Machine Learning for Data Science (CS4786)
Lecture 26

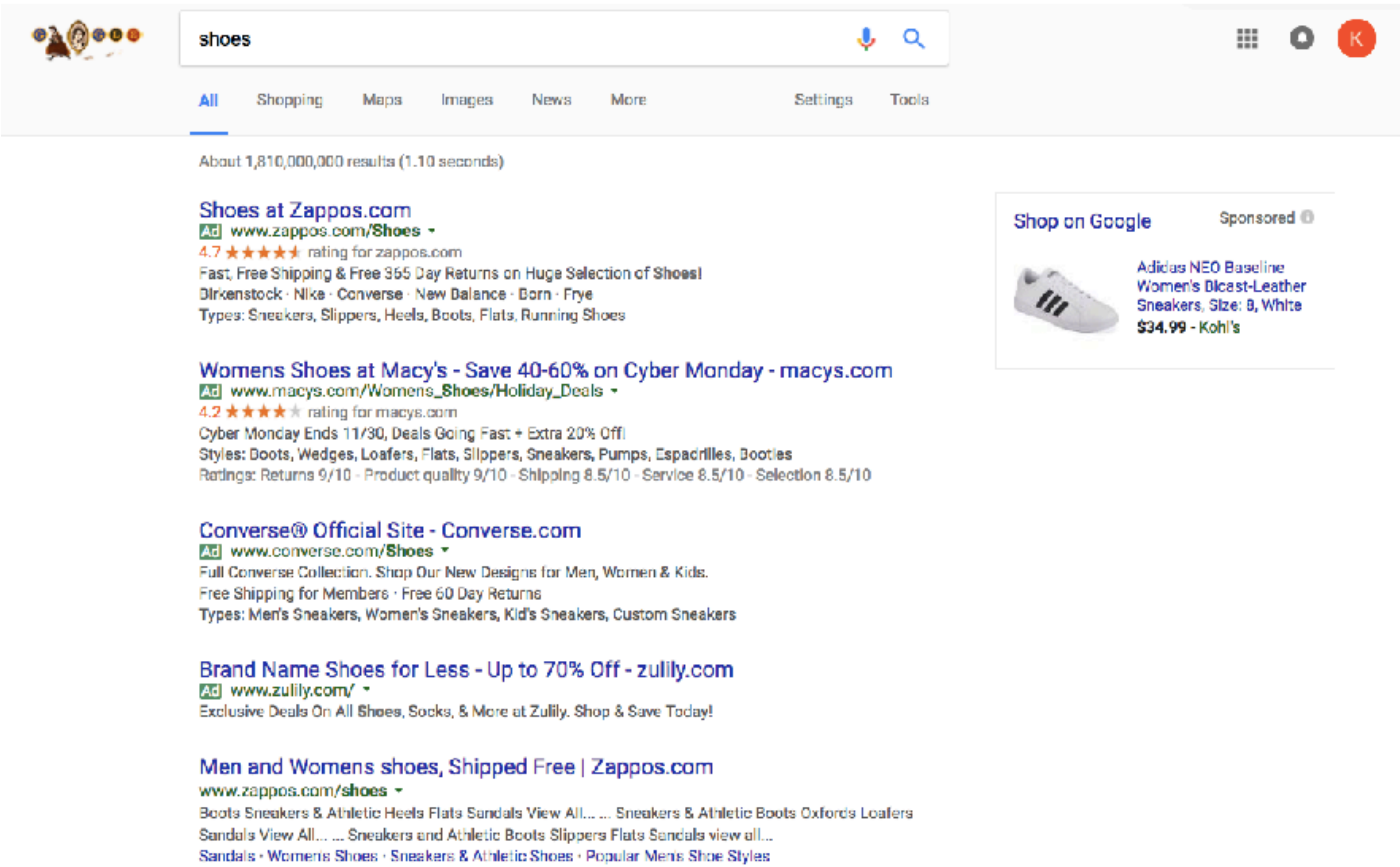
Fairness, Transparency and other Moral Issues in Machine Learning

Course Webpage :
http://www.cs.cornell.edu/Courses/cs4786/2016fa/

Announcements

- Survey 2, just over 80%
- Make sure you fill out the course eval
  - (If the participation on this is above 90% I will still drop worst assignment)

