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Street-level: Google Street View's abstraction by datafication

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Abstract
While aerial photography is associated with vertical objectivity and spatial abstractions, street-level imagery appears less political in its orientation to the particularities of place. I contest this assumption, showing how the aggregation of street-level imagery into "big datasets" allows for the algorithmic sorting of places by their street-level visual qualities. This occurs through an abstraction by "datafication," inscribing new power geometries onto urban places through algorithmic linkages between visual environmental qualities, geographic information, and valuations of social worth and risk. Though largely missing from media studies of Google Street View, similar issues have been raised in critiques of criminological theories that use place as a proxy for risk. Comparing the Broken Windows theory of criminogenesis with big data applications of street-level imagery informs a critical media studies approach to Google Street View. The final section of this article suggests alternative theoretical orientations for algorithm design that avoid the pitfalls of essentialist equations of place with social character.

Keywords
Algorithm, big data, Broken Windows theory, computer vision, criminogenesis, geoweb, Google Street View, social sorting

Introduction

Street-level imagery platforms like Google Street View have received relatively little attention in the media studies literature. Compared with aerial imaging and "earth-observing

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media," including remote sensing technologies, satellite photography, and drone imaging (Dodge and Perkins, 2009; Parks and Schwoch, 2012; Russill, 2013), street-level imagery seems free of the power geometries that attend the synoptic abstraction of space by vertical perspective (Cosgrove, 2001; Lefebvre 1992; Massey, 1993). Whereas aerial imaging and its vertical gaze provide a disengaged "view from nowhere" of the earth's surface and the array of human activities that take place there (civilian and military, urban and infrastructural, natural and meteorological, etc.), street-level imagery is always explicitly grounded in a *somewhere*; its emphasis on the particularities of place rather than cartographic abstractions of space makes it seem progressive, absolved from the visual-semiotics of scientific rationality or objectivity—at least as described by theorists such as De Certeau (1984), Haraway (1988), or Scott (1998) (Shapiro, 2016).

How, then, do we make sense of Google's ambitions to "captur[e] the world at street-level" (Anguelov et al., 2010)? Despite a dearth of information about the role that Street View plays in the coordination of everyday life (Lapenta, 2011), there is a wealth of academic literature on Street View as a methodological utility for the social sciences. Articles from criminology, public health and epidemiology, and urban sociology (e.g. Clarke et al., 2010; Curtis et al., 2013; Vandeviver, 2014) highlight how Street View imagery can be used to conduct "virtual audits" of neighborhoods, enhancing and extending methods for studying urban populations through evaluations of the places where they live, work, eat, and play—remotely and at no-cost (Clarke et al., 2010). Vandeviver (2014), for example, suggests that Street View can allow "environmental criminologists to collect data on the physical environment, often in a cost- and time-efficient manner" (p. 6). Such applications mesh well with Google's own visions for the platform, signaling an alignment of interests between the new media corporation *par excellence* and social scientific knowledge production practices that should prompt critical scrutiny (Lazarsfeld, 1941). If "Google's mission is to organize the world's information and make it universally accessible and useful, and this type of street-level imagery contains a huge amount of information" (Anguelov et al., 2010: 1), then what is this "huge amount of information," how are different actors making use of it, and how does this affect the communities who live in the places represented in Street View? (p. 1).

This article reviews two case studies in which computer scientists at elite institutions mobilize Street View imagery to make claims about geographies of social worth and risk. Though street-level imagery is typically seen as inherently less abstracting than aerial imaging, these case studies illustrate how the street-level can be implicated in the social sorting of populations by place (Graham, 2005; Lyon, 2003). In these examples, it is not only the visual richness of street-level imagery that makes it valuable, but also its amenability to aggregation: Street View imagery can be easily aggregated into massive, geocoded, image datasets and analyzed with advanced algorithmic and machine learning techniques. Through this processing, individual images of places can be transformed into "big data," with all its emphasis on the data mining of actionable, "non-obvious" correlations between disparate phenomena (Andrejevic and Gates, 2014: 186). Not only can algorithms be trained on datasets of geotagged place-images to identify visual features (such as a car, a pedestrian, a building, etc., Quercia et al., 2014), but because the digital imagery is coded with locational metadata, algorithms can also be applied to discern features that are statistically discriminative for geographic information (e.g. what visible features do areas with high real estate values share in common?). Applied to street-level imagery, these analytics have the intended potential to "software-sort" urban geographies according to their visual features (Graham, 2005). This threatens to further entrench of uneven geographies of social worth and risk, and should therefore prompt questions about objectivity, cultural authority, and inequality not typically associated with street-level imagery.

