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Disparate Impact of Artificial Intelligence Bias in Ridehailing Economy's Price Discrimination Algorithms

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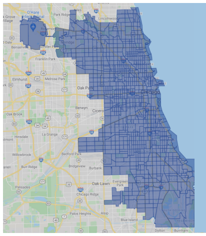
The City of Chicago releases transportation datasets including ridehailing that uses price discrimination algorithms for individualized price estimations

- We process 100 million ridehailing trips
- Each trip contains pickup and dropoff census tract information, fare pricing, duration, length, etc.
- We enhance the dataset with population survey statistics based on census tracts.

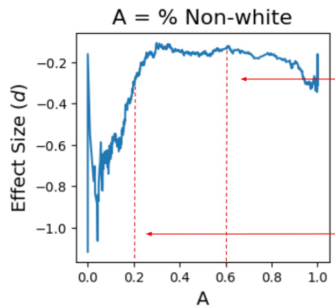


Census tracts in the city of Chicago:
American Community Survey provides statistics for each census tract regarding race, age, gender, education, income level, citizenship, house prices, etc. in the neighborhood.

Research Questions

- **Price discrimination is a type of predictive artificial intelligence (AI) algorithm.**
- **Does algorithmic bias manifest in fare pricing?**
- **What if disadvantaged neighborhoods have less supply relative to demand?**

Black box price discrimination algorithms in ridehailing estimate fare pricing based on supply, demand, duration, and length of the trip, in addition to other factors.



When A=0.60, the effect size is approximately -0.15

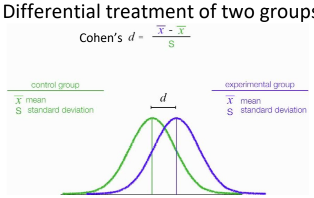
This means that neighborhoods with a non-white population ≤ 60% have a fare price approximately 0.15 standard deviations lower than neighborhoods with a non-white population > 60%

When A=0.20, the effect size is approximately -0.30

This means that neighborhoods with a non-white population ≤ 20% have a fare price approximately 0.30 standard deviations lower than neighborhoods with a non-white population > 20%

Method-1a: Effect size of bias

Differential treatment of two groups



Method-1b: Random-effects modeling from meta-analysis

Combining effect size of bias at the city level

$$ces(X,Y) = \frac{\sum_{t=[t_{min} \dots t_{max}]} d(X,Y,t) \times w(X,Y,t)}{\sum_{t=[t_{min} \dots t_{max}]} w(X,Y,t)} \quad (1)$$

$$d(X,Y,t) = \frac{\overline{Y}_{x_{t-}} - \overline{Y}_{x_{t+}}}{\sigma(Y)}$$

$$w(X,Y,t) = \frac{1}{var(X,Y) + var_t(X,Y,t)}$$

$$var(X,Y) = \underset{t=[t_{min} \dots t_{max}]}{\sigma^2}[d(X,Y,t)]$$

$$var_t(X,Y,t) = \frac{|X_{t-}| + |X_{t+}|}{|X_{t-}||X_{t+}|} + \frac{d(X,Y,t)}{2(|X_{t-}| + |X_{t+}| - 2)} \times \left(\frac{|X_{t-}| + |X_{t+}|}{|X_{t-}| + |X_{t+}| - 2}\right)$$

Results

Attribute	Ridehailing Fare Price/Mile: Pickup Combined Effect Size (d)	Pickup p	Dropoff Combined Effect Size (d)	Dropoff p	Taxi Fare Price/Mile: Pickup Combined Effect Size (d)	Pickup p	Dropoff Combined Effect Size (d)	Dropoff p
Pickup Frequency / m^2	-1.57	$< 10^{-3}$	-1.59	$< 10^{-3}$	0.24	0.04	-0.96	$< 10^{-3}$
Dropoff Frequency / m^2	-1.57	$< 10^{-3}$	-1.57	$< 10^{-3}$	-0.15	0.21	-0.88	$< 10^{-3}$
% Non-white	-0.22	0.02	-0.32	$< 10^{-3}$	0.18	0.11	0.07	0.50
% Older than 40	0.66	$< 10^{-3}$	0.69	$< 10^{-3}$	-0.04	0.72	0.52	$< 10^{-3}$
% High School education or less	0.24	0.01	0.15	0.17	0.05	0.65	0.41	$< 10^{-3}$
% Below Poverty Line	-0.19	0.05	-0.28	$< 10^{-3}$	0.01	0.94	0.05	0.59
% Non-U.S. Citizens	-0.10	0.35	-0.07	0.54	-0.02	0.83	0.04	0.71
% Below Median House Price	0.23	0.02	0.19	0.06	0.02	0.85	0.32	$< 10^{-3}$