ML DREAM



shoes
All
Shopping
Maps
Images
News
More
Settings
Tools
About 1,810,000,000 results (1.10 seconds)
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Ad www.zappos.com/Shoes
4.7 ★★★★★ rating for zappos.com
Fast, Free Shipping & Free 365 Day Returns on Huge Selection of Shoes!
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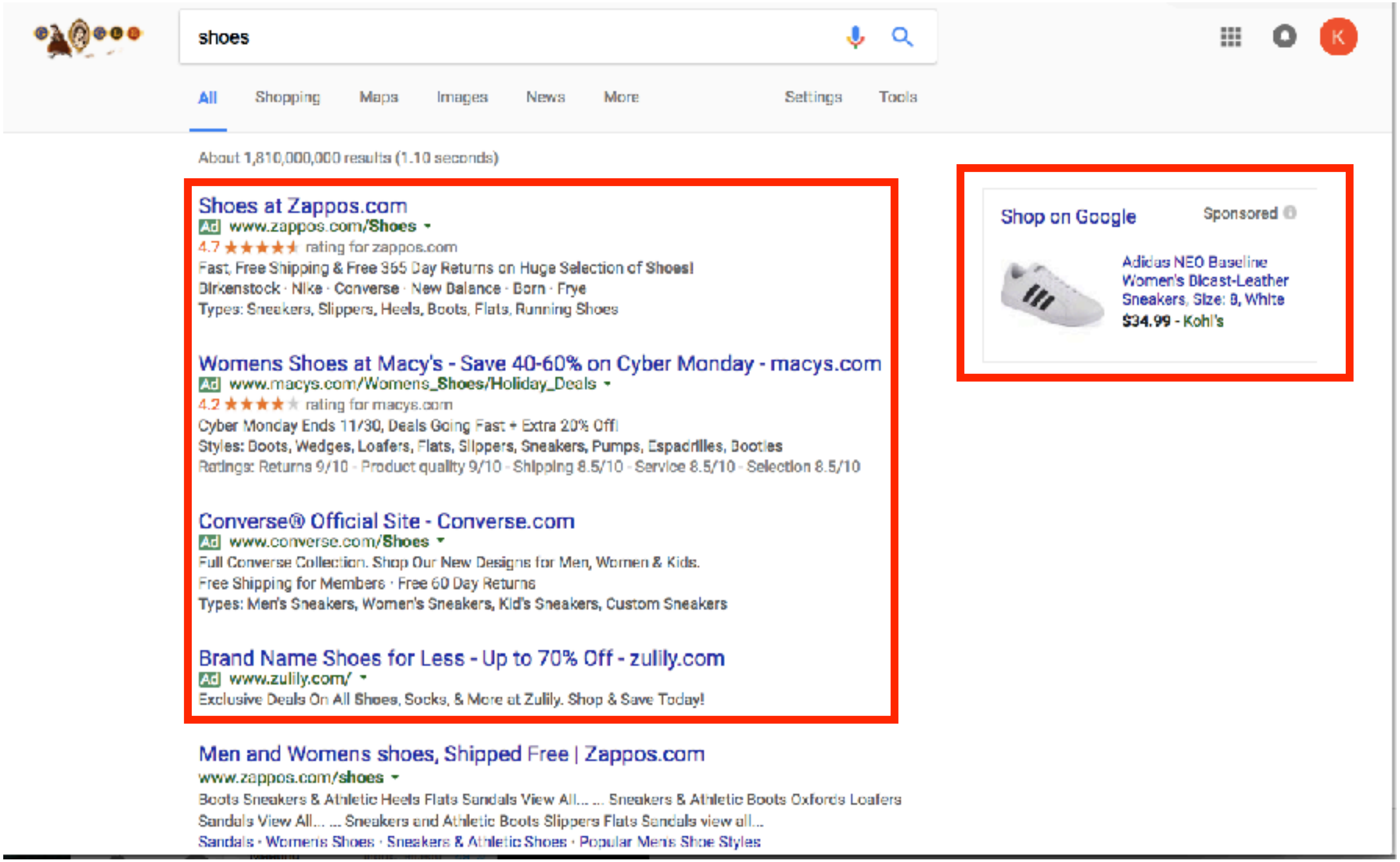
Sandals View All... ... Sneakers and Athletic Boots Slippers Flats Sandals view all...
Sandals · Women's Shoes · Sneakers & Athletic Shoes · Popular Men's Shoe Styles
Shop on Google
Sponsored
Adidas NEO Baseline Women's Blcast-Leather Sneakers, Size: 8, White
$34.99 - Kohl's

