TRUMAN STATE UNIVERSITY

Professional Program in DATA SCIENCE

# Algorithmic Bias

DISTINCT BY DESIGN

# What is Bias?

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- **In statistical analysis:** Any time the results of an analysis are not consistent with what's really true.
- *These are not unrelated! Often, one leads to the other, in either order!*

# As we go forward, it’s good to consider our own biases.

- **Unconscious Bias:** Collections of unconscious associations with a group or class that affect perceptions related to that group.

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- **Truthiness Bias:** Easier-to-understand statements, statements that "seem" right, or statements repeated multiple times tend to be believed more easily.

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# Statistical Bias is the difference between an estimator's expected value and a true parameter value.

| Name | Pop. Param. | Estimator | Bias |
|---|---|---|---|
| Mean | $\mu$ | $\bar{x}$ | $E(\bar{x}) - \mu$ |
| Std. Dev. | $\sigma$ | $s$ | $E(s) - \sigma$ |
| Variance | $\sigma^2$ | $s^2$ | $E(s^2) - \sigma^2$ |
| Proportion | $p$ | $\hat{p}$ | $E(\hat{p}) - p$ |
| Generically | $\theta$ | $\hat{\theta}$ | $E(\hat{\theta}) - \theta$ |

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- An estimator whose bias is zero is called an *unbiased estimator*.
- $\bar{x}$ and $s^2$ are unbiased, but $s$ is not.
- A mathematical statistics class might explore what makes a good estimator, and that knowledge *can* be helpful in applied machine learning.

# Sources of Bias

# Data collection is part of the calculation of any statistic, and can lead to bias!

Who is in the population?

↓

How do we take a sample?

↓

How do we ask a question?

↓

Statistic(s):
As simple as $\bar{x}$,
or as complicated as ML parameters.

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  - Interviewers/observers can have skewed perceptions.
  - Sometimes respondents just don't tell the truth.

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- Humans choose *what* to measure.
- Do we understand the direction of causal relationships between predictor and response?
- Have we thought through the possible lurking variables?
- Does a response variable have the real-world meaning that we think it does?

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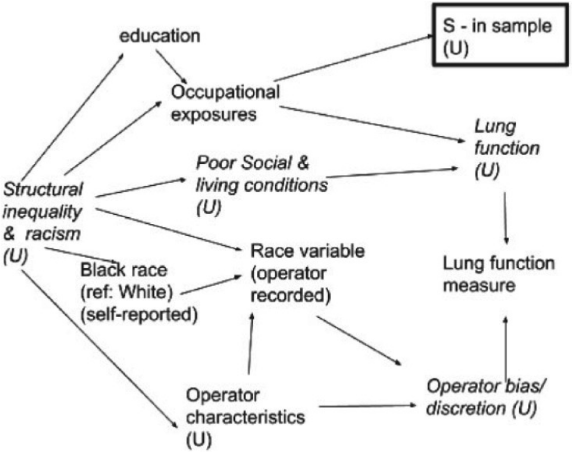
- Con's for using race:
  - Ill-defined, and usually a stand-in for other variables.
  - Promotes a view that race is *causally* related to outcomes.

# Example: What are the causal connections between race and lung function?




Source: Teaching Yourself about Structural Racism Will Improve Your Machine Learning (nih.gov)

See also: Race, Ethnicity and Lung Function: A Brief History (nih.gov)

# Example: What happens when patient health care costs are used as a proxy for health care needs?

- An algorithm was used to recommend extra support for patients with complex health-care needs.

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- Patients likely to have higher health-care costs were recommended for these programs. (Cost was presumably easier to measure than "need for care.")
- Context: Patients who are not white have historically generated lower costs because they have more barriers to accessing health care.
- Result: Non-white patients had to be sicker before they were referred to support programs.

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# Example: Bias in recidivism risk assessments illustrates the importance of algorithm evaluation on subgroups.

