. If we could isolate and subtract off its dependence on age, we could more easily determine its dependence on protected attributes such as criminal history and race. We present a conjecture of approximately how the COMPAS score may depend on age, at least in Broward County, and we have a similar conjecture for the violence recidivism counterpart:

Conjecture: The COMPAS general recidivism model is a nonlinear additive model. Its dependence on age in Broward County is approximately quadratic with function:

\[ f_{\text{age}}(x) = (4.32026931047 \times 10^{-4})x^2 - (7.2608795 \times 10^{-2})x - 8.35936927 \times 10^{-2}, \]

where \( x \) is age. (Significant digits are kept because they are needed for the higher degree coefficients, and ensure replicability. Note that the polynomial is approximate, not exact due to the finite nature of data.) Similarly, the COMPAS violence recidivism model is a nonlinear additive model, with a dependence on age that is approximately quartic with function:

\[ f_{\text{viol age}}(x) = (4.07808994845 \times 10^{-7})x^4 - (8.81767707693 \times 10^{-5})x^3 \\
+ (7.43693932415 \times 10^{-3})x^2 - (3.16106533 \times 10^{-1})x + 1.55398887. \]

\(^3\)By “age” we always mean age at time of arrest. Age at time of first arrest is a separate feature that we consider separately.
The conjecture is shown using Figure 1; these are scatter plots of age versus general recidivism COMPAS score for each individual in the ProPublica dataset on the left, and a similar plot on the right for the COMPAS violent recidivism score. Functions \( f_{\text{age}} \) and \( f_{\text{viol age}} \) are shown as curved lower bounds. Each individual, with very few exceptions, has a COMPAS general recidivism score that is at least as large as \( f_{\text{age}} \), and a COMPAS violence score that is at least as large as \( f_{\text{viol age}} \).

We think it would be unlikely that the shape of the curves \( f_{\text{age}} \) and \( f_{\text{viol age}} \) are due to unmeasured variables. For the History of Violence subscale, we know from Northpointe documentation that all the components of the subscale take on values either 0, 1, 2, 3, 4, or 5 (some of them are binary, which means they are 0- or 1-valued). It would be unrealistic to assume that any of them would contribute negatively to the subscale score, based on their meaning – they should all lead to a higher violence history score (e.g., it would be strange if “number of past violent crimes” led to a lower score.) The individuals with the lowest scores for each age group tend to have low criminal histories (as shown in the supplementary materials), so any confounding variable producing this curve would need to smoothly vary with age, be somewhat unrelated to criminal history, and have a high weight in the COMPAS score in order to influence the shape of the curve. The existence of such as variable seems unlikely under these circumstances.

![Figure 1: Scatter plot of COMPAS general recidivism score versus age and scatter plot of COMPAS violence recidivism score versus age. Hypothesized contribution of age is the lower bound, approximated by \( f_{\text{age}} \) and \( f_{\text{viol age}} \).](image)

(a) \( f_{\text{age}} \)  
(b) \( f_{\text{viol age}} \)

It is possible that age’s only contribution to the COMPAS general recidivism score is \( f_{\text{age}} \) (similarly, \( f_{\text{viol age}} \) for the violence score). Let us describe why this seems to be true. The
remainders of general COMPAS—$f_{age}$ and violent COMPAS—$f_{viol age}$ do not seem to depend on age. After subtracting out the age polynomials, we employed machine learning methods along with linear models (Table 2) to model the remainder (COMPAS score minus the age polynomial). We ran each of these algorithms on the data, once using criminal history and age features only (with-age models), and once using just criminal history (without-age models).

Machine learning methods are powerful, nonparametric models that are capable of modeling nonlinear functions very closely, given the right features. Thus, if the remainder depends on age coupled with criminal history, it is likely the accuracy will vary between the with-age and without-age models. However, instead, Tables 2 and 5 (for the general and violent scores, respectively) show the accuracy of the machine learning models was almost identical.

Importantly, if the dependence on age is additive, this implies that COMPAS might not use features that couple age and criminal history, such as the rate of crimes committed over time, despite the potential usefulness of this type of feature (see, e.g., (26)).

| Without Age | Linear Model | Random Forest | Boosted Decision Trees | SVM |
|-------------|--------------|---------------|------------------------|-----|
| With Age    | 0.565        | 0.527         | 0.513                  | 0.523 |
|             | 0.562        | 0.525         | 0.506                  | 0.519 |

Table 2: Root mean square error for several machine learning algorithms for predicting COMPAS score minus age polynomial ($f_{age}$), with age included as a feature (bottom row), and without age (top row). We are trying to determine whether the COMPAS remainder (general COMPAS after subtracting the main age terms) still depends on age. The numbers for “with age” look very similar to the numbers “without age.” Thus, age does not seem to participate in the remainder term because accuracy does not change between the two rows. Race and age at first arrest are included as predictors for both with and without age predictions.

| Without Age | Linear Model | Random Forest | Boosted Decision Trees | SVM |
|-------------|--------------|---------------|------------------------|-----|
| With Age    | 0.495        | 0.487         | 0.469                  | 0.481 |
|             | 0.489        | 0.482         | 0.456                  | 0.474 |

Table 3: Analogous to Table 2 but for the COMPAS violence recidivism score, predicting COMPAS violent score minus $f_{viol age}$. Again, age at arrest does not seem to participate in this remainder.

The fact that the lower bounds $f_{age}$ and $f_{viol age}$ seem to vary smoothly and uniformly with age, with only few outliers, indicates that the data entering into the COMPAS scores is high quality with respect to age. This has implications for our later analysis. We speculate
that the few outliers that are below the age polynomials have incorrect age data or incorrect COMPAS scores. These observations will be called “age outliers” in what follows.

Now that we have explained the dependence of COMPAS on age we wish to explain its dependence on criminal history variables. We do this separately for the general and violent scores in Sections 2.3 and 2.4 respectively.

2.3 Criminal history and the COMPAS general recidivism score

According to the COMPAS documentation, the only factor in COMPAS with a negative contribution to the score is age. In order to continue reverse-engineering, we assumed that no components of any of the COMPAS subscales contributed negatively, which allows us to continue searching for crisp lower bounds analogous to the age polynomials.

Unlike the dependence on age, the COMPAS general score does not seem to display a clear dependence on criminal history. Figure 2 shows a scatter plot of COMPAS general score remainder (COMPAS after subtracting the age polynomial $f_{\text{age}}$) against the total number of prior charges, which is one of the variables determining the Criminal Involvement Subscale (left panel), and the unweighted sum of the variables in the Criminal Involvement Subscale (right panel). Note that we would ideally plot the remainder against the Criminal Involvement Subscale itself, but we do not have these data or know how any of the subscales depend on their inputs. Even excluding the age outliers (highlighted in green), there is no smooth lower bound as seen in Figure 1. Therefore we transition from searching for simple dependence of the COMPAS general score on its subscale items to searching for more complex dependencies.

