Data Science Looks at Discrimination

A toolkit for investigating bias in race, gender, age and so on

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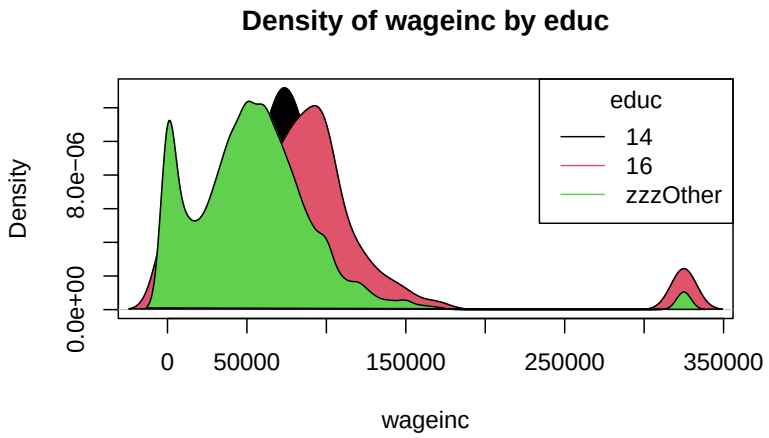
Table of contents

Overview



Discrimination is a key social issue in the US and in a number of other countries. There is lots of available data with which one might investigate possible discrimination. But how might such investigations be conducted?

Our **dsld** package provides both graphical and analytical tools for this purpose. We see it as widely applicable; here are just

a few use cases:

- Quantitative analysis in instruction and research in social science.
- Corporate HR analysis and research.
- Litigation involving discrimination and related issues.
- Concerned citizenry.

This document provides a tutorial regarding applicable methodology, as well as introduction to use of the package.

Prerequisite background

In addition to having rudimentary skill in R, the user should have a very basic knowledge of statistical inference–mean, variance, confidence intervals and tests, and histograms. A "bare bones" refresher, with emphasis on intuition, is given in Appendix A.

Python wrappers are included for most functions.

The dsld package

The **dsld** package, which this tutorial uses for examples, has two aims:

- To enable exploratory analysis of possible discrimination effects through various graphical and tabular functions.
- To enable formal statistical analysis of such effects via addition of a number of group-comparison operations to general R functions such as **lm()** and **glm()**, thereby facilitating comparisons across races, genders and so on.

Introduction and Motivating Examples

To set the stage, consider the following:

UC Berkeley discrimination claims

UC Berkeley was accused of discriminating against female applicants for graduate school, and indeed the overall acceptance rate for women was lower than that for men. This seemed odd, given Berkeley's liberal reputation.

However, upon breaking the data down according to the program students were applying to, it was found that in every department, the female acceptance rate *within that department* was either higher than the male rate or of similar level. The problem: women were applying to more selective programs, causing their overall rate to below that of men.

This data is included in R, as the built-in dataset **UCBAdmissions**.

US Census data

The **svcensus** dataset is a subset of US census data from back in 2000, focusing on six engineering occupations. The question at hand is whether there is a gender pay gap. Again, the overall pay for men is higher, by about 25%. But what if we break things down by occupation? Though it does turn out that some occupations pay more than others, and that men and women are not distributed evenly among the occupations, there still is a gender pay gap, of about 16%.

Included here in the **dsld** package.

Commonality

In both examples, we have an outcome variable Y of interest–acceptance rate and wage income–and a sensitive variable S, which was gender in both examples. But in both cases, were concerned that merely comparing mean Y for each gender was an oversimplication, due to a possible *confounder*

C–department in the first example, occupation in the second. Failure to take confounders (there can be more than one, and usually are so) into account can lead to spurious "relations" between S and Y.

> **i** Confounder Adjustment Settings
>
> So, in general, we wish to investigate the impact of a sensitive variable S on an outcome variable Y, but *accounting for confounders* C. Let's call them "confounder adjustment" settings.

Now contrast the above examples with a different kind:

COMPAS recidivism data

COMPAS is a commercial machine learning software tool for aiding judges to predict recidivism by those convicted of crimes. A 2016 **Pro Publica** article investigated, finding the tool to be racially biased; African-American defendants tended to be given harsher ratings–i.e. higher estimated probabilities of recidivism–than similarly situated white defendants.

Northpointe, the firm that developed COMPAS, disagrees with the *Pro Publica* analysis, and we are not supporting either side here. But if the COMPAS tool were in fact biased, how could the analysis be fixed?

A key point is that any remedy must not only avoid using race directly, but must also minimize the impact of variables O that are separate from race but still correlated with it, known as *proxies*. If, say, educational attainment is correlated with race, its inclusion in our analysis will mean that race is still playing a role in our analysis after all.