ML Dream

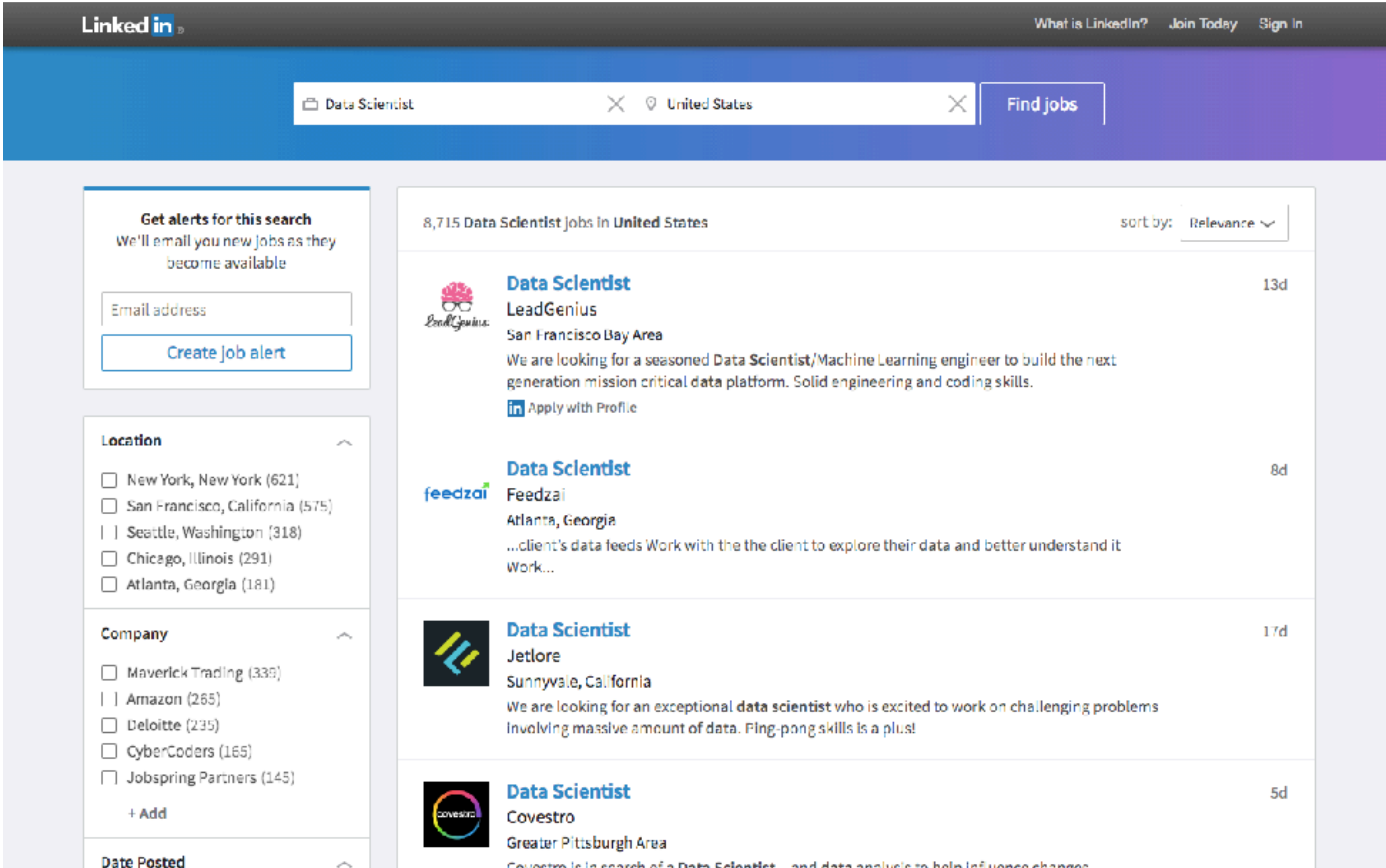
What product you would like…



What news would you prefer to read…

ML Dream

Find the best job for you…



ML Dream

- For every user predict: Ads, products, news, ...
- Have tons of data to learn this task well
- Have right models that can learn from all this data

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With Big Data comes Bigger Responsibilities …

Is ML Fair, Impartial?