To then investigate whether the COMPAS general score depends in a more complex way on the Criminal Involvement Subscale items listed in the Appendix in Table 12 we ran several machine learning algorithms (random forests (27), boosted decision trees (28), and support vector machines with a radial basis kernel function) on the subscale items our data has, to see if the COMPAS general recidivism score could be explained (either linearly or nonlinearly) by the subscale components. We tried predicting both the general score itself and the general score after subtracting $f_{\text{age}}$. Figure 3 shows a scatter plot of predictions versus the actual values for the two prediction problems. We make two observations from this figure. By comparing the two panels, we can see that the COMPAS general score depends heavily on age, as the predictions of the COMPAS score remainder (right panel) are much worse than the predictions of the COMPAS score itself (left panel); this is because criminal history is correlated with age. After subtracting our reversed engineered dependence on age (right panel), we see the ability of the
Figure 2: We do not find a clear relationship between the COMPAS general score after subtracting the age polynomial and criminal history. Note that in each plot there are a few observations with a large number of prior charges that are outside of the plot range.

criminal history variables to predict the COMPAS score remainder is surprisingly unsuccessful. Thus the dependence of the COMPAS general score on criminal history, as captured by the components of the Criminal Involvement Subscale, seems to be weak.

2.4 Criminal history and the COMPAS violent recidivism score

We gained more traction reverse-engineering the COMPAS violent recidivism score than the general score. Figure 4 shows the COMPAS violent score after subtracting the age polynomial $f_{\text{age}}$ against the unweighted sum of the Violence History Subscale components. Excluding the age outliers, this subtraction produced a crisp lower bound on the remainder, unlike the bounds we obtained trying various individual components and weighted sums of the components. We estimate the dependency on the Violence History Subscale as a piecewise linear function, which we call $g_{\text{viol hist}}$. Next, in Figure 5 we plot the remainder after also subtracting this dependency on Violence History (that is, the remainder of the COMPAS violence score after subtracting both $f_{\text{viol age}}$ and $g_{\text{viol hist}}$) against the unweighted sum of the components of the History of Noncompliance Subscale, on which the violence score should also depend. There is not a sharp lower bound that is consistent across the horizontal axis, which means this sum, by itself, is not likely to be an additive term within COMPAS. Therefore, we
Figure 3: Predicting general remainder.

(a) Predictions of COMPAS vs. actual values.  
(b) Predictions of COMPAS \(- f_{\text{age}}\) vs. actual values.

do not estimate a dependency on the unweighted sum of items in the History of Noncompliance Subscale.

As with the COMPAS general score, we investigate if the COMPAS violent score depends on its subscale components in a more complex way. Figure 6 shows the results of three separate prediction problems using all of the components in the History of Violence and History of Noncompliance subscales. From left to right, we use gradient boosted trees to predict the COMPAS violent score, the COMPAS violent score after subtracting \(f_{\text{viol age}}\), and the COMPAS violent score after subtracting \(f_{\text{viol age}}\) and \(g_{\text{viol hist}}\). Comparing the panels in Figure 6 from left to right, we see that the predictions degrade, emphasizing the importance of \(f_{\text{viol age}}\) and \(g_{\text{viol hist}}\), respectively, to the COMPAS violent score. That is, after subtracting these components, the input variables are much less able to predict the remaining COMPAS contribution. 

*Thus, the dependence of the COMPAS violent score on criminal history, as captured by the Violence History and History of Noncompliance subscales, seems to be weak.*
Figure 4: COMPAS $- f_{\text{age}}$ vs. sum of History of Violence components. Green points are age outliers.

Figure 5: COMPAS $- f_{\text{age}} - g_{\text{viol hist}}$ vs. sum of History of Noncompliance components. Green points are age outliers.
2.5 Caveats

For both the general and violent COMPAS scores, we were unable to capture the remainder of the COMPAS score (i.e., after subtracting the reverse-engineered dependency on age) using the various criminal history variables that constitute the subscales. There could be several reasons for this, including the following, among other things:

- It is possible that our data are flawed. We obtained these data from a combination of ProPublica, the Broward County Sheriff, as well as the Broward County Clerk’s office. We believe most of these data should be approximately the same as the data entered into the general COMPAS score. Furthermore, based on the analysis above, our age data on individuals seems to be high quality, so there is no a priori reason that the criminal history data would be substantially lower quality.

- It is also possible that the way we calculated the criminal history subscale items for COMPAS differs from the way the Broward County Sheriff’s Office calculates them. Our data processing is discussed in the supplementary materials.

- It is possible that we did not hypothesize the correct model form used in COMPAS; that is, our machine learning models may not have been able to express the nonlinearities present in COMPAS. While this could be true, we used very flexible models that should be able to fit or even overfit the COMPAS scores. Thus, we believe this is not a likely explanation.
• It is possible that our data are incomplete. We know this is true, as COMPAS depends on factors other than criminal history. However, this leads to questions of what COMPAS can reasonably depend heavily on. Criminal history data are less noisy and less susceptible to manipulation than other survey questions; criminal history features do not depend on the survey-taker telling the truth about the answers. If COMPAS depended more heavily on survey questions than on criminal history, it could lead precisely to a kind of bias that we might want to avoid. For instance, if COMPAS did not depend heavily on the number of prior crimes, it might depend more heavily on socioeconomic proxies (e.g., “How hard is it for you to find a job ABOVE minimum wage compared to others?” which is one of several questions on the COMPAS questionnaire that directly relates to socioeconomic status).

• There is something in the procedure of calculating the COMPAS score that causes it to be calculated inconsistently. Since we do not know COMPAS, we cannot check this possibility. In the past, there have been documented cases where individuals have received incorrect COMPAS scores based on incorrect criminal history data ([16, 17]), and no mechanism to correct it after a decision was made based on that incorrect score. We do not know whether this happens often enough to influence the scatter plot in a visible way. However, this type of miscalculation is one of the biggest dangers in the use of proprietary models. As we know from the calculations of other scoring systems besides COMPAS, if the number of crimes is not taken into account properly, or if the scoring system is calculated improperly in other ways, it could lead (and has led in the past) to unfair denial of parole, and dangerous criminals being released pre-trial.

Data quality issues, either for us or for the COMPAS score itself, are not just a problem for our analysis, but a problem that is likely to plague almost every jurisdiction that uses COMPAS or any other secret algorithm. This is discussed more in the next section.