Attention to this dynamic is largely absent from the media and visual studies literature on Google Street View. Where the objectivity and cultural authority of place-images have received attention, however, is within criminological literature. Criminological theory and policing praxis share a long history of using visual environmental cues at the neighborhood-level as a proxy for mapping geographies of social deviance and criminality (Kindynis, 2014). Kelling and Wilson's (1982) Broken Windows theory represents the most popular and concise articulation of this lineage. It focuses on the role that social and physical "disorderliness" play in constituting environments conducive to crime. Despite serious concerns raised about the Broken Windows theory's normative and essentialist social esthetics around "disorderliness" (Garland, 2001; Harcourt, 1998, 2001), it nonetheless remains prominent as a strategy in preventive policing (e.g. Bredderman, 2016), as well as a theoretical resource for criminologists and other social scientists seeking to understand how place interacts with risk and worth (e.g. Lilly et al., 2010).

Insofar as the case studies presented here share a number of epistemological and ontological premises with Broken Windows, critiques of Broken Windows can serve as a valuable starting point for a more critical perspective on street-level imagery platforms like Google Street View. The juxtaposition of something as "new" as big data with something as "old" as the Broken Windows theory (Boellstorff, 2013) works to historicize new media, creating "a possibility to learn from existing critical approaches and to develop new ones with the promise of better informed research, critique, and resistance involving big data" (Dalton and Thatcher, 2015: 2).[1] Critiques of Broken Windows are instructive not only for understanding the cases at hand, but also for garnering attention to a latent potential within street-level imagery and other virtual mapping platforms. From this perspective, the street-level ceases to be a progressive antidote to the spatial abstractions of aerial imaging, but instead has its own set of power geometries, stemming not from the abstraction of vertical perspective but from abstraction by "datafication" (Van Dijck, 2014).

Street-level imagery

As isolated photographs, street-level images differ both qualitatively and quantitatively from the synoptic view of "earth observing media" like Google Earth (Russill, 2013). A randomly generated Street View image (see Figure 1) places you at a bus stop on the busy Akademika Hlushkova Avenue. You know the street name because it is inscribed onto the image in parallel with the street's direction. You can see the people waiting at the bus stop, although their faces are blurred (Rakower, 2012). You can see a Coca-Cola billboard and street signage in the mid-ground, and you can locate yourself in Kiev, Ukraine, with the aid of a small Google Map in the top-left corner. Compare this with a

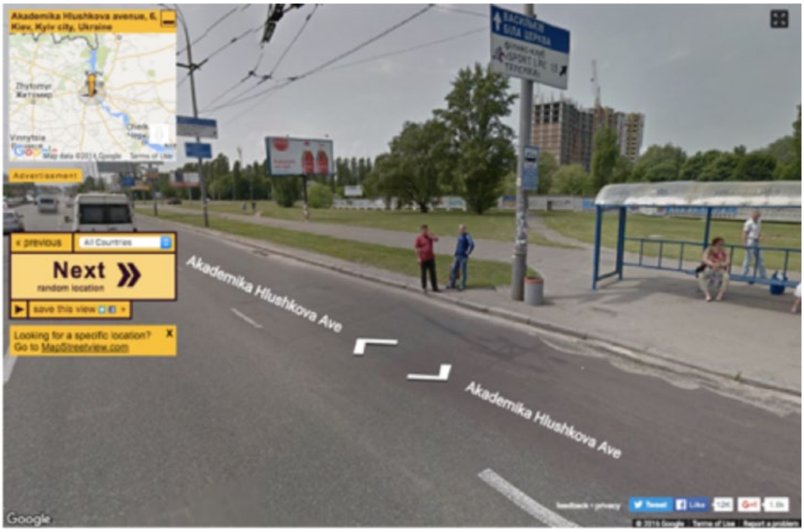

Figure 1. Randomly generated Street View image.
Source: www.randomstreetview.com

satellite view of Kiev (Figure 2). On the one hand, the street-level image reveals more visual information: you get a general sense of what the people of Kiev look like, what they wear and, from this, know something about the temperature and weather (at least on the day the image was captured), how many lanes are on this busy road, and a building under construction in the background. On the other hand, the satellite image conveys the urban footprint and land use patterns, and where this spot along Akademika Hlushkova Avenue falls within the city. Each perspective has its affordances and constraints: the rich visual detail of the street-level image against the abstraction of space by aerial view.

Using Street View in practice entails a lot of this toggling back and forth between the aerial and the street-level—between the global and the "hyperlocal." Dalton (2013) describes such toggling as a "way of seeing [that] illustrates the power of connecting highly local events within a standardized, global geographic scheme" (p. 264). Street View uses omnidirectional, street-level place-imagery, captured by roving fleets of "Google cars" mounted with specialized cameras from over 5 million miles of roads, across 39 countries and over 3000 cities (Farber, 2012). Its "Photo Spheres" are stitched together to create an immersive experience, imparting a sense of navigability into the image (Anguelov et al., 2010) as users "seamlessly move from one image into another in a virtual continuum of increasingly global spatial representations of the world" (Lapenta, 2011: 14). "Virtual explorers" on Street View (McClendon, 2010) can toggle the camera perspective, zoom in and out, and move up and down a street, as the "mechanically divided images of the world are digitally reunited in the virtual map, geolocationally pinned down … juxtaposed and merged as the jigsaw pieces of an intricate puzzle" (Lapenta, 2011: 17). In the words of former Google Maps vice president (VP) Brian McClendon (2010), Street View represents the "last zoom layer on the map," "a virtual