Google

Women less likely to be shown ads for high-paid jobs on Google, study shows

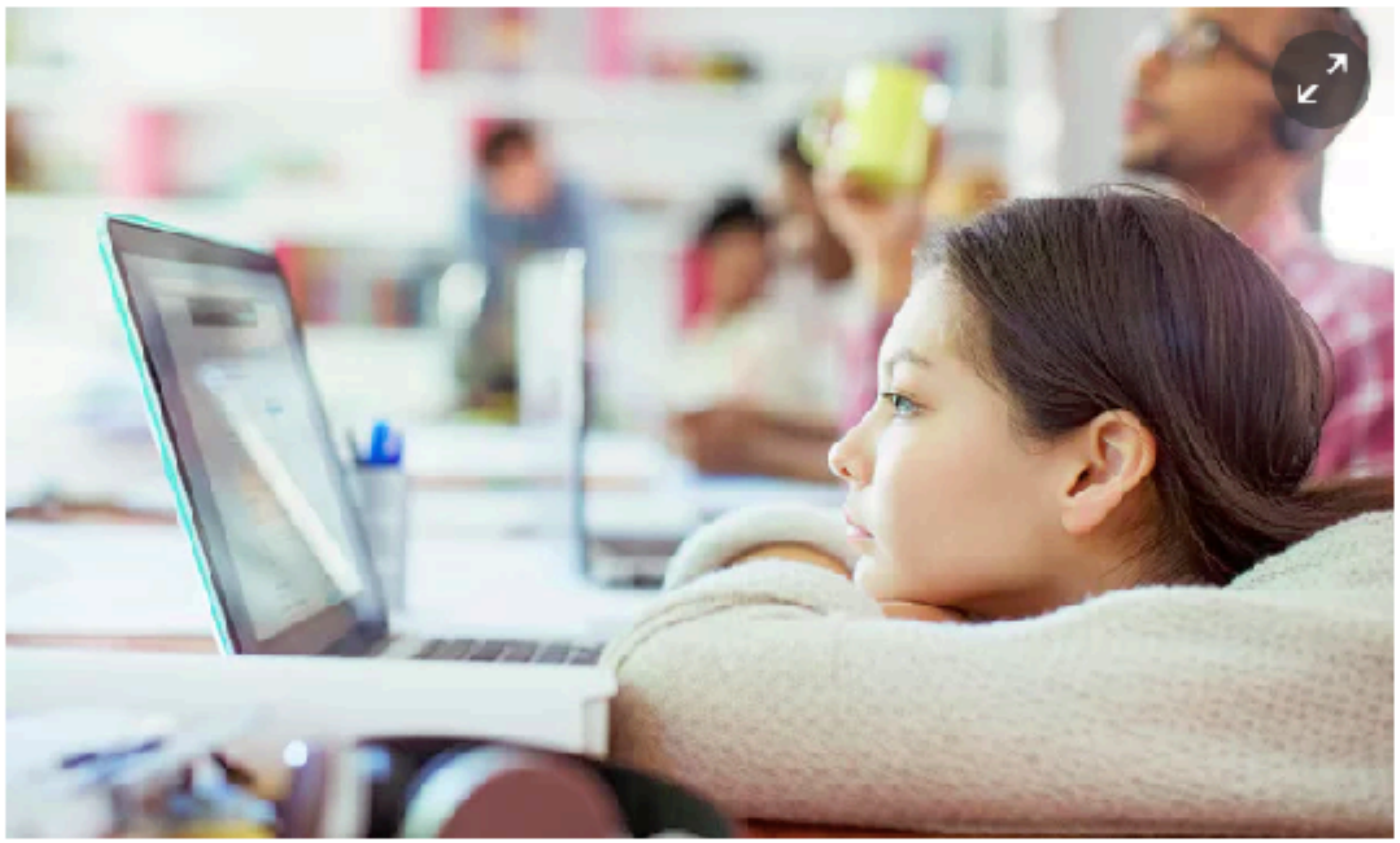
Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs

Samuel Gibbs

Wednesday 8 July 2015
06.29 EDT

This article is 1 year old

1120 140



One experiment showed that Google displayed adverts for a career coaching service for executive jobs 1,852 times to the male group and only 318 times to the female group. Photograph: Alamy

Female job seekers are much less likely to be shown adverts on Google for highly paid jobs than men, researchers have found.

Is ML Fair, Impartial?

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

WHY NOW?

Why Now?

Loads of data collected everywhere!

Why Now?

galvanize

Startup.ML

coursera

METIS

datascience@berkeley

The Data Incubator

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METIS

Raise in number of Data Scientists!

Why is ML Unfair?

the algorithms in themselves are neutral. "This program had absolutely nothing to do with race... but multi-variable equations,"

Why is ML Unfair?

- Data collection, labeling etc. can have unintentional biases
  - We learn from past data, historic biases
- Data in itself nor algorithms explicitly know of social inequities

Fairness Through Blindness?

- Ignore all protected attributes.

  Eg. Don't look at race, gender etc.

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- Problem: You don't need to look to be able to predict

  Eg. User visits "www.artofmanliness.com"

  ...highly likely to be male

Eg. Real Vs Fake Names

- Biases are often not intentional . . .