2.6 Propublica seems to be incorrect in its claims of how COMPAS depends on race

If age and the components we have of the Criminal Involvement, History of Noncompliance, and History of Violence subscales can only explain COMPAS scores to a limited extent, then either the few components of these subscales that we are missing, or the remaining subscales, Substance Abuse for the violent score and Vocational/Educational for both scores, must be a
large component of the scores. Reasoning these two subscales are highly correlated with race, we then tried to model the COMPAS remainders (i.e., after subtracting the age polynomials) with race as a feature, in addition to the available subscale components. Tables 4 and 5 respectively, show the results of several machine learning methods for predicting the general and violence score remainders. We see that these features cannot explain the COMPAS violent score remainders very well. Thus we conclude COMPAS has at most weak dependence on race.

We replicated ProPublica’s finding that a model with race predicts COMPAS well, but disagree with their conclusions. We repeated ProPublica’s linear logistic regression on our slightly modified dataset, leading to a model, provided in the supplementary materials in Table 9, whose race coefficient is large and significantly different from zero. Coefficients both for age and race are both large.

There are several flaws in this analysis. First, the linearity assumption is wrong, as we know from the age analysis above. Second, the existence of an accurate model that depends on race is not sufficient to prove that COMPAS depends on race. Race is correlated with both criminal history and with age in this dataset. Because the linearity assumption is wrong, it is definitely possible that race would appear to be significant, regardless of whether COMPAS is actually using race or its proxies (aside from criminal history and age) as important variables. As shown in Tables 4 and 5, including race as a variable to predict COMPAS does not improve prediction accuracy. That is, for each model we created that uses race, we found another almost equally accurate model that does not use race. Thus, it is not clear that race or its proxies (aside from

| Without Race | Linear Model | Random Forest | Boosting | SVM |
|--------------|--------------|---------------|----------|-----|
| With Race    | 0.498        | 0.493         | 0.468    | 0.475 |

Table 5: RMSE of machine learning methods for predicting COMPAS violence recidivism raw score after subtracting $f_{\text{viol age}}$ with and without race as a feature. Age at COMPAS screening date and age at first offense are included as a features.

| Without Race | Linear Model | Random Forest | Boosting | SVM |
|--------------|--------------|---------------|----------|-----|
| With Race    | 0.489        | 0.482         | 0.456    | 0.474 |

Table 4: RMSE of machine learning methods for predicting COMPAS general recidivism raw score after subtracting $f_{\text{age}}$ with and without race as a feature. There is little difference with and without race. The differences between algorithms are due to differences in model forms. Age at COMPAS screening date and age at first offense are included as a features.
criminal history and age) are necessarily important factors in COMPAS.

In a separate analysis, Fisher et al. (29) show that no accurate linear model for predicting general recidivism can have a high variable importance for the race variable, given age and criminal history. This result is not at odds with the ProPublica findings that we replicated. First, Fisher et al. (29)’s result is about predicting recidivism, whereas ProPublica was trying to predict the COMPAS score. Also, the statistical significance of the race variable in the ProPublica analysis is misleading because the linearity assumption underlying the regression does not hold. The result of (29) makes no such assumption, and does not compute significance. Their analysis relies only on permutation-based variable importance.

3 COMPAS sometimes labels individuals with long or serious criminal histories as low-risk

We examine whether COMPAS scores can be low for individuals who pose a serious threat. Recently in California (18, 19), a defendant with a long criminal history was released pre-trial after a criminal history variable was inadvertently mistyped into a scoring system as being much lower than its true value. The defendant murdered a bystander before his trial.

Typographical (data-entry) errors are extremely common (30), which means risk-score errors occur regularly. For instance, if each person’s COMPAS questionnaire contains 100+ questions, even a 1% error rate could cause multiple wrong entries on almost every person’s questionnaire. Data entry errors are a serious problem for medical records (31), and in numerous other applications. The threat of typographical errors magnifies as the complexity of the scoring system increases; California had a very simple scoring system, and still typographical errors have caused serious events discussed above.

In what follows, we use real names and public records found easily on the Internet, following ProPublica, which is a news organization that compiled this public database and published real names and pictures of individuals within their report. It has been long debated whether this kind of information should be public, with citizen protection being a main argument (e.g., background checks for potential employees in sensitive jobs). There is an irony of this information being public, in contrast to the information actually used to make high-stakes decisions about these individuals being secret. However, this public information may allow us to determine that the secret information is potentially sometimes incorrect.

Consider the case of Desmond Rolle, whose criminal history included trafficking cocaine
and aggravated battery of a pregnant woman, (felony battery — domestic battery by strangulation). He was given a COMPAS score of 1 (the lowest possible risk). A similar problem occurs for several individuals in the database. Tables shows several such individuals who have COMPAS scores that appear to have been calculated with incorrect inputs, or whose criminal history information somehow has not been considered within the COMPAS formula. None of these individuals has scores below the age polynomial (none are age outliers).

Table 6: Individuals whose COMPAS violence decile score is low (low-risk), but who have significant criminal histories. # Priors counts the prior charges up to but not including the current offense (i.e., the offense we believe triggered the COMPAS score calculation), since this is how COMPAS counts prior offenses. However, the current offense may be included in Selected Prior Charges. Note that any Subsequent Crimes beyond the 2 year mark of the COMPAS score calculation or outside of Broward County may not be contained in our database. The notation “(F/M,N)” next to each charge gives the charge degree (F=Felony or M=Misdemeanor) and the number of instances of this charge (N).

| Name            | COMPAS Violence Decile | # Priors | Selected Prior Charges                              | Selected Subsequent Charges                                      |
|-----------------|------------------------|----------|-----------------------------------------------------|-----------------------------------------------------------------|
| Vilma Dieppa    | 1                      | 4        | Aggravated Battery (F,1), Child Abuse (F,1), Resist Officer w/Violence (F,1) |                                                                  |
| David Selzer    | 1                      | 14       | Battery on Law Enforc Officer (F,3), Aggravated Assault W/Dead Weap (F,1), Aggravated Battery (F,1), Resist/obstruct Officer W/viol (F,1) |                                                                  |
| Berry Sanders   | 1                      | 15       | Attempted Murder 1st Degree (F,1), Resist/obstruct Officer W/viol (F,1), Agg Battery Gt/Bod/Harm (F,1), Carrying Concealed Firearm (F,1) | Armed Sex Batt/vict 12 Yrs + (F,2), Aggravated Assault W/dead Weap (F,3), Kidnapping (F,1) |
| Fernando Walker | 1                      | 22       | Aggrav Battery w/Deadly Weapon (F,1), Driving Under The Influence (M,2), Carrying Concealed Firearm (F,1) |                                                                  |
| Steven Glover   | 1                      | 28       | Robbery / Deadly Weapon (F,11), Poss Firearm Commission Felony (F,7) |                                                                  |
| Rufus Jackson   | 1                      | 40       | Resist/obstruct Officer W/viol (F,3), Battery on Law Enforc Officer (F,2), Attempted Robbery Deadly Weapo (F,1), Robbery 1 / Deadly Weapon (F,1) |                                                                  |
| Miguel Gonzalez | 2                      | 6        | Murder in the First Degree (F,1), Aggrav Battery w/Deadly Weapon (F,1), Carrying Concealed Firearm (F,1) |                                                                  |