> **i** Fair ML Settings
>
> Thus our goal is to predict the outcome variable Y, without using the sensitive variable S, while making only limited use of the proxy variables O.

Summary: the two kinds of discrimination analysis covered here

This COMPAS example falls in the category of *fairness in machine learning ML*.

Note the difference between accounting for confounders on the one hand, and fair ML on the other. Here is a side-by-side comparison:

aspect	confounder adjustment	fair ML
goal	estimate an effect	predict an outcome
harm	comes from society	comes from an algorithm
side info	adjust for confounders	limit impact of proxies

Summary of symbols

We'll use X to denote the rest of the variables, i.e. those that are related to Y but are not S, C or O. The general terminology is that Y is variously termed the *outcome variable*, *target variable* or *dependent variable*; the X, C, S and O variables are known collectively as *covariates*, *features* or *independent variables*.

example	Y	C	S	O
UCB admits	acceptance	program	gender	-
Census	wage	e.g. occupation	gender	-
COMPAS	sentence	-	race	e.g. education

Format of this tutorial

We treat the topics in this order:

- adjusting for confounders
- fair ML

Within each of the above topics, we cover:

- graphical and tabular exploration

- formal quantitative analysis

In each case, we present explanations of the relevant concepts, so that this is a general tutorial on methodology for analysis of discrimination, and show the details of using our **dsld** package to make use of that methodology.

So, let's get started.

Part I: Adjustment for Confounders

How do we adjust for confounders? The most common approach involves linear models, with which we express the mean Y for given values of the X, C and S variables in a linear form.

There will also be the question of *which* possible confounders to use.

Example: a simple gender wage gap analysis

Consider the **svcensus** data example above, investigating a possible gender pay gap. So Y is wage and S is gender. We might treat age as a confounder C, reasoning as follows. Older workers tend to have more experience and thus higher wages, and if there is an age differential in our data, say with female workers tending to be older, this may mask a gender pay gap.

So, let's take the set of confounders C to consist of age, and for simplicity in this introductory example, not include any other confounders, such as occupation, and let's not include any other variables X.

Initial analysis

Our linear model would thus be

$$\text{mean W} = b_0 + b_1 \text{ A} + b_2 \text{ M}$$

where W is wage, A is age and M is an indicator variable, with M = 1 for men and M = 0 for women. The parameters b_i are estimated by fitting the model to the data:

The column svcensus$gender is an R factor. Our function **dsldLinear** calls R's **lm**, which replaces that column by a dummy variable **gendermale**, our M above.

```
svcensus1 <-
   svcensus[,c(1,4,6)]  # age, wage, gender
z <- dsldLinear(svcensus1,'wageinc','gender')
coef(z)  # print the estimated coefficients b_i
```

```
$gender
(Intercept)         age  gendermale
 31079.9174    489.5728  13098.2091
```

Interpretation of b_2

Lots here to discuss, which we will gradually cover below. For now, note that the *estimated* b_2 turns out to be about \$13,000, which is the wage gap, if any. Here's why:

Always keep in mind that statistical quantities are only estimated, since we work only with sample data from some population, real or conceptual. Hence the need for standard errors, confidence intervals and so on.

Under the model, the mean wage for, say, 36-year-old men is

$$b_0 + 36\ b_1 + 1\ b_2$$

while for women of that wage it is

$$b_0 + 36\ b_1$$

The difference is b_2. But if we look at, for instance, people of age 43, the mean wages for men and women are

$$b_0 + 43\ b_1 + 1\ b_2$$

and

$$b_0 + 43\ b_1$$

and the difference *is still* b_2. So we can speak of b_2 as *the* gender wage gap, at any age. According to the model, younger men earn an estimated \$13,000 more than younger women, with the same-sized gap between older men and older women.

The above approach to dealing with confounders is a very common one. But it raises questions, such as:

- What are the assumptions underlying that model? And how might we check whether they are (approximately) valid?

In addition, the data here are, as is commonly the case, *observational*, as opposed to being the result of a *randomized clinical trial*; there may be serious issues, due to unobserved confounders. Such problems might be solvable via an advanced (and rather controversial) methodology known as *causal inference*. Unfortunately, details are beyond our scope in this tutorial, but we will explain some basic concepts in

- We chose only one C variable here, age. We might also include occupation, as noted earlier. In some datasets, might have dozens of possible confounders. How do we choose which ones to use in our model? And for that matter, why not use them all?
- The above model, in which the gender wage gap was uniform across all wages, may not be adequate. How can we determine this, and what alternative models might we use?