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- Most training examples standard white American names: James, John, Robert, Jennifer, Michael, …
- Ethnic names often unique, much fewer training examples

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Most ML models aim for accuracy for the majority at the expense of mistakes on the smaller protected class

Fairness Through Awareness

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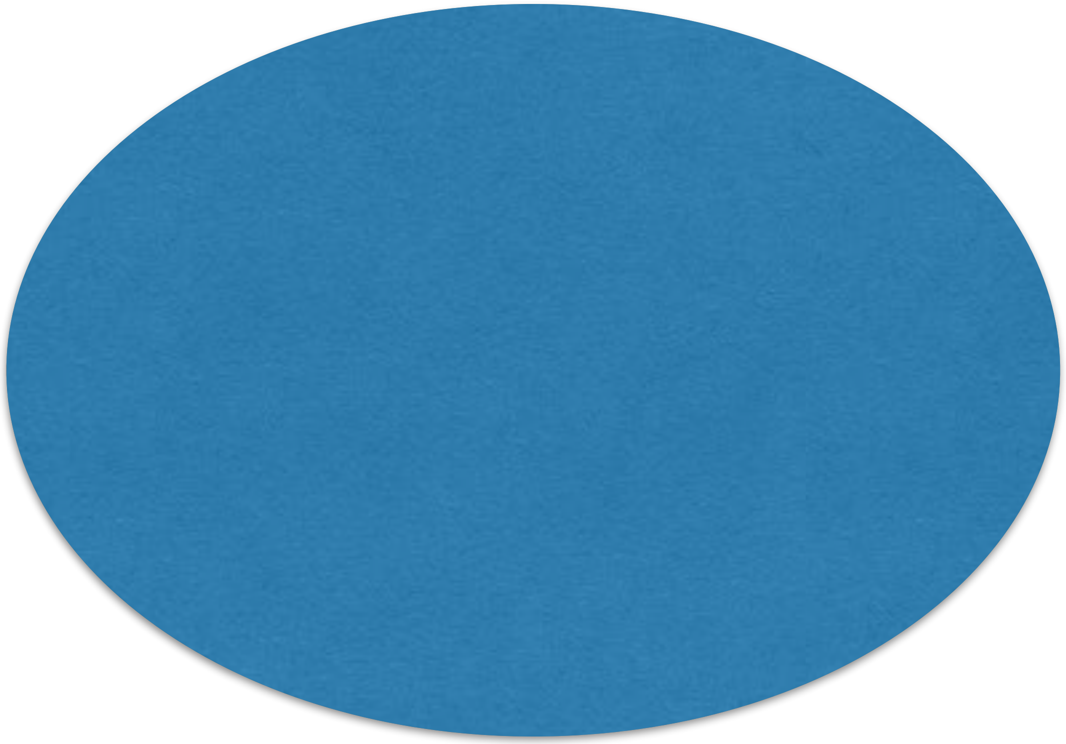
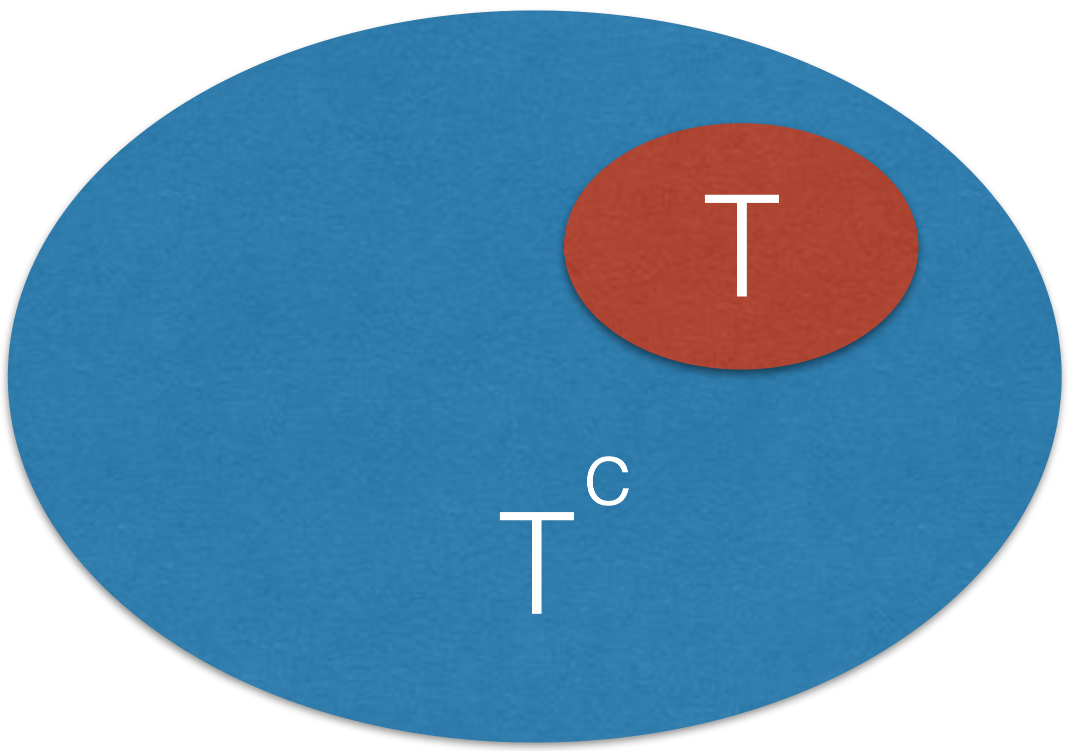