Continued on next page
Table 6 — Continued from previous page

| Name             | COMPAS Violence Decile | # Priors | Selected Prior Charges                                                                 | Selected Subsequent Charges                      |
|------------------|------------------------|----------|----------------------------------------------------------------------------------------|--------------------------------------------------|
| William Kelly    | 2                      | 17       | Aggravated Assault (F,5), Aggravated Assault W/dead Weap (F,2), Shoot/throw Into Vehicle (F,2), Battery Upon Detainee (F,1) |                                                  |
| Richard Campbell | 2                      | 21       | Armed Trafficking In Cocaine (F,1), Poss Weapon Commission Felony (F,1), Carrying Concealed Firearm (F,1) |                                                  |
| John Coleman     | 2                      | 25       | Attempt Murder in the First Degree (F,1), Carrying Concealed Firearm (F,1), Felon in Pos of Firearm or Amm (F,1) |                                                  |
| Oscar Pope       | 2                      | 38       | Aggravated Battery (F,3), Robbery / Deadly Weapon (F,3), Kidnapping (F,1), Carrying Concealed Firearm (F,2) | Grand Theft in the 3rd Degree (F,3)               |
| Travis Spencer   | 3                      | 16       | Aggravated Assault W/dead Weap (F,1), Burglary Damage Property>$1000 (F,1), Burglary Unoccupied Dwelling (F,1) |                                                  |
| Michael Avila    | 3                      | 17       | Aggravated Assault W/dead Weap (F,2), Aggravated Assault w/Firearm (F,2), Discharge Firearm From Vehicle (F,1), Home Invasion Robbery (F,1) | Fail Register Vehicle (M,2)                       |
| Terrance Murphy | 3                      | 20       | Solicit to Commit Armed Robbery (F,1), Armed False Imprisonment (F,1), Home Invasion Robbery (F,1) | Driving While License Revoked (F,3)               |
| Anthony Hawthorne| 3                      | 25       | Attempt Sexual Batt / Vict 12+ (F,1), Resist/obstruct Officer W/viol (F,1), Poss Firearm W/alter/remov Id# (F,1) |                                                  |
| Stephen Brown    | 3                      | 36       | Carrying Concealed Firearm (F,2), Battery On Law Enforce Officer (F,1), Kidnapping (F,1), Aggravated Battery (F,1) | Driving While License Revoked (F,3)               |
| Samuel Walker    | 3                      | 36       | Murder in the First Degree (F,1), Poss Firearm Commission Felony (F,1), Solicit to Commit Armed Robbery (F,1) | Petit Theft 100–300 (M,1)                        |
| Jesse Bernstein  | 4                      | 10       | Aggravated Battery / Pregnant (F,1), Sex Battery Vict Mental Defect (F,1), Shoot/throw In Occupied Dwell (F,1) | Tresspass in Struct/Convey Occupy (M,1)           |
| Shandedra Hardy  | 4                      | 16       | Aggravated Battery w/Deadly Weapon (F,1), Felon in Pos of Firearm or Amm (F,4) | Resist/Obstruct W/O Violence (M,1), Possess Drug Paraphernalia (M,1) |

While it is possible that COMPAS includes mitigating factors (employment, education, drug treatment) that reduce its score, it seems unlikely that they would reduce the score all the way
to the lowest possible value, but since the model is not published, we cannot actually determine this. According to (32), the only negatively weighted factors in COMPAS are age and age at first arrest, but according to our analysis above, these variables remain essentially constant with age for older individuals. This indicates there is no way to reduce a high score that might arise from a lengthy criminal history. Thus, what we are observing (long criminal histories with a low COMPAS violence score) should be impossible unless inputs have been entered incorrectly or omitted from the COMPAS score altogether.

COMPAS general or violent scores do not include the current charges. Thus, in the case of Martin Owens in the ProPublica database, charged with a serious crime (kidnapping) but no prior crimes, he still receives the lowest-risk COMPAS score of 1.

There are many individuals in the database whose COMPAS scores appear to be unreasonably high; however, it is possible that for those individuals, there are extra risk factors that cause them to be labeled high risk that are not in our database (e.g., incomplete criminal history information). Missing information would be able to explain COMPAS scores that seem too high, but it cannot explain COMPAS scores that are too low, such as the ones we presented above in Table 6. Figure 7 shows the predictions of a machine learning model versus COMPAS score. There are a huge number of individuals whose COMPAS score is much larger than the machine learning predictions, and also, there are many individuals for whom the machine learning model (a boosted decision tree) indicates high risk of recidivism, but the COMPAS score indicates a lower risk.

In cases like that of Glenn Rodríguez (16, 17), he did not notice the error on his COMPAS form until after his parole was denied. Complicated forms, even if one is asked to check them over, lead to human error. We are certain, for instance, that there are still errors in this paper, no matter how many times we have checked it over.

4 Is age unfair? Fairness through the lens of transparent models

Age is a well-known determining risk factor for recidivism. Many recidivism scoring systems depend on age (20, 33–40) since it has no direct causal relationship with race (race does not cause age, age does not cause race), and it is a good predictor of future crime. For adults, the
risk of recidivism decreases with age.\footnote{Figure 9 in the appendix plots the probability of 2-year recidivism (defined by arrest within 2 years) as a function of age for individuals in Broward County, Florida, showing how it decreases as a function of age.}

On the other hand, in the Broward County data, African-Americans tend to be disproportionately represented at younger ages than Caucasians; the median age of a COMPAS assessment on an African American is 27 years whereas the median age of a Caucasian is 33 years.\footnote{see the supplementary materials for full distributions}

This means that more African-Americans will be labeled as high risk than Caucasians. This also means that more African-Americans will be \textit{mistakenly} labeled as high risk than Caucasians. It also means that more Caucasians will be mistakenly labeled as low risk than African-Americans.

Figure 8 shows the true positive rate (TPR), false positive rate (FPR), true negative rate (TNR) and false negative rates (FNR) for the model \textit{age}, which is defined to be “If age \leq 24, then predict arrest within 2 years, otherwise predict no arrest.” The figure also shows the rates for the COMPAS general recidivism score. The data were divided into 10 randomly chosen folds, and the rates are plotted for all folds, showing a consistent pattern across folds. Indeed, we observe higher false positive rates for African-Americans, and higher false negative rates for...
Figure 8: Rates for the simple age model and for the COMPAS score. Age appears also to be unfair.

