CS 182: Ethics, Public Policy, and Technological Change

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Technical Assignment #1 on Algorithmic Decision-Making is out
  • See “Handouts” link on class webpage to get assignment handout and information on using PyCharm
  • See “Assignment” link on class web site to get starter code
  • Using Python (and PyCharm) for the assignment
    • See “Software” link on class webpage to download PyCharm
  • Assignment #1 due at 11:59pm on January 26th
    • Submission through Gradescope
      • Will submit code and write-up to questions separately
    • Gradescope CS182 Entry Code in Assignment #1 handout (at end)

Sections start this week (on Thursday)
  • Will get your section assignment via email by tonight
  • If you missed section sign-ups, email head TAs
“It’s COMPASlicated...” paper presentation and Q&A with Michelle Bao
  • 3:00pm today in CEMEX Aud

Python Refresher Workshop
  • 9:00pm this Thursday (Jan. 19) on Zoom
  • Hosted by Ayelet and Muhammad
  • Covers Python basics, setting up the first assignment and starter code walkthrough
  • Zoom link on Canvas and Ed
Today’s Agenda

1. Introduction to machine learning and Perceptron algorithm
2. Definitions of “fairness” (with a brief intro. to probability)
3. Discussion of ProPublica analysis of COMPAS algorithm
4. Overview of technical assignment
Promises/Perils of Machine Learning

• Promises
  • Provide insights about domain
  • Improve accuracy of prediction compared to humans
    • Diminish/eliminate bias and inconsistency
  • Greater efficiency than human decision-making
    • Humans are slow and error-prone

• Perils
  • Encode existing biases and reduce fairness
  • Lack transparency and threaten due process
  • Increased efficiency is not always a benefit (thanks Rob!)
Machine Learning for Prediction

- Many different forms of machine learning
  - We focus on the prediction (or classification) task

- Want to make a prediction based on observations
  - Set of $n$ observed variables: $<X_1, X_2, ..., X_n>$
    - $X_1, X_2, ..., X_n$ are called “input features/variables”
    - For example: age, annual income, gender, education, etc.
    - Referred to as $\mathbf{X}$ for short (it’s a vector, but that’s not important)

- Given observed $\mathbf{X}$, want to predict other variable $Y$
  - $Y$ called “output feature/variable”
  - Example 1: whether applicant should be issued a credit card
  - Example 2: whether defendant will commit a crime in future (recidivate)

- Seeking to “learn” a function $d(\mathbf{X})$ to predict $Y$:
  \[
  Y_{\text{prediction}} = d(\mathbf{X})
  \]
Training a Learning Machine

- We are given set of $M$ “training” instances
  - Each training instance is really a pair: $(<x_1, x_2, ..., x_n>, y)$
  - Training instances are previously observed data
  - Provides output value $y$ associated with each observed set of input values $x = <x_1, x_2, ..., x_n>$

- Learning: use training data to specify $d(X)$
  - Generally, first select a functional form for $d(X)$
  - Then, determine parameters (weights) of model $d(X)$ using training data
The Machine Learning Process

Training data: set of $M$ pre-classified data instances
- $M$ training pairs: $(x, y)^{(1)}, (x, y)^{(2)}, \ldots, (x, y)^{(M)}$
  - Use superscripts to denote $i$-th training instance

Learning algorithm: method for determining $d(X)$
- Given a new input observation of $x = <x_1, x_2, \ldots, x_n>$
- Use $d(X)$ to compute a corresponding output (prediction)
- When prediction is discrete, we call $d(X)$ a “classifier” and sometimes call the output the predicted “class” of the input
Basic Perceptron Algorithm

\[ \text{sum} = \sum_{i=1}^{n} x_i \cdot w_i \]

if \( \text{sum} > 0 \):
    prediction = 1
else:
    prediction = 0

if prediction \neq y: \quad \text{(incorrect prediction)}
    if prediction == 1:
        for each weight \( w_i \) (where \( i = 1 \) to \( n \))
            \( w_i = w_i - x_i \)
    else:
        for each weight \( w_i \) (where \( i = 1 \) to \( n \))
            \( w_i = w_i + x_i \)
Basic Perceptron Algorithm

\[ \text{sum} = \sum_{i=1}^{n} x_i \cdot W_i \]

if sum > 0:
    prediction = 1
else:
    prediction = 0

# Mathematically equivalent, but more compact update rule

error = y - prediction

if error != 0:       \textit{(incorrect prediction)}
    for each weight \( w_i \) (where \( i = 1 \) to \( n \))
    \[ w_i = w_i + (\text{error} \times x_i) \]
Batch Perceptron Pocket Algorithm