- Pro Publica published an evaluation of the proprietary COMPAS risk assessment algorithm.

| Race | Actual | Low Risk | High Risk | True % | Accuracy |
|---|---|---|---|---|---|
| All | Didn’t Recidivate | 2681 | 1281 | 68% | 65% |
| All | Recidivated | 1216 | 2035 | 63% | |
| Black | Didn’t Recidivate | 990 | 805 | 55% | 64% |
| Black | Recidivated | 532 | 1369 | 72% | |
| White | Didn’t Recidivate | 1139 | 349 | 77% | 67% |
| White | Recidivated | 461 | 505 | 52% | |

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- Contingency tables compare risk assessment to actual recidivism within two years of arrest.

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- Humans tend to invest too much authority in algorithms.
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- Algorithms can create feedback loops: negative decisions can create negative outcomes which reinforce negative decisions.

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  - Right to challenge decisions.
- Diversify data science teams to help eliminate blind spots.

# Some Technical Approaches: Balancing Data

# Example: Balancing Data in Predicting Insurance Expense for Smokers and Non-Smokers

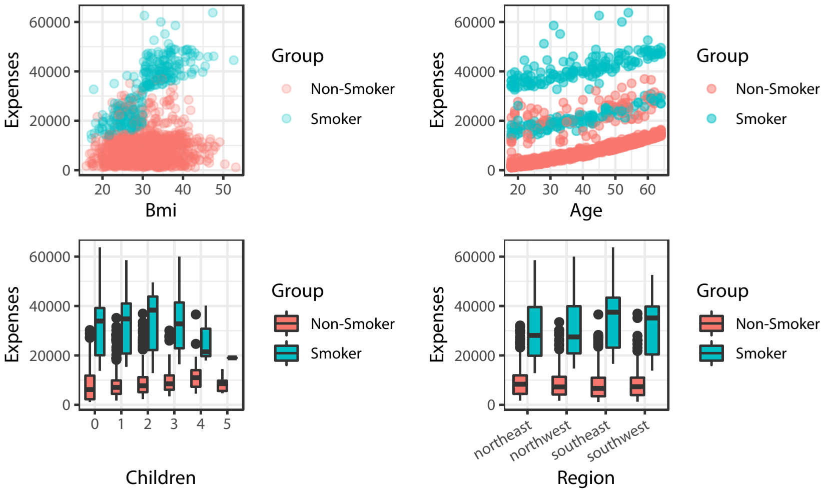
```r
# Load the data.
ins <- read.csv("data/Insurance_A.csv", stringsAsFactors=TRUE) %>%
  mutate(smoker = factor(if_else(smoker=="yes", "Smoker", "Non-Smoker"))) %>
  rename(Group = smoker)
names(ins) = str_to_title(names(ins))             # Just nice graph labels.
head(ins, 2)
```

```
##   Age    Sex  Bmi Children      Group    Region Expenses
## 1  19 female 27.9        0     Smoker southwest 16884.92
## 2  18   male 33.8        1 Non-Smoker southeast  1725.55
```

```r
# Make a training and test set.
set.seed(892)                                     # For repeatability
ind <- sample(1:nrow(ins), round(0.7*nrow(ins)))
ins.train <- ins[ind, ]
ins.test <- ins[-ind, ]
```

Data set in the public domain, from *Machine Learning with R* by Brett Lantz. See here for deatils (github.com)

# Expenses depend most strongly on BMI and Age.



# A Helpful Visualization Function for Bias and RMSE

```
library(randomForest)
library(caret) # For the downSample and upSample commands.
fit.stats <- function(fit, test){
  test$res <- test$Expenses - predict(fit, newdata=test)
  rbind(test %>% group_by(Group) %>%
          summarize(Bias = -mean(res),
                    RMSE=sqrt(mean(res^2))),
        test %>%
          summarize(Group="ALL", Bias = -mean(res),
                    RMSE=sqrt(mean(res^2))))
}
```