Caucasians. There is an elevated $\approx 10\%$ higher FPR for African-Americans than for Caucasians for age, and a $\approx 10\%$ higher FNR for Caucasians than African-Americans for age. These differing levels constitute the definitions of unfairness used by ProPublica, which means that age is an unfair risk prediction model by this definition. COMPAS seems to be more “unfair” than age, but as we have seen, it may be possible to explain this unfairness by a combination of age and other features that differ between the distributions of African-Americans and Caucasians and have little to do with the COMPAS score itself. In fact, we also know from (23) that a very simple model involving age and the number of priors is just as unfair as COMPAS by this definition.

This logic carries over to criminal history as well. People with long criminal histories are more likely to commit further crime in the future. By ProPublica’s definition of fairness, using criminal history is unfair because criminal history correlates with race. However, if we do not use criminal history, we could be releasing dangerous criminals based on poor pre-trial risk assessments, which leads to poor decisions for the public (This is explained nicely by (41).) Northpointe has also pointed this out in its response to ProPublica, on the grounds that the sampling population is not the target population (42). ProPublica’s definition of fairness would eliminate the most important predictors of recidivism (age and criminal history). Without age and criminal history, it is not clear that any useful predictors of criminal recidivism remain.

The point of this exercise is not to determine whether the age model is fair by any given definition—the age model is transparent, which makes it much easier to debate, and useful for
explaining different possible definitions of fairness and how they may never intersect. Is age unfair? If we cannot decide on whether the age model is fair, we certainly cannot decide on whether COMPAS is unfair. However, it is certainly much easier to debate about the transparent and simple age model than about a black-box scoring system. While a review of the numerous definitions of fairness (43, 44) is outside the scope of this work, a potentially easy way to alter the definition of fairness is to control for non-protected covariates such as age.

5 Discussion

After attempting to isolate COMPAS’ dependence on age, we were able to investigate how much COMPAS can depend on criminal history and proxies for race. We found that it is unlikely that COMPAS depends heavily on either of them. Machine learning methods for predicting COMPAS scores performed equally well with or without direct knowledge of race. This seems to contradict ProPublica’s claims, but ProPublica’s methodological assumptions (at least about COMPAS depending linearly with age) were wrong, which caused their conclusions to be faulty.

Northpointe claims the current charge is not helpful for prediction of future violent offenses (32). (Oddly, they have a separate “Current Violence” scale that includes the current charges, but which is not claimed to be predictive.) How much should one weigh the current charges with the COMPAS scores? This is not clear. Because COMPAS is a black box, it is difficult for practitioners to combine the current charge (or any other outside information) with the COMPAS scores. Because the current charges are separate, COMPAS scores are not single numbers that represents risk. Instead their interpretation has a large degree of freedom. Could decision-makers fail to realize that the COMPAS score does not include the current charge? Perhaps this alone could lead to faulty decision-making.

We showed examples where COMPAS scores can label individuals with long criminal histories as low-risk. This could easily stem from a lack of transparency in COMPAS and could lead to dangerous situations for the public. Even if COMPAS were completely fair, by some reasonable definition of fairness, this would not stop it from being miscalculated. Since it is known that COMPAS is no more useful for predicting recidivism than simple, interpretable models, there is no good reason to continue using complicated error-prone proprietary models for this purpose.

Furthermore, if COMPAS does not depend heavily on most of the 137 variables, including the proxies for socioeconomic status, it is not clear if Northpointe is justified in collecting such
private information. This issue is beyond the scope of this article, but is important. Northpointe’s control over criminal risk scores is analogous to Equifax’s control over credit scores, and leads to inherent privacy risks.

The problems with COMPAS pertain to many industries. Without community standards or policy requirements for transparency, business considerations disincentivize creators of models to disclose their formulas. However, this lack of transparency is precisely what allows error to propagate and results in damage to society. Merely being able to explain black box models is not sufficient to resolve this—the models need to be fully transparent, and in criminal justice, there is no loss in predictive accuracy for using a transparent model.

**Code**

Our code is here: [https://github.com/beauCoker/age_of_unfairness](https://github.com/beauCoker/age_of_unfairness)

**References**

1. J. Larson, S. Mattu, L. Kirchner, J. Angwin, How we analyzed the COMPAS recidivism algorithm, *Tech. rep.*, ProPublica (2016).

2. J. Angwin, J. Larson, S. Mattu, L. Kirchner, Machine bias, *Tech. rep.*, ProPublica (2016).

3. T. Brennan, W. Dieterich, B. Ehret, Evaluating the predictive validity of the COMPAS risk and needs assessment system, *Criminal Justice and Behavior* **36**, 21 (2009).

4. D. Citron, (Un)fairness of risk scores in criminal sentencing, *Forbes, Tech section* (2016).

5. S. Corbett-Davies, E. Pierson, A. Feller, S. Goel, A computer program used for bail and sentencing decisions was labeled biased against blacks. it’s actually not that clear., *Washington Post (op-ed)* (2016).

6. unknown, Risk Assessment Project Phase III: Racial Impact Analysis of the Proposed Risk Assessment Scales, *Tech. rep.*, Pennsylvania Commission on Sentencing (2018).

7. B. Netter, Using group statistics to sentence individual criminals: an ethical and statistical critique of the virginia risk assessment program, *The Journal of Criminal Law and Criminology* pp. 699–729 (2007).
8. C. T. Lowenkamp, E. J. Latessa, Understanding the risk principle: How and why correctional interventions can harm low-risk offenders, *Topics in community corrections* **2004**, 3 (2004).

9. S. D. Gottfredson, G. R. Jarjoura, Race, gender, and guidelines-based decision making, *Journal of Research in Crime and Delinquency* **33**, 49 (1996).

10. R. E. Redding, Evidence-based sentencing: the science of sentencing policy and practice, *Chap. J. Crim. Just.* **1**, 1 (2009).

11. S. Baradaran, Race, prediction, and discretion, *Geo. Wash. L. Rev.* **81**, 157 (2013).

12. J. Petersilia, S. Turner, Guideline-based justice: Prediction and racial minorities, *Crime & Justice* **9**, 151 (1987).

13. M. S. Crow, The complexities of prior record, race, ethnicity, and policy: Interactive effects in sentencing, *Criminal Justice Review* (2008).

14. A. W. Flores, C. T. Lowenkamp, K. Bechtel, False positives, false negatives, and false analyses: A rejoinder to “Machine bias: There’s software used across the country to predict future criminals”, *Federal probation* **80** (2016).

15. Measurement & treatment implications of COMPAS core scales, *Tech. rep.*, Northpointe Inc. (2009).

16. R. Wexler, When a computer program keeps you in jail: How computers are harming criminal justice, *New York Times* (2017).

17. R. Wexler, Code of silence: How private companies hide flaws in the software that governments use to decide who goes to prison and who gets out, *Washington Monthly* (2017).

18. E. Westervelt, Did a bail reform algorithm contribute to this San Francisco man’s murder?, NPR, August 8 (2017).

19. V. Ho, Miscalculated score said to be behind release of alleged twin peaks killer, *SFGate (San Francisco Chronicle)* (2017).