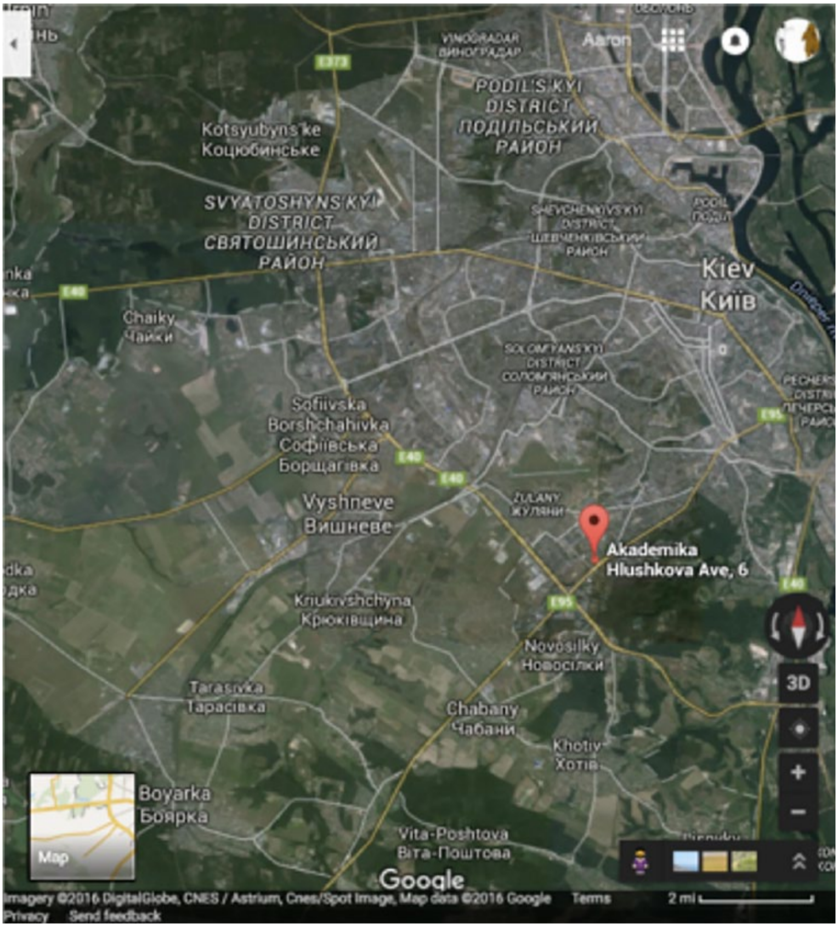

Figure 2. Google Maps satellite view of Kiev, Ukraine.
Source: Google Maps.

reflection of the real world," and "a way to show you what a place looks like as if you were there in person."

Most of the academic literature focusing on Street View as a media object (as opposed to a methodological tool) comes from visual studies. This research focuses most intently on the immersive experience of the Street View image, even as it highlights some of the social implications of virtual mapping—particularly, the mediation between the viewing subject, the object, and spatial articulation. Pink (2011) uses Street View and its "phenomenological" affordances as a way to rethink the relationship between movement and the image; its virtual navigability is "the outcome of a moving digital camera on its way through an environment, that represents a route through, and indeed that becomes a component of, an environment" (p. 11). Uricchio (2011) discusses the techniques used in the construction of Street View as "new ways of representing and seeing the world [which are] dependent on algorithmic interventions between the viewing subject and the object viewed" (p. 25). Lapenta (2011) describes Street View and other "geomedia" as "social navigation systems," "adopted by the individual to reduce the complexity of global information systems to individually manageable and socially relevant information exchanges" (p. 21).

Unlike the visual studies literature, media studies research into Street View has focused less on the implications of such mediation than on the politics of representation. Power et al.'s (2012) study of a stigmatized Irish housing estate and its omission from the Street View platform is exemplary. Missing from this literature, however, are discussions of the datafication of street-level imagery, the abstractions that this enables, and the implications that it might have for the neighborhoods represented (see Wilson, 2011). In Power et al. (2012), for instance, research questions stem from the *exclusion* of an Irish housing estate from Street View's social representations, not the implications of its inclusion. The research that comes closest to focusing on the politics of data abstraction is Hoelzl and Marie's (2014) characterization of Street View as "operative imagery,"

> Images that no longer represent objects but are part of an operation, an operation which is not restricted to user navigation, but which is part of a larger circular operation of data exchange, with the users' trajectories feeding back into the database. (p. 261)

In this perspective, Street View reconfigures the place-image, shifting its presentation from "tableau" to "databases that are navigable as images" (Hoelzl and Marie, 2014: 266).