# Initial Random Forest Fit with Original Data Set

```r
fit.orig <- randomForest(Expenses ~ ., data=ins.train)
```

```r
table(ins.train$Group) %>%
  kable()
```

| Var1 | Freq |
|---|---|
| Non-Smoker | 750 |
| Smoker | 187 |

```r
fit.stats(fit.orig, ins.test) %>
  kable()
```

| Group | Bias | RMSE |
|---|---|---|
| Non-Smoker | -411.5110 | 5438.676 |
| Smoker | -772.9750 | 3384.287 |
| ALL | -489.9334 | 5064.254 |

# Initial Random Forest Fit with Non-Smokers Downsampled

```
ins.train.ds <- downSample(x=select(ins.train, -Group),
                           y=ins.train$Group, yname="Group")
fit.ds <- randomForest(Expenses ~ ., data=ins.train.ds)
```

```
table(ins.train.ds$Group) %>%
  kable()
```

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```
fit.stats(fit.ds, ins.test) %>%
  kable()
```

| Group | Bias | RMSE |
|---|---|---|
| Non-Smoker | 255.7121 | 5395.480 |
| Smoker | -321.5732 | 2957.973 |
| ALL | 130.4657 | 4969.266 |

# Initial Random Forest Fit with Smokers Upsampled

```r
ins.train.us <- upSample(x=select(ins.train, -Group),
                         y=ins.train$Group, yname="Group")
fit.us <- randomForest(Expenses ~ ., data=ins.train.us)
```

```r
table(ins.train.us$Group) %>%
  kable()
```

| Var1 | Freq |
|---|---|
| Non-Smoker | 750 |
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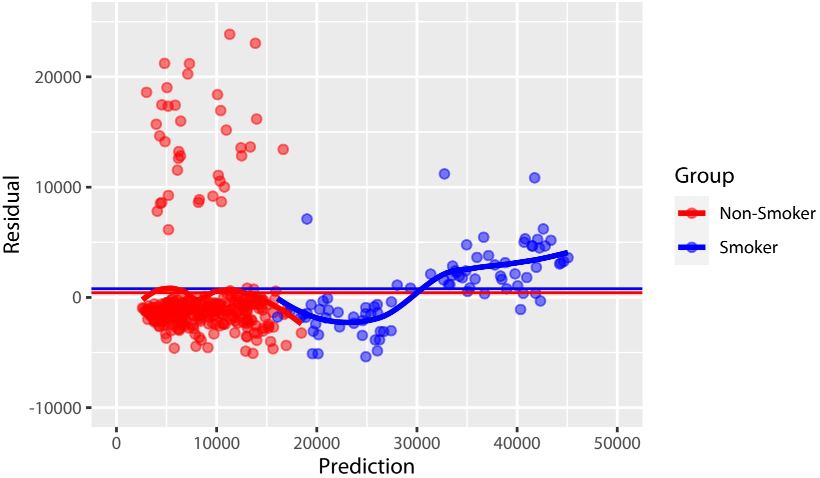
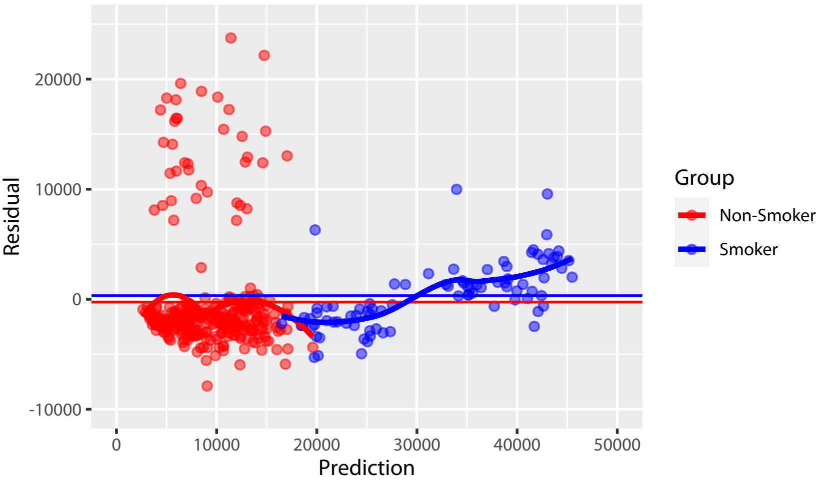
```r
fit.stats(fit.us, ins.test) %>%
  kable()
```

| Group | Bias | RMSE |
|---|---|---|
| Non-Smoker | -355.9894 | 5436.022 |
| Smoker | -379.3473 | 2760.703 |
| ALL | -361.0571 | 4979.227 |

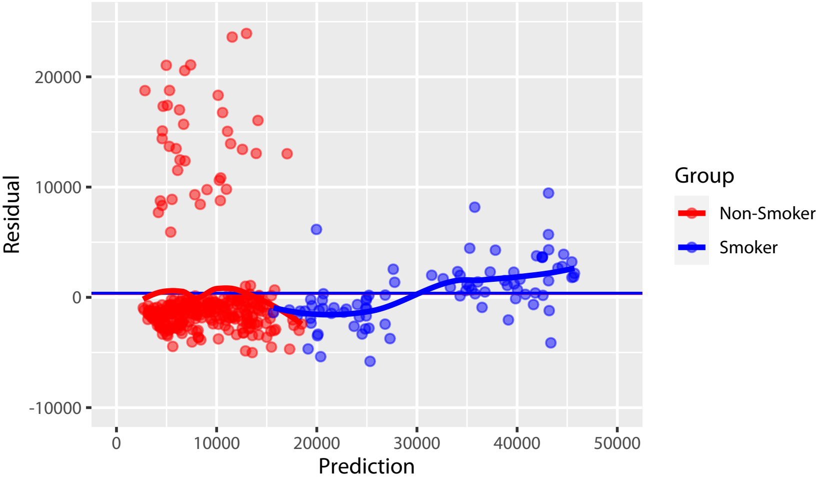
# Residuals vs. Fit for Original Data



# Residuals vs. Fit for Downsampled Data



# Residuals vs. Fit for Upsampled Data



# Example: Weighting a Categorical Response

- Our data set has measurements of several varieties of dry beans.

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beans <- read.csv("data/dry_bean_dataset.csv")
names(beans)
```