20. J. Zeng, B. Ustun, C. Rudin, Interpretable classification models for recidivism prediction, *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **180**, 689 (2017).
21. N. Tollenaar, P. van der Heijden, Which method predicts recidivism best?: a comparison of statistical, machine learning and data mining predictive models, *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **176**, 565 (2013).

22. E. Angelino, N. Larus-Stone, D. Alabi, M. Seltzer, C. Rudin, Learning certifiably optimal rule lists for categorical data, *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)* (2017).

23. E. Angelino, N. Larus-Stone, D. Alabi, M. Seltzer, C. Rudin, Certifiably optimal rule lists for categorical data, *Journal of Machine Learning Research* **19**, 1 (2018).

24. C. Coglianese, D. Lehr, Transparency and algorithmic governance, *Tech. rep.*, Working Paper. Penn Program on Regulation, University of Pennsylvania Law School (2018).

25. S. Tan, R. Caruana, G. Hooker, Y. Lou, Distill-and-compare: Auditing black-box models using transparent model distillation, *AAAI/ACM Conference on AI, Ethics, and Society* (2018).

26. S. D. Bushway, A. M. Piehl, The inextricable link between age and criminal history in sentencing, *Crime & Delinquency* **53**, 156 (2007).

27. A. Liaw, M. Wiener, Classification and regression by randomforest, *R News* **2**, 18 (2002).

28. T. Chen, C. Guestrin, Xgboost: A scalable tree boosting system, *22nd SIGKDD Conference on Knowledge Discovery and Data Mining* (2016).

29. A. Fisher, C. Rudin, F. Dominici, Model class reliance: Variable importance measures for any machine learning model class, from the “rashomon” perspective, *arXiv:1801.01489 [stat.ME]* (2018).

30. S. D. Bushway, E. G. Owens, A. M. Piehl, Sentencing guidelines and judicial discretion: Quasi-experimental evidence from human calculation errors, *Tech. Rep. 16961*, National Bureau of Economic Research (2011).

31. M. M. Wahi, D. V. Parks, R. C. Skeate, S. B. Goldin, Reducing errors from the electronic transcription of data collected on paper forms: A research data case study, *J Am Med Inform Assoc.* **15**, 386 (2008).
32. Northpointe, Practitioner’s Guide to COMPAS Core, *Tech. rep.*, Northpointe (2013).

33. Pennsylvania Commission on Sentencing, Risk Assessment Project Phase III: The Development and Validation of the Proposed Risk Assessment Scales (2012).

34. M. Nafekh, L. L. Motiuk, *The Statistical Information on Recidivism, Revised 1 (SIR-R1) Scale: A Psychometric Examination* (Correctional Service of Canada. Research Branch, 2002).

35. P. Howard, B. Francis, K. Soothill, L. Humphreys, OGRS 3: The revised offender group reconviction scale, *Tech. rep.*, Ministry of Justice (2009).

36. L. Helmus, D. Thornton, R. K. Hanson, K. M. Babchishin, Improving the predictive accuracy of static-99 and static-2002 with older sex offenders: Revised age weights, *Sexual Abuse: A Journal Of Research & Treatment* 24, 64 (2012).

37. C. M. Langton, *et al.*, Actuarial assessment of risk for reoffense among adult sex offenders evaluating the predictive accuracy of the static-2002 and five other instruments, *Criminal Justice and Behavior* 34, 37 (2007).

38. G. C. Barnes, J. M. Hyatt, Classifying adult probationers by forecasting future offending, *Tech. rep.*, National Institute of Justice, U.S. Department of Justice (2012).

39. P. B. Hoffman, S. Adelberg, The salient factor score: A nontechnical overview, *Fed. Probation* 44, 44 (1980).

40. S. Turner, J. Hess, J. Jannetta, Development of the California Static Risk Assessment Instrument (CSRA), University of California, Irvine, Center for Evidence-Based Corrections (2009).

41. K. Patrick, Should an algorithm determine whether a criminal gets bail?, *Inside Sources* (2018).

42. W. Dieterich, C. Mendoza, T. Brennan, COMPAS risk scales: Demonstrating accuracy equity and predictive parity: Performance of the COMPAS risk scales in broward county (2016).

43. [https://www.fatml.org](https://www.fatml.org) (2018). [Online; accessed 10-June-2018].
44. R. Berk, H. Heidari, S. Jabbari, M. Kearns, A. Roth, Fairness in criminal justice risk assessments: The state of the art, *Sociological Methods & Research* (2017).

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Supplementary materials

Supporting figures and tables

Probability of recidivism as a function of age

Figure 9 shows the probability of a new charge within 2 years as a function of age. The probability is a decreasing function of age.

![Figure 9: Probability of charge within 2 years as a function of age (red). The blue scatter plot is useful for understanding the distribution of ages of individuals; each individual who was arrested has a dot at their age on the horizontal axis, and a “1” on the vertical axis.](image)

Age histograms

Figure 10 shows the normalized histograms of African-Americans and Caucasians within Broward County who were evaluated with COMPAS between the beginning of 2013 and the end of 2014. These histograms do not involve COMPAS scores themselves, only information about the set of individuals who received COMPAS scores. The histogram for African-Americans is skewed to the left, which means African-Americans tend to be younger on average when their COMPAS score is calculated in the Broward County dataset.

Predictions of recidivism with and without race

Tables 7 and 8 show predictions of recidivism and violent recidivism, respectively, with and without race as a feature. The results are very similar with and without race.
Figure 10: Normalized histograms of age for African-Americans and Caucasians within the Broward County dataset.

|                | Logistic Regression | Random Forest | Boosting | SVM  |
|----------------|---------------------|---------------|----------|------|
| Without Race   | 0.330               | 0.321         | 0.312    | 0.298|
| With Race      | 0.328               | 0.318         | 0.309    | 0.313|

Table 7: Misclassification error of machine learning methods for predicting general recidivism with and without race as a feature. Age at COMPAS screening date and age at first offense are included as features. Unlike when predicting the COMPAS raw score remainder, we include the current offense in criminal history features.

|                | Logistic Regression | Random Forest | Boosting | SVM  |
|----------------|---------------------|---------------|----------|------|
| Without Race   | 0.159               | 0.165         | 0.158    | 0.160|
| With Race      | 0.159               | 0.161         | 0.160    | 0.160|

Table 8: Misclassification error of machine learning methods for predicting violent recidivism with and without race as a feature. Age at COMPAS screening date and age at first offense are included as features. Unlike when predicting the COMPAS raw score remainder, we include the current offense in criminal history features.
Quantile regression

In this subsection we warn the reader against a type of analysis that should not be done, and discuss why.