- **Batch**: for each pass through training data (called an "epoch")
  - Compute what the change in weights would be for each instance
  - Average the changes over all instances ("average difference")
  - Update weights with average difference

- **Pocket**: for each pass through training data
  - Compute number of correct predictions made with current weights
  - If number of correct predictions is higher than any previous pass, save this set of weights in our "pocket"
  - After making some number of passes through the data for training, we use the set of weights in our "pocket" as the final model

- More details (and pseudocode) in the “Probability and Machine Learning” handout/reading
  - That is the algorithm implemented in Assignment #1
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What is “Fair”? 

• There are many definitions of fairness 
  • Narayanan (2018) provided 21 definitions of fairness 
  • We will focus on some of the most commonly discussed definitions 
  • Requires a bit of background in probability to formalize 
    • So, here’s a working introduction to probability 

• Probability: Chance that something will happen 
  • Coin flip can be heads or tails. Set X = 1 if heads, 0 otherwise 
  • \( \text{Pr}(X = 1) \) Chance that variable X = 1 (flipped “heads”) 

• Conditional probability: Probability that something will happen given that something else has been observed 
  • \( \text{Pr}(X = 1 \mid Y = 1) \) Chance that variable X = 1 given that we know Y = 1
Legal Concepts Related to Fairness

• Protected characteristics
  • Some characteristics cannot be used to discriminate individuals in decision-making in particular circumstances
  • For example, in employment decisions, protected characteristics include: race, gender, and age (among others)
  • In medicine, however, it may make sense to prescribe different treatments to different genders

• Disparate impact
  • Definition: Impact of a policy is different between two groups distinguished by a protected characteristic
  • Does not require discriminatory intent
Definitions Related to “Fairness” - I

- **Anti-classification**: decisions do not consider “protected” characteristics (e.g., race, gender, age, etc.)
  - Consider only unprotected characteristics of two individuals X and X’
  - Implies: if the unprotected characteristics of X and X’ are the same, then the decision made for X and X’ should be the same

- **Classification parity**: Classification error is equivalent across groups defined by protected characteristics ($X_p$)
  - E.g., Parity of false positives: $\Pr(d(X) = 1 \mid Y = 0, X_p) = \Pr(d(X) = 1 \mid Y = 0)$
    - If you would not recidivate, then knowing your protected characteristics should not change the probability that we predict you will recidivate (chance of false positive prediction)
Definitions Related to “Fairness” - II

- **Calibration**: Outcomes should be independent of protected characteristics conditional on risk scores, \( s(X) \)
  - Formally: \( \Pr(Y = 1 \mid s(X), X_p) = \Pr(Y = 1 \mid s(X)) \)
  - Given your risk score, the probability that you will recidivate should not change if we additionally knew your protected characteristics
  - In Perceptron, could think of the sum \( \sum_{i=1}^{n} x_i \cdot w_i \) as a form of risk score that is then thresholded to make a prediction. (Risk scores often binned.)

- (Lack of) **Disparate impact**: *impact* of a policy should not be different between two groups (based on protected characteristic)
  - Recall, disparate impact does not require discriminatory intent, only that the impact is disparate between the two groups
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COMPAS Algorithm

- “Opaque box” model by Northpointe to assess risk of recidivism
  - Predicts a risk score of recidivism based on features of individual
  - Race is not one of the input features to the model

<table>
<thead>
<tr>
<th>Contingency Table</th>
<th>Recidivated</th>
<th>Did not recidivate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labeled High-risk</td>
<td>True positive (A)</td>
<td>False positive (B)</td>
</tr>
<tr>
<td>Labeled Low-risk</td>
<td>False negative (C)</td>
<td>True negative (D)</td>
</tr>
</tbody>
</table>

- ProPublica analysis (no classification parity)
  - Score correctly predicted recidivism: 61% \( \frac{A}{A+B} \)
    - Correct for white defendants: 59% \( \frac{A}{A+B} \)
    - Correct for black defendants: 63% \( \frac{A}{A+B} \)
  - But, the way misclassification were made were different
    - Blacks who did not recidivate, % labeled high-risk: 45% \( \frac{B}{B+D} \)
    - Whites who did not recidivate, % labeled high-risk: 23% \( \frac{B}{B+D} \)
    - Blacks who recidivated, % labeled low-risk: 28% \( \frac{C}{A+C} \)
    - Whites who recidivated, % labeled low-risk: 48% \( \frac{C}{A+C} \)
Northpointe responds that the algorithm is fair because risk scores are equally predictive of recidivism for both blacks and whites.