Population

Fairness Through Awareness



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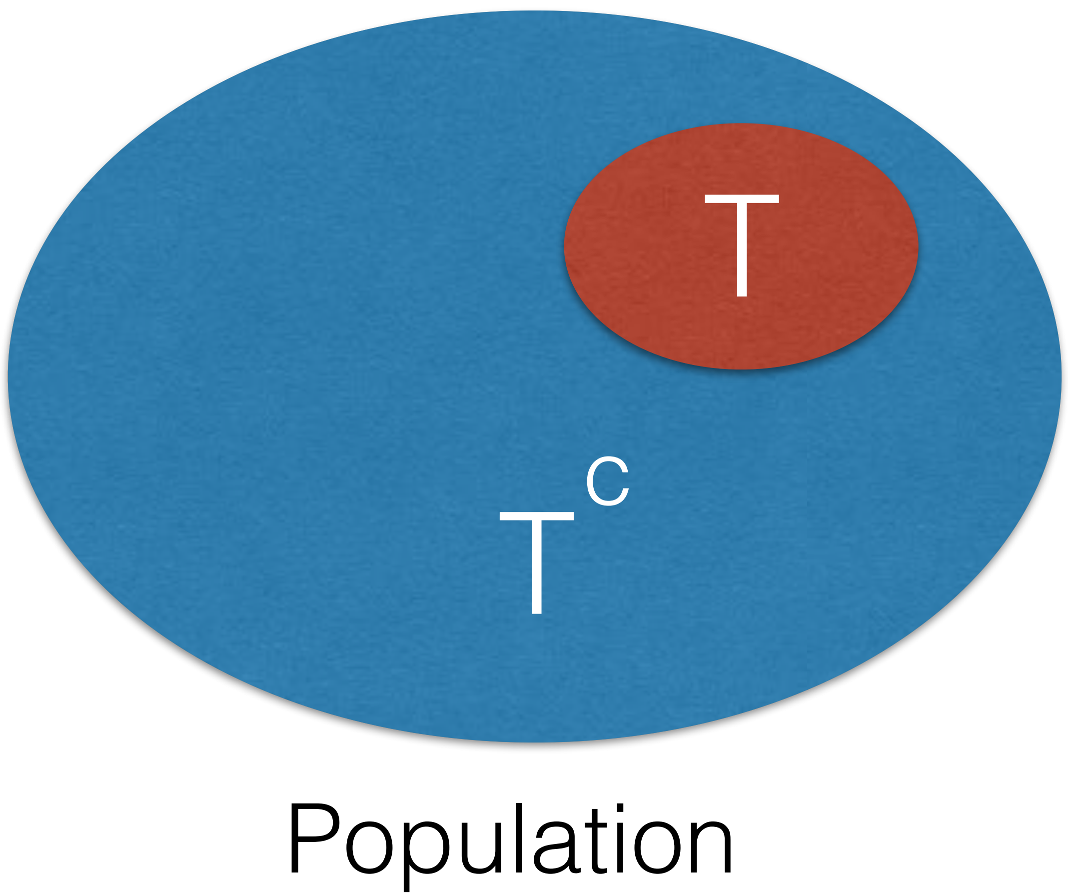