One might try to show that the age polynomial is independent of the remainder term COMPAS − f_{age} (or COMPAS − f_{viol age} for the violence remainder term). However, age is not independent of the remainder because of the correlation of age with criminal history. In an attempt to show this independence (which will fail), one might try to plot the quantiles of COMPAS for each age group. If these quantiles are evenly spaced, it would show independence. As Figure 11 shows, the lines are not evenly spaced. Thus, this type of analysis is not helpful.

![Figure 11](image)

Figure 11: An experiment that cannot work because age is not independent from criminal history.

Characteristics of individuals who are close to the age polynomials

The 78 individuals comprising the age polynomials are those who have the lowest COMPAS scores for each age group. Among these 78 individuals:

- All of the individuals have a sum of Violence History subscale items that is strictly below 5, and only one individual has a sum of Violence History subscale items above 2. According to Figure 4, summed Violence History subscale scores below 5 probably have little to no impact on the COMPAS score. Note that we have data to compute all but one of the Violence History subscale items (see later in this supplement).

- One of the 78 individuals has exactly one of the Noncompliance History subscale items. All other 77 individuals have exactly zero subscale items (no history of non-compliance...
|                           | Our Results       | ProPublica’s Results |              |
|---------------------------|-------------------|----------------------|--------------|
|                           | Estimate          | Standard Error       | Estimate     | Standard Error |
| Female                    | 0.123***          | 0.085                | 0.221***     | 0.080          |
| Age: Greater than 45      | -1.489***         | 0.129                | -1.356***    | 0.099          |
| Age: Less than 25         | 1.445***          | 0.071                | 1.308***     | 0.076          |
| Black                     | 0.521***          | 0.072                | 0.477***     | 0.069          |
| Asian                     | -0.271            | 0.503                | -0.254***    | 0.478          |
| Hispanic                  | -0.301*           | 0.130                | -0.428***    | 0.128          |
| Native American           | 0.390             | 0.678                | 1.394*       | 0.766          |
| Other                     | -0.713***         | 0.159                | -0.826***    | 0.162          |
| Number of Priors          | 0.155***          | 0.006                | 0.269***     | 0.011          |
| Misdemeanor               | -0.464***         | 0.069                | -0.311***    | 0.067          |
| Two year Recidivism       | 0.491***          | 0.068                | 0.686***     | 0.064          |
| Constant                  | -1.593***         | 0.082                | -1.526***    | 0.079          |

Table 9: Logistic regression coefficient estimates and standard errors computed in a similar way to ProPublica. The significance levels are not valid, since the model assumptions of linearity are broken. *p < 0.1; **p < 0.05; ***p < 0.01. Our results are based on 5759 observations while ProPublica’s results are based on 6,172 observations.

These results indicate that individuals close to the age polynomial may tend to have low subscale scores. This adds supporting evidence to a hypothesis that individuals on the age polynomial have COMPAS score determined by their age, with few (or no) additional risk factors.

**Logistic Regression**

We attempt to replicate ProPublica’s logistic regression of the COMPAS score category (Medium or High Risk vs. Low Risk) on various features, including race. Coefficient estimates and standard errors are shown in Table 9. Since recidivism (the outcome for our recidivism prediction models) is used as a covariate in ProPublica’s analysis, we exclude any observation for which there is less than two years of data beyond the screening date. Note that if 2-year recidivism is used in ProPublica’s model, it is using information that by definition is not available at the time that the COMPAS score is calculated.
Data processing

Our data includes the same raw data collected by ProPublica, which includes COMPAS scores for all individuals who were scored in 2013 and 2014, obtained from the Broward County Sheriff’s Office. There are 18,610 individuals, but we follow ProPublica in examining only the 11,757 of these records which were assessed at the pretrial stage. We also used public criminal records from the Broward County Clerk’s Office to obtain the events/documents and disposition for each case, which we used in our analysis to infer probation events.

In their analysis (1, 2), ProPublica processed the raw data, which includes charge, arrest, prison, and jail information, into features aggregated by person, like the number of priors or whether or not a new charge occurred within two years. We too process the raw data into features, partly to ensure the quality of the features and partly to create new features as defined by the components of the COMPAS subscales (see Tables 10-14). Note that while ProPublica publishes the code for their analysis and the raw data, they do not publish the code for processing the raw data. Thus we did that from scratch.

The **screening date** is the date on which the COMPAS score was calculated.

- Our features correspond to an individual on a particular screening date. If a person has multiple screening dates, we compute the features for each screening date, such that the set of events for calculating features for earlier screening dates is included in the set of events for later screening dates.

- On occasion, an individual will have multiple COMPAS scores calculated on the same date. There appears to be no information distinguishing these scores other than their identification number. We take the scores with the larger identification number.

- Any charge with degree “(0)” seems to be a very minor offense, so we exclude these charges. All other charge degrees are included, meaning charge degrees other than felonies and misdemeanors are included.

- Some components of the Violence Subscale require classifying the type of each offense (e.g., whether or not it is a weapons offense). We infer this from the statute number, most of which correspond to statute numbers from the Florida state crime code.

- The raw data includes arrest data as well as charge data. Because the arrest data does not include the statute, which is necessary for the Violence Subscale, we use the charge data
and not the arrest data throughout the analysis. While the COMPAS subscales appear to be based on arrest data, we believe the charge data should provide similar results.

- For each person on each COMPAS screening date, we identify the offense — which we call the *current offense* — that we believe triggered the COMPAS screening. The *current offense date* is the date of the most recent charge that occurred on or before the COMPAS screening date. Any charge that occurred on the current offense date is part of the current offense. In some cases, there is no prior charge that occurred near the COMPAS screening date, suggesting charges may be missing from the dataset. For this reason we consider charges that occurred within 30 days of the screening date for computing the current offense. If there are no charges in this range, we say the current offense is missing. For any part of our analysis that requires criminal history, we exclude observations with missing current offenses. All components of the COMPAS subscales that we compute are based on data that occurred prior to (not including) the current offense date, which is consistent with how the COMPAS score is calculated according to (32).

- The events/documents data includes a number of events (*e.g.*, “File Affidavit Of Defense” or “File Order Dismissing Appeal”) related to each case, and thus to each person. To determine how many prior offenses occurred while on probation, or if the current offense occurred while on probation, we define a list of event descriptions indicating that an individual was taken on or off probation. Unfortunately, there appear to be missing events, as individuals often have consecutive “On” or consecutive “Off” events (*e.g.*, two “On” events in a row, without an “Off” in between). In these cases, or if the first event is an “Off” event or the last event is an “On” event, we define two thresholds, \( t_{on} \) and \( t_{off} \). If an offense occurred within \( t_{on} \) days after an “On” event or \( t_{off} \) days before an “Off” event, we count the offense as occurring while on probation. We set \( t_{on} \) to 365 and \( t_{off} \) to 30. On the other hand, the “number of times on probation” feature is just the count of “On” events and the “number of times the probation was revoked” feature is just the count of “File order of Revocation of Probation” event descriptions (*i.e.*, there is no logic for inferring missing probation events for these two features).