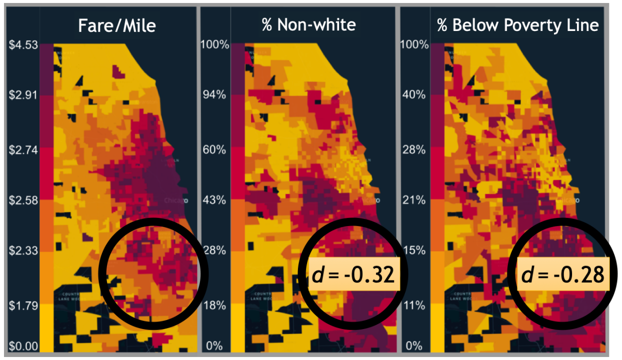
Table 1: Combined effect sizes on fare price per mile by neighborhood attributes - Combined effect sizes scores are shown for the fare price per mile given a set of neighborhood attributes. Combined effect sizes are weighted using a random effects model [11]. The "Ridehailing" column contains combined effect sizes calculated for ridehailing trip fares, and the "Taxi" column contains combined effect sizes calculated for "Taxi" trip fares. "Pickup" and "Dropoff" columns designate fare price per mile when being picked up or dropped of in a neighborhood and "p" presents the p-value for effect size calculations.

Results

Attribute	Ridehailing Trip Frequency / m^2: Pickup Combined Effect Size (d)	Pickup p	Dropoff Combined Effect Size (d)	Dropoff p	Ridehailing Trip Seconds/Mile: Pickup Combined Effect Size (d)	Pickup p	Dropoff Combined Effect Size (d)	Dropoff p
% Non-white	0.25	$< 10^{-3}$	0.23	$< 10^{-3}$	-0.14	0.17	-0.31	$< 10^{-3}$
% Older than 40	0.38	$< 10^{-3}$	0.38	$< 10^{-3}$	0.67	$< 10^{-3}$	0.70	$< 10^{-3}$
% High School Education or less	0.69	$< 10^{-3}$	0.69	$< 10^{-3}$	0.20	0.05	0.08	0.43
% Below Poverty Line	0.27	$< 10^{-3}$	0.26	$< 10^{-3}$	-0.13	0.19	-0.25	$< 10^{-3}$
% Non-U.S. Citizens	-0.09	0.21	-0.11	0.13	-0.21	0.02	-0.11	0.32
% Below Median House Price	0.42	$< 10^{-3}$	0.43	$< 10^{-3}$	0.30	$< 10^{-3}$	0.17	0.08

Table 2: Combined effect sizes on trip frequency and trip seconds per mile by neighborhood attributes - combined effect sizes are shown given a set of neighborhood attributes. The "Ridehailing Trip Frequency / m^2" column contains combined effect sizes of neighborhood demographic attributes on the frequency of trips in a neighborhood, and the "Ridehailing Trip Seconds/Mile" column contains combined effect sizes measuring the effect size of neighborhood attributes on the time taken per mile for trips in a neighborhood. "Pickup" and "Dropoff" columns designate frequency and trip time when being picked up or dropped of in a neighborhood and "p" presents the p-value for effect size calculations.

Ridehailing in Chicago: Disparate impact of price discrimination algorithms



Conclusion

- Higher fare pricing in neighborhoods with more residents that are non-white and live below the poverty line cannot be explained with demand.
- Neighborhoods with larger non-white populations, higher poverty levels, younger residents, and high education levels are significantly associated with higher fare prices, with combined effect sizes, measured in Cohen's *d*, of -0.32, -0.28, 0.69, and 0.24 for each demographic.
- Our methods hold promise for identifying and addressing the sources of disparate impact in AI algorithms learning from datasets that contain U.S. geolocations.

Do monetary incentives that pull supply from minority and impoverished neighborhoods manipulate traffic and cause disadvantaged neighborhoods to surge?

- This image displays an anonymous driver's view when driving for Uber.
- Blue areas with bonuses listed on them (e.g. "15 for 3") are boost zones, where drivers are incentivized to receive bonuses when they complete rides.
- Red areas are in surge, meaning that low supply of drivers in these areas might have resulted in relatively high demand, which in turn could cause prices to rise in the area.