T : Protected subset

T^c : Rest of the population

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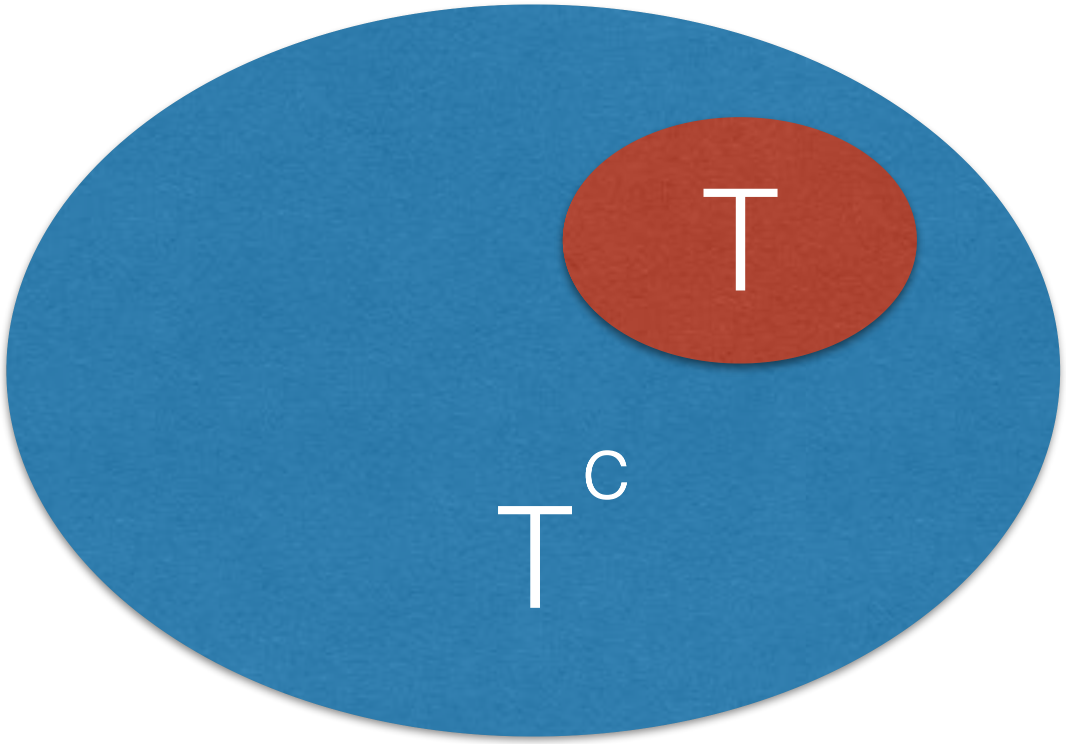