- Age is defined as the age in years, rounded down to the nearest integer, on the COMPAS screening date.

- Recidivism is defined as any charge that occurred within two years of the COMPAS
screening date. For any part of our analysis that requires recidivism, we use only observations for which we have two years of subsequent data.

- A juvenile charge is defined as an offense that occurred prior to the defendant’s 18th birthday.

**Machine learning implementation**

Here we discuss the implementation of the various machine learning methods used in this paper. To predict the COMPAS general and violent raw score remainders (Tables 2, 4, and 5), we use a linear regression (base R), random forests (randomForest package), Extreme Gradient Boosting (xgboost package), and SVM (e1071 package). To clarify, we predict the COMPAS raw scores (not the decile scores, since these are computed by comparing the raw scores to a normalization group) after subtracting the age polynomials ($f_{age}$ for the general raw score and $f_{viol age}$ for the violent raw score). For XGBoost and SVM we select hyperparameters by performing 5-fold cross validation on a grid of hyperparameters and then re-train the method on the set of hyperparameters with the smallest cross validation error. For random forest we use the default selection of hyperparameters. For the COMPAS general raw score remainder, we use the available Criminal Involvement Subscale features (Table 12), while for the COMPAS violent raw score remainder, we use the available History of Violence Subscale and History of Noncompliance Subscale features listed in tables Tables 10 and 11, respectively. For both types of COMPAS raw scores, we also use the age at first offense. Race and age at screening date may or may not be included as features, as indicated when the results are discussed. To predict general and violent two-year recidivism (Tables 7 and 8), we use the same methods, features, and cross validation technique as used to predict the raw COMPAS score remainders, except we adapt each method for classification instead of regression (for linear regression, we substitute logistic regression) and we include the current offense in the features. All code is written in R and is available on GitHub.

**Subscale tables**

The features that compose the subscales used by COMPAS and that we use for prediction are listed in Tables 10-14. The Criminal History, Substance Abuse, and Vocation/Education Subscales (Tables 12, 14, and 13, respectively) are inputs to the COMPAS general recidivism score,
Table 10: History of Violence Subscale. We compute the components in bold font. We do not have the data to compute the other components. The feature for family violent arrests is always 0 so it is not useful for prediction. We classify a charge as family violence if the statute is 741.28, which corresponds to the definition of domestic violence in the Florida crime code. In our dataset there were no instances of this statute.

| Subscale Items                                      | Values          |
|----------------------------------------------------|-----------------|
| Prior juvenile felony offense arrests               | 0,1,2+          |
| Prior violent felony property offense arrests        | 0,1,2,3,4,5+    |
| Prior murder/voluntary manslaughter arrests         | 0,1,2,3+        |
| Prior felony assault offense arrests (excluding murder, sex, or domestic violence) | 0,1,2,3+        |
| Prior misdemeanor assault offense arrests (excluding murder, sex, domestic violence) | 0,1,2,3+        |
| Prior family violence arrests                       | 0,1,2,3+        |
| Prior sex offense arrests                            | 0,1,2,3+        |
| Prior weapons offense arrest                         | 0,1,2,3+        |
| Disciplinary infractions for fighting/threatening other inmates/staff | Yes/No          |

while the History of Violence, History of Noncompliance, and Vocation/Education Subscales (Tables 10, 11, and 13 respectively) are inputs to the COMPAS violent recidivism score.
Table 11: History of Noncompliance Subscale. We compute the components in bold font. We do not have the data to compute the other components.

| Subscale Items                                                                 | Values                              |
|-------------------------------------------------------------------------------|-------------------------------------|
| **On probation or parole at time of current offense**                          | **Probation/Parole/Both/Neither**   |
| Number of parole violations                                                  | 0,1,2,3,4,5+                        |
| Number of times person has been returned to prison while on parole             | 0,1,2,3,4,5+                        |
| **Number of new charge/arrests while on probation**                          | 0,1,2,3,4,5+                        |
| **Number of probation violations/revocations**                               | 0,1,2,3,4,5+                        |

* = Only “On Probation” and “Not On Probation” computed.

Table 12: Criminal Involvement Subscale. We computed all the components. To compute the number of arrests component, we interpreted a charge as an arrest.

| Subscale Items                                                                 | Values                              |
|-------------------------------------------------------------------------------|-------------------------------------|
| **Number of times offender has been arrested as adult/juvenile for criminal offense** | Any value accepted                  |
| **Number of times offender sentenced to jail for ≥30 days**                    | 0,1,2,3,4,5+                        |
| **Number of new commitments to state/federal prison (include current)**       | 0,1,2,3,4,5+                        |
| **Number of times person sentenced to probation as adult**                    | 0,1,2,3,4,5+                        |
Table 13: Vocation/Education Subscale. We do not have the data to compute any of these components.

| Subscale Items                                               | Values                                    |
|--------------------------------------------------------------|-------------------------------------------|
| Completed high school diploma/GED                            | Y/N                                      |
| Final grade completed in school                             | ---                                      |
| Usual grades in high school                                 | A,B,C,D,E/F, did not attend              |
| Suspended/expelled from school                               | Y/N                                      |
| Failed/repeated a grade level                                | Y/N                                      |
| Currently have a job                                        | Y/N                                      |
| Have a skill/trade/profession in which you can find work    | Y/N                                      |
| Can verify employer/school (if attending)                    | Y/N                                      |
| Amount of time worked or in school over past 12 months       | 12 months full time, 12 months part time, 6+ months FT, 0-6 months PT/FT |
| Feel that you need more training in new job or career skill | Y/N                                      |
| If you were to get (or have) a good job, how would you rate your chance of being successful? | Good, Fair, Poor |
| How hard is it for you to find a job above minimum wage compared to others? | Easier, Same, Harder, Much Harder |
Table 14: Substance Abuse Subscale. We do not have the data to compute any of these components.

| Subscale Items                                                                 | Values |
|-------------------------------------------------------------------------------|--------|
| Do you think your current/past legal problems are partly because of alcohol or drugs? | Y/N    |
| Were you using alcohol when arrested for your current offense?                 | Y/N    |
| Were you using drugs when arrested for your current offense?                   | Y/N    |
| Are you currently in formal treatment for alcohol/drugs?                      | Y/N    |
| Have you ever been in formal treatment for alcohol/drugs?                     | Y/N    |
| Do you think you would benefit from getting treatment for alcohol?             | Y/N    |
| Do you think you would benefit from getting treatment for drugs?               | Y/N    |
| Did you use heroin, cocaine, crack, or methamphetamines as a juvenile?        | Y/N    |