The "databasing" of the image identified by Hoelzl and Marie is symptomatic of broader changes deriving from the blurring of securitization and entertainment technologies (see Thrift, 2011). It portends forms of surveillance that target consumers in and through their navigation of the social world (Lapenta, 2011; Lyon, 2003), and thus serves as an instructive starting point for examining what elite technology producers and computer scientists are doing with place-image databases like Street View. My argument is that the databasing of street-level imagery that Hoelzl and Marie describe is a prerequisite for a technique of abstracting place information through the "datafication" of street-level imagery.

The social sorting of place

When put into practice, the abstraction by datafication of street-level imagery portends a "software-sorting" of geographies based on the visible environmental properties of places captured on platforms like Street View. Graham (2005) describes the software-sorting of geographies as the use of computer code to "directly, automatically and continuously allocat[e] social or geographical access to all sorts of critical goods, services, life chances or mobility opportunities to certain social groups or geographical areas, often at the expense of others" (p. 3). Social sorting describes the assignment of value to individuals in relation to their social grouping in terms of worth or risk (Gandy, 1993; Lyon, 2003), while the geographic component that Graham highlights reflects the primacy of location as an emergent "organizational logic" in the management, sorting, and delivery of information (Gordon and De Souza e Silva, 2011: 7).

There is a history to location's central role in social informatics (Rose-Redwood, 2006). In large part this history derives from a complex interplay of state, military, and private actors, their intersecting interests, and changing norms of governmentality in terms of territory and communications technology (Dalton, 2013; Rose-Redwood, 2006). However, a sea change occurred after the year 2000, when the United States ended its "intentional degradation" of global positioning system (GPS) signal for commercial usage (White House, 2000). The bulk of geographic information production has since shifted from the relatively arcane worlds of academic geography, military strategy, and government planning, and into the popular realm of consumer-oriented information technologies (Barreneche, 2012; Sutko and De Souza e Silva, 2011; Thrift, 2011). The primacy of location as organizational logic is now tied to political economic landscapes (Leszczynski, 2012), normative assumptions about mobile subjectivities (Wilson, 2012), the infrastructural conditions necessary for the coding of places within online databases, and the tracking of user locations within those places (Kitchin and Dodge, 2011; Kitchin and Lauriault, 2014). The ubiquity of location-aware systems has rendered the organizational primacy of location nearly invisible; cars, phones, and other electronic devices (such as digital cameras) now come default-equipped with GPS capabilities. As Barreneche (2012) writes,

> Th[e] increasing and seamless integration of geocoding into our everyday communications may make location a default protocol setting of communication, and soon a taken-for-granted dimension of our media experience … to the point of rendering the prefix "geo" in geomedia superfluous. (p. 332)

Myriad "geo" technologies share with one another an implicit "sociological assumption" that location "signals social and cultural characteristics of a given population" (Barreneche, 2012: 337). Dalton and Thatcher (2015) review how this assumption became actionable for marketers, first with geodemographic systems in the 1970s and 1980s, and more recently within the "spatial Big Data" practices of data brokerage firms. Where geodemographic systems operate at the level of geocoded spaces (zip code, census tract, etc.), spatial big data purports to operate at the level of the individual and her microsociological movements and transactions within places. For data brokers, spatial big data open up the possibility of understanding the individual not only in terms of where they live, but also in terms of where they have been and where they go (Dalton and Thatcher, 2015; Wilson, 2012).

Algorithms that affect our mobility decisions (such as routing or wayfinding) cannot avoid the reductionism of a "sociological assumption" that equates social personae with place (Barreneche, 2012). This prefaces both utopian and dystopian visions for the future in which algorithms quietly "nudge" us into certain behaviors and forms of mobility that in turn effect new social sortings of place through tracked and logged geographies (Graham, 2005; Thrift, 2011). Thatcher (2013) argues that the notorious "avoid the ghetto" smartphone app captures the anxieties and hopes that attend the ubiquitous production of locational data. While technology promises to enhance the efficiency and safety of our movement through urban landscapes, it also threatens to reinforce uneven geographies, already shaped by and entrenched in racism and classism. Urban technologists are particularly excited about the possibilities:

> How much more powerful and actionable will things like [online crime mapping] be when they're ambient—when the information about a place comes to you when you're in that place? When, instead of shaded circles on a screen, you experience the output as a rising tone in your headphones, as a tickle in your shoe or a sudden wash of yellow over the view through your glasses, as you're actually walking through the streets of Oakland? (Greenfield and Shepard, 2007: 11)

The risk is that such nudges—the shaded circles, the rising tone, and the tickle—will accumulate, driving a wedge into already divided urban landscapes through processes of "digital redlining" (White House, 2014) in which the negatively affected life chances of disadvantaged groups are exaggerated and amplified through algorithmically generated geographies of mobility. The aggregation and data mining of street-level imagery represents a further step along this trajectory.

Informatic in aggregate

If the literature on Street View and other virtual mapping applications has failed to capture the geographic implications of its datafication, then the critical studies of the "geoweb" outlined above have likewise failed to consider the use of imaging in the social sorting of place. The case studies, presented below, prompt a convergence of these two strands. Before reviewing these, however, it is first necessary to preface the role of "aggregability" in the datafication of street-level imagery.