Statistical inference

The full output of **dsldLinear()** goes to the heart of discrimination analysis, enabling statistical inferences on differences in levels of the sensitive variable S. Let's take a look:

```
summary(z)
```

```
$`Summary Coefficients`
    Covariate   Estimate Standard.Error        PValue
1 (Intercept) 31079.9174     1378.08158 3.012511e-111
2         age   489.5728       30.26461  1.733205e-58
3  gendermale 13098.2091      790.44515  2.897184e-61

$`Sensitive Factor Level Comparisons`
         Factors Compared Estimates Standard Errors      P-Value
Estimate    male - female  13098.21        790.4451 2.897184e-61
```

The first half of this output is from **lm()**, which is called by **dsldLinear()**. The second half is the "value added" material from **dsld**.

So, an approximate 95% confidence interval for the gender wage gap is

13098.2091 ± 1.96 x 790.44515

or (11548.94,14647.48).

Since the gender gap here is simply b_2, the CI could of course have also been obtained directly from the **lm** half of the output. But with an S having more than two levels, e.g. race, the **dsld** enhancement is quite valuable.

With-interactions model

As discussed above, in our model

$$\text{mean W} = b_0 + b_1 \text{ A} + b_2 \text{ M}$$

we identified b_2 as *the* difference in mean wage between men and women, regardless of age, so that for instance:

> According to the model, younger men earn about $13,000 more than younger women, with the same-sized gap between older men and older women.

But that may not be true. On the contrary, gender discrimination and age discrimination may interact. It may be, for instance, that the gender gap is small at younger ages but much larger for older people.

Interaction between two types of discrimination is called *intersectionality* by some analysts.

Assessing linearity

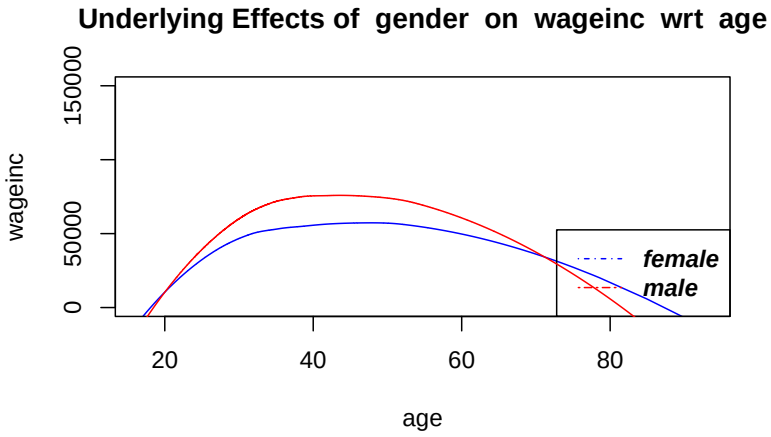
As noted, linear models are ubiquitous in observational data analysis. Open any professional journal in medicine, sociology, economics and so on, and you'll see many applications of this methodology. But how would one check that most basic assumption, the linearity of the mean Y for given X, C and S values?

> **i** Assumptions–not just a formality
>
> Assumptions *matter*. They are never perfectly satisfied, but failure to be even approximately valid can mean deciding that there is no discrimination when it actually is there, or vice versa. It can mean bad medication being declared by the government as good, or vice versa. In litigation, if a key expert witness is exposed by opposing counsel as not having checked the assumptions in his/her analysis, the side for which the witness was testifying will likely lose the case on the spot.

Typically, linearity is checked graphically. A common approach involves plotting the *residuals*, which are the differences between the fitted line and the Y values. Here, though, we use

another graphical approach, via a **dsld** function that may be more informative.

```
dsldConditDisparity(svcensus1,'wageinc','gender',
   'age','age > 0',yLim=c(0,150000))
```



The function plots a smoothed graph of Y against a user-specified C variable, once for each level of S. So, the call here says, "Plot wage income against age, for each gender."

The function has a 'conditions' argument; we have none here, so we just used a trival one, 'age > 0'

The model has mean Y being a linear of function of age, so we should expect to see approximate straight lines here. Yet the relation certainly looks nonlinear, possibly reflecting age discrimination against both very young and very old workers. We are already investigating one kind of discrimination here, gender, so again for simplicity let's keep age as a confounder.

Updated model

But we must do something about the substantial nonlinearity we've discovered, and one possible remedy is to add an age^2 term be added to the equation:

mean W = $b_0 + b_1$ A + b_2 A^2 + b_3 M

Adding a squared term does not make our model nonlinear, as it is still linear in the b_i; if we, say, double each of those, the entire expression is doubled, the definition of linearity. The model is nonlinear in age but linear in the b_i.

```
svcensus1$age2 <- svcensus1$age^2
z <- dsldLinear(svcensus1,'wageinc','gender')
coef(z)  # print the estimated coefficients b_i
```

```
$gender
  (Intercept)           age    gendermale          age2
-104196.65579   7251.30962   15270.56685    -79.16059
```

So we see that the original wage gap figure of about $13,000 was incorrect, underestimating it by about 15%.