Population

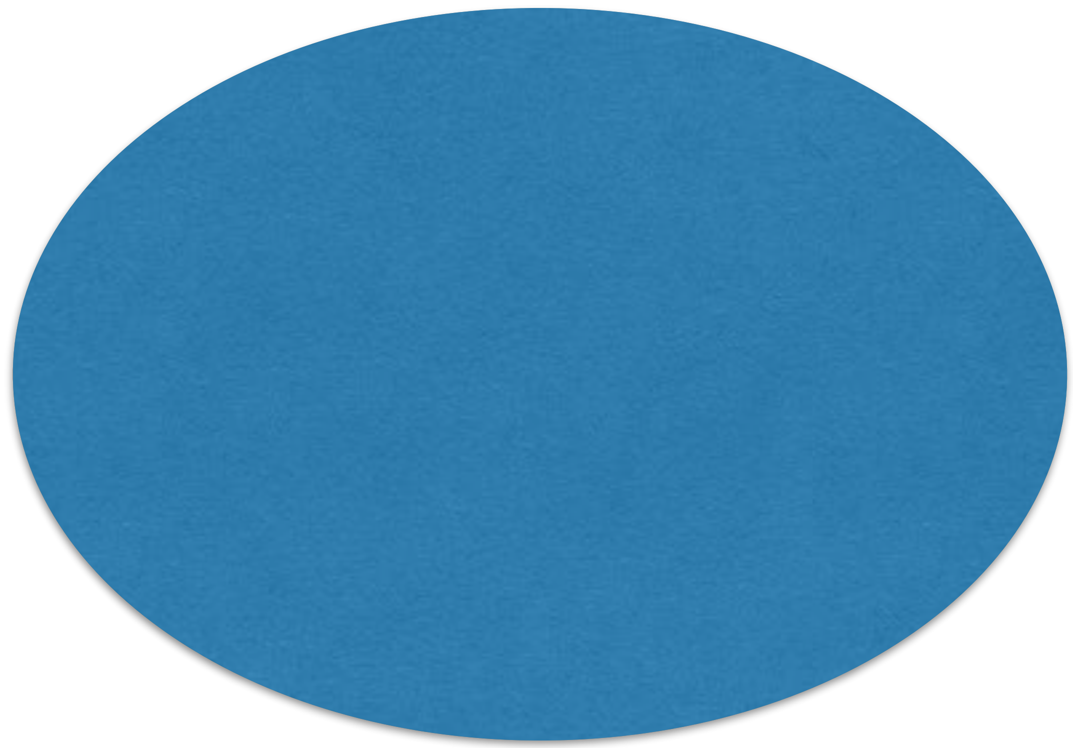
T : Protected subset

T^c : Rest of the population

$$P(\text{Outcome}|T) \approx P(\text{Outcome}|T^c)$$

Eg. Fraction of people shown high paying jobs in T and in T^c is equal

Fairness Through Awareness



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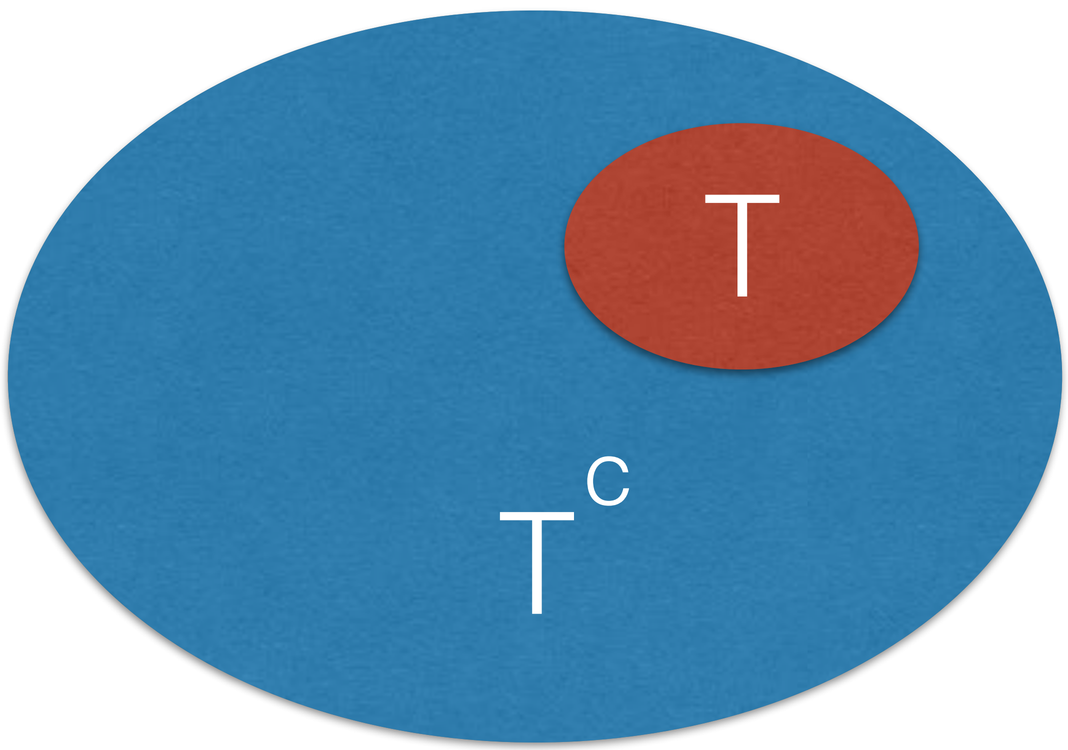

Population

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Eg. Fair K-means Clustering (very naive)

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$$\text{Objective} = \sum_{j=1}^{K} \sum_{t \in C_j} \left\| \mathbf{x}_t - \mathbf{r}_j \right\|_2^2$$

$$\text{where } \mathbf{r}_j = \frac{1}{|C_j|} \sum_{\mathbf{x}_t \in C_j} \mathbf{x}_t$$

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Number of protected in cluster j = Number of unprotected in cluster j

Fair Classification

A view from a mile above:

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Minimize Classification objective
(or whatever other surrogate loss you use usually)

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NOT REALLY FAIR!

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Added Constraint: subject to proportion of labels for **similar instances** in each class being same for protected and unprotected population

Its not always about fairness
There are other issues too!

What news would user prefer to read…

ML Dream

- Just because we can predict, should we?

ML DREAM

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- Say we have a fair, unbiased algorithm for prediction

ML Dream

- Just because we can predict, should we?
- Say we have a fair, unbiased algorithm for prediction
- Can there be other issues?

Extremizing Effect of ML

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User 1

User 2

Extremizing Effect of ML

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Apples are extremely rich in important antioxidants, flavanoids, and dietary fiber. The phytonutrients and antioxidants in **apples** may help reduce the risk of developing cancer, hypertension, diabetes, and heart

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But a very important one …

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- Another issue: ML methods are complex and we don't understand semantic meaning
- We need transparency of method for accountability
- Transparency via interpretability.
    - Provide explanation for each decision
    - What makes an instance a negative instance according to the algorithm

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conference
November 16-19th
Columbia University
New York City

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Time for General Questions