The datafication and "mining" of street-level imagery hinges on its aggregability. An untold affordance of Street View is that image datasets for entire cities can be scraped from the Street View platform by computer scientists and aggregated for analysis (Doersch et al., 2015; Gronát et al., 2011). Despite rhetoric from Google engineers about the qualitative richness of visual information available in street-level images (e.g. Anguelov, 2010), it is actually the quantitative immensity of the Street View database that opens it up to aggregation, datafication, databasing, and, subsequently, information extraction (Hoelzl and Marie, 2014; Van Dijck, 2014).

Aggregation is a distinct form of collectivization "that makes up for what it lacks in depth, comprehension and meaning, with breadth, speed and predictive power" (Andrejevic, 2011: 612). Algorithms are trained on aggregated datasets; aggregated metadatabases are a hallmark of the "bigness" of big data (cf. Mayer-Schönberger and Cukier, 2013). Though most critical media and cultural studies have approached "big data" in relation to consumer data mining (Andrejevic et al., 2015; Andrejevic and Gates, 2014), hallmark big data techniques and analyses are also presently applied in the field of computer vision (Prince, 2012). In the 1990s, teaching computers to "see"—to identify objects—required pairing two-dimensional imagery with para-visual technologies for measuring space, such as laser scanners and ultrasounds (Manovich, 1997: 14). However, recent advances in processing, storage, and asynchronous computing have prompted a shift away from direct range measurement toward the analysis of massive image datasets (Prince, 2012; Szeliski, 2010). These datasets, previously too memory-intensive for computers to do much with, are now used to train algorithms to identify target-objects with varying degrees of certainty.[2] For example, a team at Google recently trained an algorithm

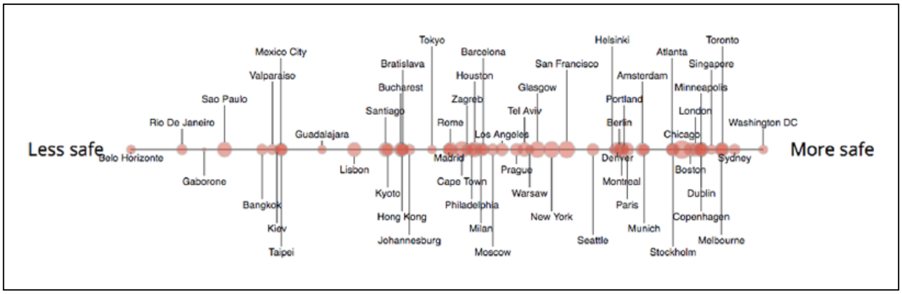

Figure 3. Rankings from MIT's PlacePulse study.
Source: http://pulse.media.mit.edu/rankings/

to discern the location in which a photograph was taken without using any locational metadata—"using only the pixels it contains" (Brokaw, 2016). The training data for the algorithm contained approximately 91 million geotagged images scraped from Flickr, while an additional batch of 2 million geotagged photos were then used to test the accuracy of the algorithm's location predictions. The size of these datasets are what makes the algorithm's predictive capabilities so powerful, even if "success" at present means the correct identification of country of origin only 28.4% of the time (Brokaw, 2016).

The following case studies illustrate how elite technology producers are applying such techniques to aggregated street-level imagery datasets. In doing so, they make claims about geographies of social worth and risk that betray a social sorting of populations based on the visual characteristics of urban places.

Visual correlates of geographic data

The Macro Connections group at the Massachusetts Institute of Technology's (MIT) MediaLab has developed a tool called PlacePulse to "quantitatively measure urban perception by crowdsourcing visual surveys to users around the globe" (Macro Connections, 2014). On the project website's homepage, visitors wishing to participate in the research are presented with a game-like scenario. Two randomly generated Street View images are presented, above which is a pull-down menu of questions prompting evaluative judgments of the places represented: Which place looks safer? Livelier? More boring? Which place looks wealthier? More depressing? More beautiful? To answer, participants select one of the two images. To date, PlacePulse has recorded 1.3 million clicks.[3] These data are available for users to peruse as a series of visualizations that illustrate how 50 or so cities rank against one another for each of the six evaluative prompts (see Figure 3). These visualizations take the form of one-dimensional graphs, linking together cities from across the globe on an ontologically flat plane of comparison. Gaborone and Houston are the two most "boring" cities, while Atlanta and Washington, DC, are the most "beautiful."

