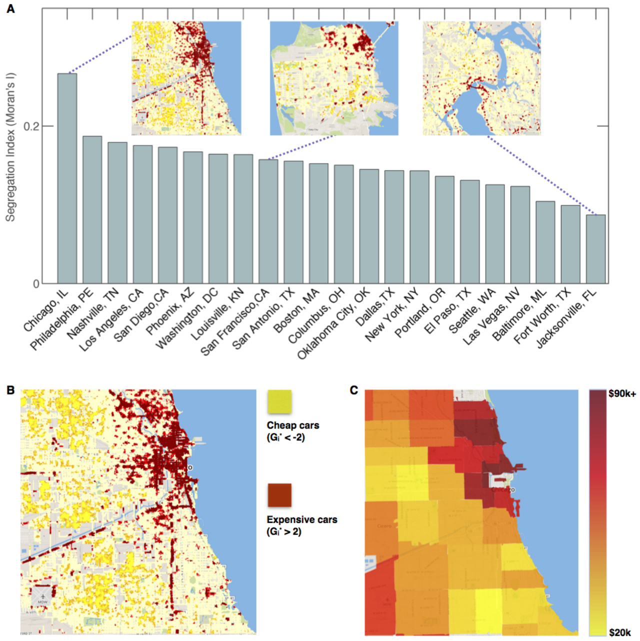

Figure 4: (A) Twenty two major American cities ranked by segregation of car price. Our segregation index is Moran's I statistic (**?**). Insets show maps of statistically significant clusters of cars with high prices (red), low prices (yellow) as well as no statistically significant clustering (white) for the cities of Chicago, IL, San Francisco, CA and Jacksonville, FL respectively using the Getis-Ord Gi statistic (**?**). Chicago has large clusters of expensive and cheap cars whereas Jacksonville shows almost no clustering of cars by price. (B) Expensive/Cheap clusters of cars in Chicago. (C) Zip code level median household income in Chicago. Large clusters of expensive cars are in wealthy neighborhoods whereas large clusters of cheap cars are in unwealthy neighborhoods.

tributes across all images in each city. The average number of instances of a particular car in a region is the sum of the expected number of instances of that car across all images in the region. Thus, computing the average number of cars with a particular attribute in a city (or zip code) consists of calculating this expectation for each image in the region and aggregating this value over all images in the city (or zip code).

With I an image and c one of the 2,657 classes, we calculate the expected number of cars of type c in a single image as

$$\mathbb{E}[\#\text{class}\, c|I] = \sum_{\text{bbox}\, b} P(\text{car}|b, I) P(\text{class}\, c|\text{car}, b, I) \quad (2)$$

where bbox b is the set of all detected car bounding boxes in the city (or zip code), $P(\text{car}|b, I)$ is the probability of a bounding box containg a car (determined by our detection system) and $P(\text{class}\, c|\text{car}, b, I)$ corresponds to the conditional probabilities output by the softmax layer of our CNN classifier.

To obtain the expected value of a particular car attribute, e.g. the percentage of Hummers in a region, we aggregate category level expectations for all classes whose make is Hummer. We follow this setup in all other experiments, and note that a similar procedure can be used to find expected values for any other car attribute, including car price, miles per gallon, and country of origin.

To estimate the accuracy of our city-level car attribute predictions, we compared the distribution of cars we detect in Street View images with the distribution of registered cars in Boston, Worcester and Springfield, MA (the three Massachusetts cities in our dataset). We perform this comparison using records from Massachusetts DMV, the only state to publicly release extensive vehicle registration data (**?**). We measured the Pearson correlation coefficient between each detected and registered make's distribution across zip codes. Twenty five of the top thirty makes have a Pearson's r correlation of r>0.5. Beyond Massachusetts, we measure the correlation between our detected car make distribution and the 2011 national distribution of car makes as r=0.97, verifying the efficacy of our approach.

Car attributes can reveal aspects of a city's character that are not directly car-related. For example, our measurements show Burlington, Vermont to be the greenest city, with the highest average miles per gallon (MPG) of any city in our dataset (average MPG=25.34). Burlington is also the first city in the United States to be powered by 100% renewable energy (**?**). In contrast, we measured the lowest average MPG for Casper, WY (average MPG=21.28). Wyoming is the highest coal-mining state in the US, producing 39 percent of the nation's coal in 2012 and emitting the highest rate of CO_2 per person in the country (**?**). We aggregate these city-level statistics by state to discover patterns across the country. For example, by mapping our detected average MPG for each state in Fig. 5, we can see that coastal states are greener than inland ones, a finding that agrees with published carbon footprints (**?**) (r=-0.66 between our calculated MPG and carbon footprints).

Income and Crime We can compare cities' income-based segregation levels using our car detections. After calculating the average car price for each GPS point, we measure the level of clustering between similarly priced cars using Moran's I statistic (**?**) defined as

$$I = \frac{N \sum_{i,j} w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i,j} w_{i,j} \sum_i (x_i - \bar{x})^2} \quad (3)$$

where each x_i is a distinct GPS point, $\bar{x}$ is the average of x and $w_{i,j}$ is a weight describing the similarity between points i and j. We use the squared inverse Euclidean distance as a similarity metric. Moran's I of 1, -1 and 0 indicate total segregation, no segregation and a random pattern of segregation respectively. To gain further insight we visualize statistically significant clusters of expensive and cheap cars using the Getis-Ord statistic, a more local measure of spatial autocorrelation (**?**; **?**). Fig. 4 shows our results for 22 cities with dense GPS sampling.

Chicago is the most segregated city, with two large clusters of expensive and cheap cars on the West and East side of the city respectively. Conversely, Jacksonville is the

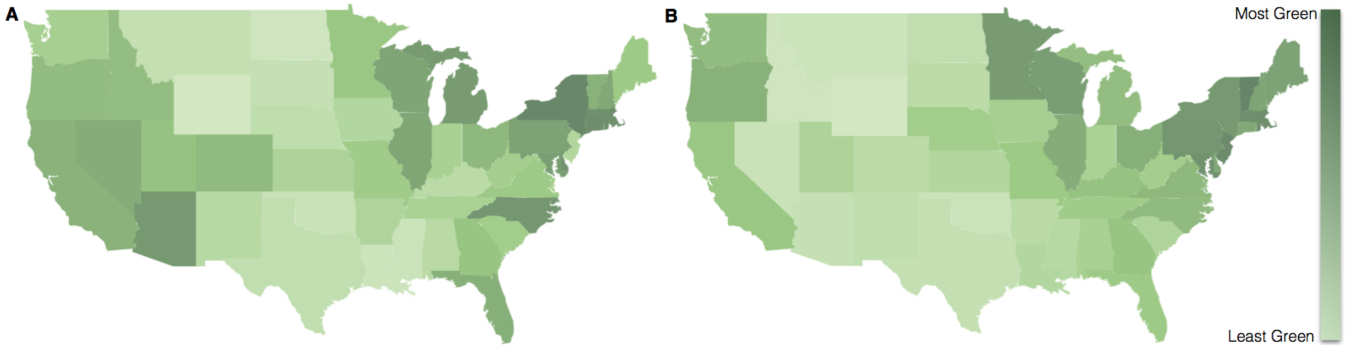

Figure 5: (A) A map ranking each state's carbon footprint from the transportation sector in 2012 using data from (?). (B) A map ranking each state's average miles per gallon (MPG) calculated from car attributes detected from Google Street View. We measure a Pearson correlation coefficient of -0.66 between 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.

least segregated city with a Morans I only 33% as large 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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