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##  [1] "Area"            "Perimeter"       "MajorAxisLength" "MinorAxisLength"
##  [5] "AspectRation"    "Eccentricity"    "ConvexArea"      "EquivDiameter"
##  [9] "Extent"          "Solidity"        "roundness"       "Compactness"
## [13] "ShapeFactor1"    "ShapeFactor2"    "ShapeFactor3"    "ShapeFactor4"
## [17] "Class"
```

```r
table(beans$Class)/sum(table(beans$Class))
```

```
## 
##   BARBUNYA     BOMBAY       CALI   DERMASON      HOROZ      SEKER       SIRA 
## 0.09712732 0.03835133 0.11975608 0.26052458 0.14165014 0.14892366 0.19366689
```

KOKLU, M. and OZKAN, I.A., (2020), “Multiclass Classification of Dry Beans Using Computer Vision and Machine Learning Techniques.” Computers and Electronics in Agriculture, 174, 105507. DOI: https://doi.org/10.1016/j.compag.2020.105507

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- Note that Sira makes up only about 19% of the data.

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## [13] "ShapeFactor1"    "ShapeFactor2"    "ShapeFactor3"    "ShapeFactor4"
## [17] "Class"
```

```
table(beans$Class)/sum(table(beans$Class))
```

```
##
##   BARBUNYA     BOMBAY       CALI   DERMASON      HOROZ      SEKER       SIRA
## 0.09712732 0.03835133 0.11975608 0.26052458 0.14165014 0.14892366 0.19366689
```

KOKLU, M. and OZKAN, I.A., (2020), "Multiclass Classification of Dry Beans Using Computer Vision and Machine Learning Techniques." Computers and Electronics in Agriculture, 174, 105507. DOI: https://doi.org/10.1016/j.compag.2020.105507