Beside ranking cities, the PlacePulse researchers also employ aggregated user evaluations as "ground truth" (or training data) for algorithms to predict an evaluative response to a randomly generated place-image. The idea is that places labeled as "safe" or "lively" or "depressing" will share visual characteristics that ambiently influence the evaluative outcome (Naik et al., 2014; Nasar, 1998). Another algorithm, called StreetScore (Naik et al., 2014), applies machine learning techniques to the PlacePulse data in order to predict perceived levels of safety. This involves dissecting the Street View images' scene composition into discrete visual elements, identifying any correlations between those elements and the "ground truth" data (Naik et al., 2014), and cross-referencing this against crime maps. High-scoring images in StreetScore, for instance, tended to include "suburban houses with manicured lawns and streets lined with trees; while the typical low scoring image contains empty streets, fences, and industrial buildings" (Naik et al., 2014: 2). From the perspective of algorithm design, these visual elements are not in themselves meaningful, but rather become informatic as statistical objects that represent features common to positive or negative evaluative outcomes (Nasar, 1998: 60). This, in turn, is seen to negate the "subjectivity" of perception. Feature selection is driven "not by biases in age, gender, or location of the participants, but by differences in the visual attributes of images" alone (Naik et al., 2014: 2).

A group at University of California, Berkeley has also built an algorithm for studying correlations between visible features and geographic attributes of urban environments (Arietta et al., 2013, 2014). Compared with PlacePulse, however, the Berkeley group is concerned less with evaluative perceptions than it is with predictive correlations between visible environmental features and the non-visual, "location-specific attributes" of criminality (Arietta et al., 2013, 2014). Trained on crime and real estate data (Arietta et al., 2013), the "City Forensics" algorithm identifies visual features that are statistically discriminative for reports of specific crime types. Using the locational metadata for each Street View image scraped and aggregated into a database, the City Forensics team built positive and negative subsets of images for areas with and without crime, respectively; these subsets were then used as "ground truth." Images from areas with high percentages of graffiti reports, for example, would contain common visual elements—certain types of window frames or street lamps (see Figure 4)—that might be "non-obvious" to the human eye but statistically significant as an index of risk (Andrejevic and Gates, 2014).

Once a set of visual elements are identified as statistically discriminative for a given crime within a specific city, the team then tested the efficiency of the algorithm across urban regions (are the visual elements predictive of crime in San Francisco also predictive for crimes in Boston?) and against human evaluations of the positive and negative image subsets used to train the predictors. Mechanical Turk workers were asked to examine a series of Street View images from a number cities and to "decide based on the image along whether [they] would feel safe in the area or not at any time of day" (Arietta et al., 2014: 5) (effectively reproducing the PlacePulse methodology); the predictors identified by the City Forensics algorithm reportedly outperformed the human evaluations in correlating dangerous looking places with crimes by 33%.

Although the PlacePulse and City Forensics projects offer two slightly different approaches to the datafication of street-level imagery, together they illustrate how the aggregation and databasing of street-level images enables a social sorting of urban environments. How geographic information about places is selected and coded effects a "transduction of space by data" (Wilson, 2011: 862)—which, in the case of street-level imagery, might be better understood as a transduction of *place* by data. Indicators of

Figure 4. Visual elements discriminative of graffiti in Chicago.
Source: Arietta et al. (2014).

deviance and normativity, worth and risk, are embedded within the algorithm (boyd and Crawford, 2012), and applied to the analysis of place. In both cases, computer-aided, data-mined correlations between the visible features, geographic information, and social character of place are framed as objective, if "ambient," social facts (Andrejevic, 2011).

Both projects also envision the potential application of their algorithms similarly. The PlacePulse researchers imagine their work as creating "quantitative bridges" between visual cues and "social, political, economic, and cultural aspects of cities" (Salesses et al., 2013: 11) that might inform the future design of urban landscapes. The City Forensics team likewiseintends to effect new geographies based on the algorithmically predicted distribution of crime and risk throughout space. They describe one application of their algorithm as a wayfinding system:

> That allows a user to route him/herself between two points in a city while either avoiding or encountering one of these statistics [the presence of visual cues discriminative for street crime]. Extending the system to other statistics would be a relatively trivial effort. (Arietta et al., 2013: 9)

The intended implications of this type of software-sorting is the production of new geographies and mobilities, customizable to users' cultural preferences for consuming the city (Thatcher, 2013), while also opening up the potential for police or governmental intervention in areas deemed high risk.

Geovisual spatial abstraction and the social sorting of place

If social theory has approached the aerial perspective as power-laden, perspectival abstraction (Cosgrove, 2001; De Certeau, 1984; Haraway, 1988; Lefebvre, 1992), then street-level imagery was seen as its implicit antidote: situated, on-the-ground, embodied, "subjective" (Shapiro, 2016). However, the two case studies outlined above illustrate how the aggregation and abstraction by "datafication" of street-level imagery have the potential to inscribe new power geometries onto urban *places* through algorithmic linkages between visual environmental qualities, geographic information, and valuations of social worth and risk.