Calibration: $\Pr(Y = 1 \mid s(X), X_p) = \Pr(Y = 1 \mid s(X))$
Algorithms as a Mirror

- Algorithms require formalization of what should be optimized

- In machine learning, often try to optimize for overall accuracy of predictions.
  - Any potential problems with that?

- If we want to use algorithms to make decisions, it forces us to be precise about what we think "fairness" is and how we would define it

- How do you define fairness?

- What should the algorithm try to optimize?
Here Come the Computer Scientists

• Can’t we have just have all definitions of fairness
  • Let me just crank up my deep neural network...

• Sorry, Kleinberg et al (2017) prove you can’t (generally) get both calibration and classification parity

• And, you can have proxies for protected characteristics
  • (Sets of) features that are not protected, but correlate strongly with protected features
  • And it can be hard to determine which such features should be allowed
    • Here come the lawyers...

• And, there can be historical bias or disproportionality in the data that will be reflected in results of machine learning algorithms
  • E.g., A classifier built to predict a condition that only occurs in 0.5% of the population is 99.5% accurate if it always predicts that no one has condition

• And, there’s the problem of infra-marginality (Say what?!)
Risk Distributions Differ

• Distribution of defendants across risk categories by race (Corbett-Davies et al, 2016):

In the data, Black defendants recidivism rate is higher than whites
  • So higher proportion of black defendants are deemed medium or high risk
  • As a result, black defendants who do not reoffend are also more likely to be classified higher risk than white defendants who do not reoffend
Risk Distributions Differ

Slide thanks to Sam Corbett-Davies
Risk Distributions Differ

- Use a single threshold based on risk scores for detention
  - Might produce disparate false positive rates (what ProPublica found)
Risk Distributions Differ

- Use different thresholds based on race to equalize error rates
  - Violates notion of anti-classification since you discriminate based on a protected characteristic (race)
MACHINE BIAS

Bias in Criminal Risk Scores Is Mathematically Inevitable, Researchers Say
Issues to Keep in Mind

• This isn't just a data issue
  • Choice of what to optimize in the model impacts results we get

• This isn't just a machine learning/modeling issue
  • Bias in data leads to bias in the model
    • Context, measurement, and representation matter
  • Sample bias – who is well represented in the data (and who is not)
  • Measurement bias – how well data reflects measurement of real-world
  • Label bias – data may not be labeled consistently
  • Exclusion bias – important aspects of data are not included
    • E.g., Complex factors of individuals not captured/represented in data
  • Real-world (prejudicial) bias – data collection reflects biased decisions in real-world
    • E.g., More crime is found in locations with more policing

• This isn't just a computing issue
  • Data and modeling alone do not consider broader social context of issue
“Amazon scraps secret AI recruiting tool that showed bias against women”

-- Business News, Oct. 9, 2018

By 2015, the company realized its new system was not rating candidates for software developer jobs and other technical posts in a gender-neutral way.

That is because Amazon’s computer models were trained to vet applicants by observing patterns in resumes submitted to the company over a 10-year period. Most came from men, a reflection of male dominance across the tech industry.

It penalized resumes that included the word “women’s,” as in “women’s chess club captain.” And it downgraded graduates of two all-women’s colleges...

The Seattle company ultimately disbanded the team by the start of last year because executives lost hope for the project...
Overview of Assignment

• Should we consider protected characteristics in an algorithm, if it can yield:
  • higher predictive accuracy?
  • error rate parity between different racial/gender groups?
  • correct for historical bias in the data?

• We want you to explore questions like this in your assignment
  • There are many other questions that could be explored
  • Some parts of assignment are focused on grappling with specific issues to keep them tractable for a class assignment
  • But, please feel free to explore more broadly in your write-up, keeping in mind the audience that you are writing for in the assignment

• Quick overview of assignment