# An unweighted model has good accuracy, but

```r
library(e1071)
# Focus only on Sira.
beans$Class <- fct_other(beans$Class, keep="SIRA")
summary(beans$Class)
```

```
##  SIRA Other
##  2636 10975
```

```r
# Create training and test set.
set.seed(9084)
ind <- sample(1:nrow(beans), round(0.70*nrow(beans)))
beans.train <- beans[ind, ]
beans.test <- beans[-ind, ]
unweighted.svm <- svm(Class ~ ., data=beans.train)
unweighted.pred <- predict(unweighted.svm, newdata=beans.test)
```

# An unweighted model has good accuracy, but is better at predicting beans that aren't Sira.

```r
cm <- confusionMatrix(unweighted.pred, beans.test$Class, positive="SIRA")
cm$table
```

```
##            Reference
## Prediction SIRA Other
##      SIRA   660   102
##      Other  101  3220
```

```r
c(cm$overall["Accuracy"], cm$byClass[c("Sensitivity", "Specificity")])
```

```
##    Accuracy Sensitivity Specificity
##   0.9502817   0.8672799   0.9692956
```

# We can balance the model's predictions by weighting the levels of the categorical response.

- Most predictive model commands allow this with a command option.

```
class.pcts <- table(beans.train$Class)/sum(table(beans.train$Class))
class.pcts
```

```
## 
##      SIRA     Other 
## 0.1967884 0.8032116
```

```
weighted.svm <- svm(Class ~ ., data=beans.train,
                    class.weights=c("SIRA"=1/.197, "Other"=1/.803))
weighted.pred <- predict(weighted.svm, newdata=beans.test)
```

# We can balance the model's predictions by weighting the levels of the categorical response.

- Most predictive model commands allow this with a command option.
- Weights determine how much each element counts towards the cost function that determines the model's fit.

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# We can balance the model's predictions by weighting the levels of the categorical response.

- Most predictive model commands allow this with a command option.
- Weights determine how much each element counts towards the cost function that determines the model's fit.
- You might try weights inverse to each category's proportion.

```
class.pcts <- table(beans.train$Class)/sum(table(beans.train$Class))
class.pcts
```

```
##
##      SIRA     Other
## 0.1967884 0.8032116
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weighted.svm <- svm(Class ~ ., data=beans.train,
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```

# The weighted model improved sensitivity at the cost of sensitivity and overall accuracy.

```r
cm <- confusionMatrix(weighted.pred, beans.test$Class, positive="SIRA")
cm$table
```

```
##             Reference
## Prediction SIRA Other
##      SIRA   721   251
##      Other   40  3071
```

```r
c(cm$overall["Accuracy"], cm$byClass[c("Sensitivity", "Specificity")])
```

```
##    Accuracy Sensitivity Specificity
##   0.9287289   0.9474376   0.9244431
```

# Further Information on Weighting.

- Algorithms like SMOTE and ROSE combine up and down-sampling, while *synthesizing* new data points in the minority class, as opposed to simply duplicating existing data points. See the `caret` documentation for examples (github.io).

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- Weighting may reduce overall performance to predict one group better. You can't really create something out of nothing.
- Weighting can accentuate any problems with subgroup data.
- **Remember:** bias doesn't always have a technical solution!

# The Final Case Weighting Example from the Lecture

An unweighted data set might contain more beans grown in wet conditions that are not Sira variety. To counteract that imbalance, we might weight each case, or row, perhaps with the inverse of its frequency.

| Moisture | Variety | Weight |
|---|---|---|
| Dry | Other | 1/1=1.0 |
| Dry | Sira | 1/1=1.0 |
| Wet | Other | 1/5=0.2 |
| Wet | Other | 1/5=0.2 |
| Wet | Other | 1/5=0.2 |
| Wet | Sira | 1/1=1.0 |
| Wet | Other | 1/5=0.2 |
| Wet | Other | 1/5=0.2 |