An understanding of this abstraction by datafication can be informed by looking to cultural precedents that make explicit the "geovisual"[4] relationship between places, visible environmental features, and social character. Though largely absent from discussions of Street View and other virtual mapping applications, this relationship has been explored in regard to criminological theory and its long history of geovisual knowledge production. Connections between place-level environmental features and social character are evident, for instance, in how the 19th century liberal state understood the morality of the urban subject as shaped by milieu. Osborne and Rose (1999) describe the relationship between place and character that emerged within an outpouring of "pamphlets, programmes, demands, solutions, tracts, scientific investigations, bureaucratic documentation, commissions of enquiry, medical reports, and the like," that were used to intervene unto neighborhoods of "low moral standing":

> Poor character, which may be inherited from one's forbears, [was seen to lead] not only to conduct and ways of living that degraded ones' surrounding milieu; it also led one to gravitate towards a certain kind of milieu, which itself has an effect upon character—an effect which, in turn, might be passed down to future generations through a weakened constitution. (Osborne and Rose, 1999: 743)

This type of geovisual governmental orientation mobilized the programs of reformers and nascent police forces alike. Edwin Chadwick's *Sanitary Report of London*, for instance, incorporated "ocular inspection" of poor and working-class neighborhoods in order to make decisions about whom and where to target intervention (Poovey, 1995: 36). Similarly, the Benthamite economy of space characteristic of early police departments used ocular inspection in order to most efficiently target interventions at problematized places (Reeves and Packer, 2013).

The criminological epistemology of place, character, and criminality survives into contemporary "actuarial" accounts of crime (Foucault, 2008; Harcourt, 2006). Garland (2001) uses the term "criminogenic situation" to describe the relationship between crime and its environmental determinants: "The assumption is that criminal actions will routinely occur [in places where] controls are absent and attractive targets are available, whether or not the individuals have a 'criminal disposition'" (Garland, 2001: 129). Identifying such places allows police and other governmental agencies to sort through the geographic distribution of social risk—to discern between places with enough social cohesion to effectively govern themselves and those requiring state intervention.

The Broken Windows theory is the most popular and concise articulation of this logic (Kelling and Wilson, 1982)—a common sense explanation for neighborhood decline among social scientists, the public, and police departments (Sampson and Raudenbush, 2004). Broken Windows posits that visible signs of physical or social disorder in neighborhoods, if left unchecked, foster a breakdown of social cohesion, and thus create places conducive to crime. This occurs through a "developmental sequence" in which "disorder and crime are usually inextricably linked" (Kelling and Wilson, 1982). Broken Windows argues for police to intervene in this sequence by sorting and separating the orderly from disorderly elements of the urban landscape. Police, for instance, are tasked with distinguishing a "stable neighborhood" requiring little policing from the "inhospitable and frightening jungle" that needs order to be imposed from the outside (Kelling and Wilson, 1982). This amounts to an implicitly visual assessment of places for determining which neighborhoods deserve stricter applications of the law (Sampson and Raudenbush, 2004). As Harcourt (1998) summarizes, Broken Windows theory is based on "categorical distinctions between disorderly people and law abiders [that] reflects an aesthetic of orderliness, cleanliness, and sobriety. And, on the basis of these categories, it weaves a theory of deterrence" (p. 305).

Critics have pointed to serious flaws in Broken Windows' assumptions about the symptoms and causes of criminality (Harcourt, 2001). Labeling visible signs of poverty or other non-normative public behaviors as "disorderly" at once creates normative categorizations of places and legitimizes the theory's own "sociological assumption" about the relationship between the qualities of place, social character, and criminality. Police and other governmental agencies that invoke Broken Windows target low-income neighborhoods for intervention through increasingly carceral and repressive state surveillance practices (Garland, 2001; Harcourt, 2001; Harcourt and Ludwig, 2006; Howell, 2009).

Despite these critiques, both the PlacePulse researchers and the City Forensics team cite the Broken Windows theory in their publications, suggesting that the theory's crime-deterrent logic served as a major influence on algorithmic design (Kitchin, 2016; Winner, 1980). There are three ways in which this influence can be discerned. First, both the Broken Windows theory and the case studies share the "sociological assumption" that links place with social character. Just as the Broken Windows theory figures the developmental sequence of criminogenic environments as a means of deterring crime, the PlacePulse and City Forensics algorithms operate by identifying visual cues that, as statistical objects, are seen to influence the social character of urban places "ambiently" (Andrejevic, 2011). Visual cues associated with perceived safety levels in PlacePulse, or the correlations between "non-obvious" visual elements with specific crime types in City Forensics, illustrate how algorithmic design can imagine contextual cues as operating on social behaviors, even if only at the aggregate level.

Second, in both Broken Windows and the two case studies, an aura of objectivity is inscribed unto geovisual relationships between place and social character. In the Broken Windows theory, this hinges on the legitimacy and discretion of the figure of the police officer tasked with identifying "disorderly" areas for intervention; the assumption is that place evaluations are not based on "subjective" preference but on some essentialized notion of the visual cues of "disorderliness" (Sampson and Raudenbush, 2004). The PlacePulse and City Forensics projects, by contrast, do not in themselves make this assumption; rather, they investigate and validate "objectivity" through statistical analyses. Whether the categorizations of places are "safe," "lively," "depressing" or "beautiful," or algorithmically identified visual features discriminative for the presence of a given crime, the established categories upon which algorithmic analysis work to transduce space by data, fostering "software-sorted" geographies of place based on social coding (Graham, 2005; Wilson, 2011).