We see in this example that misspecifying a linear model can have a major impact on its accuracy. Further issues of model assumptions are beyond the scope of this book, but the interested reader is referred one of the most popular applied linear models books, *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*, by Prof. Frank Harrell, Jr. of the Vanderbilt University School of Medicine.

Other assumptions

Other than linearity, the standard errors reported by **lm()** also assume that variance of wage income is approximately constant across ages and genders. Lack of this property has some effect on the accuracy of reported standard errors, but this can be adjusted via the so-called *sandwich* operation, an option in **dsldLinear()**.

It is also assumed that wage income has a normal/gaussian distribution at each level, but the Central Limit Theorem's implications for the sums created by **lm()** are in fact approximately normal.

Part II: Fairness in Machine Learning

Motivation

why the need for fairml...

Example

introduce example + context...

FairML Methodology

introduce solutions they offer, what the results would be on the example, etc.

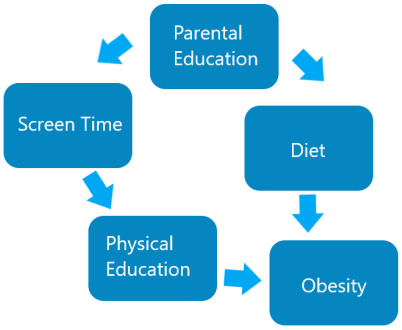
EDF Fair Methodology

introduce solutions they offer, what the results would be on the example, etc.

Appendix A: Fast Lane to Statistics

Appendix B: A Note on Causal Inference

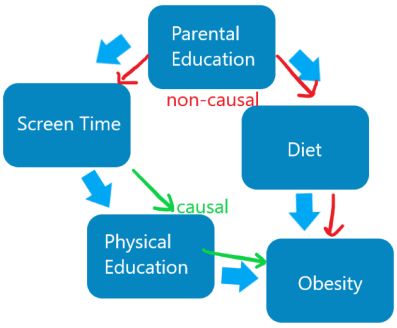
Let's say we are trying to establish the effect of screen time with the chances of developing obesity in children. However, given what you know, there may be many other factors that may exaggerate the effect of this relationship shown in some data. Lets assume you constructed a DAG that looks like this.



What's nice about depicting the relationships with a DAG is that you can see if one variable will have a statistical effect on another by following the arrows. If you follow the arrows in the direction they are pointing in you can see there is a direct path from screen time to obesity. This a causal path.

However, if you treat the arrow that goes into screen time as if it were pointing out of it, you can see there is an otherwise "back path" from screen time to obesity that is different from the

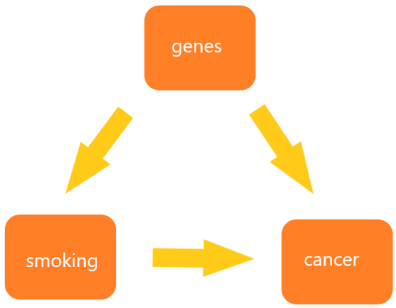
causal path. This path indicates an additional statistical effect between screen time and obesity but one that isn't associated with a causal relation- a non-causal path.



By controlling any variable along this back path, you can essentially block this effect, allowing you to isolate the true relation between the two variables. Once you know what variables to control, you can get the numerical relationship by methods such as linear regression.

But often the problem with observed data is that there may be confounders that are impossible to control. How would you control a variable that you can't measure?

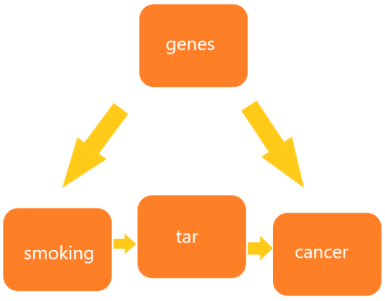
A classic example of this is trying to control for a hypothetical genetic factor in trying to determine the relationship between smoking and cancer. Genetics may play a role in whether someone is more likely to be a smoker and whether someone is more likely to develop cancer from it. There is a non-causal path between smoking and cancer, but unlike before, we can't exactly only look at people with certain unidentifiable genes.



However, we can still control for it by adding an additional step in between smoking and

cancer, that isn't correlated with genetics at all. In this case, that step is the presence of tar in the lungs.

To isolate the effect of smoking and cancer, now you can add the effects of smoking on tar with those of tar and cancer.



To isolate the effect of the latter, you can do the same as we've done before: block the back path by controlling the smoking variable. The effect on smoking tar is much similar, as there is no back path. Therefore, by combining the effects of the half steps, you get the relation of the full step from smoking to cancer.

Just like that, we were able to control the effect on an unmeasurable confounder.

Appendix C: Standard Errors via the Bootstrap