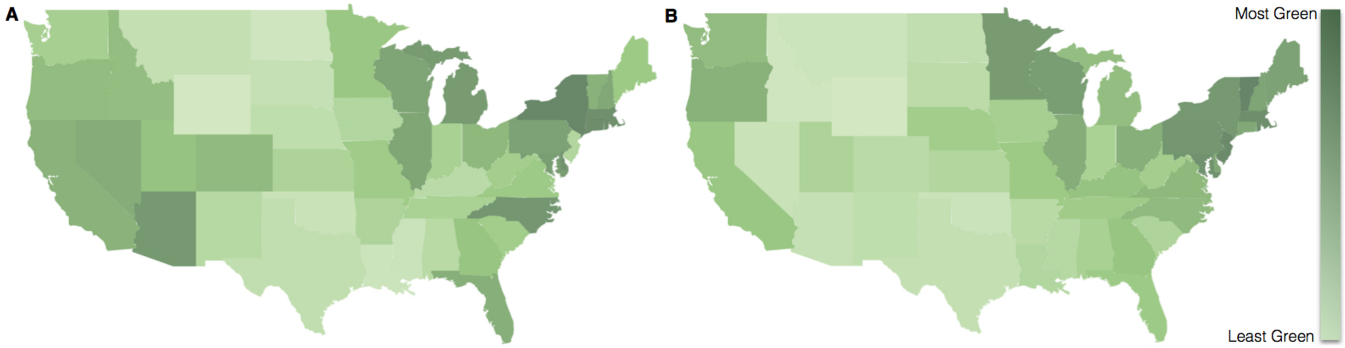

Figure 5: (A) A map ranking each state's carbon footprint from the transportation sector in 2012 using data from (?). (B) A map ranking each state's average miles per gallon (MPG) calculated from car attributes detected from Google Street View. We measure a Pearson correlation coefficient of -0.66 between 2012 state level carbon footprint from the transportation sector and our calculated state average MPGs. Both maps show that coastal states are greener than inland ones.

as Chicago's and exhibits little clustering of expensive and cheap cars. As shown in Fig. 4B and Fig. 4C, Chicago's clusters of expensive and cheap cars fall in high and low income neighborhoods respectively. Our results agree with findings from the Martin Prosperity Institute (?), ranking Chicago, IL and Philadelphia, PA among the most segregated and Jacksonville, FL among the least segregated American cities. Our segregation analysis suggests that we can train a model to accurately predict a region's income level from the properties of its cars. To this end we first represent each zip code by an 88 dimensional vector comprising of car-related attributes such as the average MPG, the percentage of each body type, the average car price and the percentage of each car make in the zip code. We then use 18% of our data to train a ridge regression model (?) predicting median household income from car features. Remarkably, our model achieves a city level correlation of r=0.82 and a zip code level correlation of r=0.70 with ground truth income data obtained from ACS (?) ($p<1e-7$).

Investigating the relationship between income and individual car attributes shows a high correlation between median household income and the average car price in a zip code (r=0.44, $p << 0.001$). As expected, wealthy people drive expensive cars. Perhaps surprisingly however, we found the most positively correlated car attribute with income to be the percentage of foreign manufactured cars (r=0.47). In agreement with our results, Experian Automotive's 2011 ranking shows that all of the top 10 car models preferred by wealthy individuals were foreign, even when the car itself was comparatively cheap (e.g. Honda Accord or Toyota Camry) (?). Following the same procedure, we predict burglary rates for cities in our test set and achieve a pearson correlation of 0.61 with ground truth data obtained from (?). While one of the best indicators of crime is the percentage of vans (r=0.30 for total crime against people and properties), the single best predictor of unsafe zip codes is the number of cars per image (r=0.31 and r=0.36 for crimes against people and properties respectively). According to studies conducted by law enforcement, many crimes are committed in areas with a high density of cars such as parking lots (?), and some departments are helping design neighborhoods with a lower number of parked cars on the street in order to reduce crime (?).

Conclusion

Through our analysis of 50 million images across 200 cities, we have shown that cars detected from Google Street View images contain predictive information about our neighborhoods, cities and their demographic makeup. To facilitate this work, we have collected the largest and most challenging fine-grained dataset reported to date and used it to train an ultra large scale car detection model. Using our system and a single source of visual data, we have predicted income levels, crime rates, pollution levels and gained insights into the relationship between cars and people. In contrast to our automated method which quickly determines these variables, this data is traditionally collected through costly and labor intensive surveys conducted over multiple years. And while our method uses a single source of publicly available images, socioeconomic, crime, pollution, and car related market research data are collected by disparate organizations who keep the information for private use. Our approach, coupled with the increasing proliferation of Street View and satellite imagery has the potential to enable close to real time census prediction in the future—augmenting or supplanting survey based methods of demographic data collection in the US. Our future work will investigate predicting other demographic variables such as race, education levels and voting patterns using the same methodology.

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