Finally, Broken Windows and the case studies both involve a circumscription of authority around who can "speak" about the qualities of place. Evaluative power exists at a remove from the places and communities evaluated. As Wilson (2011) shows, even with attempts to distribute the evaluative authority traditionally ascribed to police officers in Broken Windows, evaluations of place involve instruments often comprised of *a priori* codifications that reinforce Broken Windows' normative assumptions. Another example is Kefalas's (2003) research on race- and class-divided working-class neighborhoods, in which the politics of visual orderliness are imbricated in contests over the cultural authority to speak for the community. PlacePulse and City Forensics algorithms similarly circumscribe cultural authority, but do so through automation. In these cases, evaluative authority is delimited by its technological embeddedness. The apparent objectivity of aggregate data and algorithms work to distance communities from the inherently political act of place-sorting.[5]

Alternative theoretical directions

These case studies point to the need for a critical reexamination of platforms for street-level imagery. A potent starting point can be located in recent theoretical interventions that emphasize the import of "erosion, breakdown, and decay," rather than the "orderly" functioning of both technology and urban processes (Jackson, 2014: 221; Graham and Thrift, 2007). With the Heideggerian move positioning the breakdown and decay of objects and technological systems as the cornerstone around which sociality emerges (Graham and Thrift, 2007), these theories inherently work against the grain of Broken Windows-thinking. Rather, in this "broken world thinking," as Jackson (2014) calls the theoretical intervention, the stability of normative perceptions upon which place evaluations are built becomes shaky: the apparent objectivity of evaluative criteria propped up by Broken Windows theory and embedded into algorithmic analyses of street-level imagery is called into question. The codifications that make evaluation possible become contestable cultural constructs, seen to have historically worked in favor of carceral police states (Garland, 2001; Harcourt, 2001). As opposed to Broken Windows, broken world thinking fosters an appreciation for "the subtle arts of repair by which rich and robust lives are sustained against the weight of centrifugal odds" (Jackson, 2014: 222). It promotes a "repair-centered ethics" of "mutual care and responsibility" (Jackson, 2014: 231).

What would such broken world thinking mean for a productive critique of street-level imagery platforms such as Google Street View? If researchers designing algorithms adopted a broken world approach, it could prompt lines of questioning that cut through the ties between visually-informed place evaluation and Broken Windows theory that animate its social sorting. For instance, if all places were seen to require forms of repair and upkeep, then researchers could ask: Which communities lack the resources to perform repair? What forms of repair do they desire? What are the forces that render geographies of repair as uneven and disparate along lines of race and class? And what structural forces inhibit attempts to disrupt the reproduction of uneven geographies? Instead of algorithms that impose Broken Windows' aesthetic inscriptions of "orderliness," they could instead be designed for, with, or by community leaders—to address local needs, to hi-jack the cultural authority of the algorithm in service of community campaigns, to demonstrate systematic disinvestment in low-income neighborhoods of color, or to advocate for public or private investment in municipal services that analysis reveals to disproportionately benefit some communities over others. Although redefining research and development programs at elite institutions according to these tenets would not be a one-stop solution for ameliorating entrenched urban disparities, it is not unthinkable that algorithms might be able to work against—rather than reproduce—techno-social processes that exploit the relationship between place and people.

Conclusion

From the perspective of broken world thinking, street-level imagery, with its "embodied," "subjective" and situated dispositions, is not in itself an antidote to the power geometries itinerant to the synoptic abstractions of space. The case studies presented here demonstrate as much. Rather, our conclusion should be that virtual mapping applications like Street View illuminate novel configurations of sociality and surveillance that both promise and threaten to reorganize social landscapes, to reaffirm or undermine our normative categorizations of space and place. Broken world thinking shows that the "immersive," "phenomenological," and "experiential" qualities ascribed to street-level imagery can easily be subsumed by the imperative to abstract information from images—to evaluate urban environments and sort through populations for targeting—if left unchecked against an ethics of repair. The task at hand, for media scholars and technology producers, is to remain vigilant about which commitments are embedded within technologies designed to abstract place through datafication and to circumscribe the authority to know and speak for communities.

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Notes

1. On calls to "historicize big data," see Boellstorff, 2013; Dalton and Thatcher, 2015; Kitchin and Lauriault, 2014.
2. Because the datasets used in computer vision are so memory-intensive, innovation in the field often involves new processing and storage methods that increase the speed of analysis or enlarge the potential scale of the dataset (e.g. Arietta et al., 2013, 2014; Doersch et al., 2015; Quercia et al., 2014).
3. "Clicks" are not defined as unique users; the total number of participants represented in the PlacePulse data is not explicitly disclosed.
4. By "geovisual," I mean the blurring of socio-geographic information and visual environmental qualities.
5. Such technological deference aligns with broader anxieties around the automation of decision-making and especially the algorithmic sorting of places (Barreneche, 2012; Thrift, 2011).

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