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Feeling Alone While Surrounded? Urban Loneliness Mapped

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Abstract

Loneliness affects a significant number of people in the United States. As a public health risk, loneliness is consistently associated with a variety of adverse health impacts. The literature on loneliness delves into two types: objective loneliness (physical isolation) and subjective loneliness (feeling of isolation), with several measures of these loneliness types including familial, spousal, social, and existential loneliness.[1] Interventions on loneliness depend on the unique needs of lonely individuals who live and work within their built environment: the human-made systems that define the boundaries of culture, habit, and daily life. These include the location of amenities like daycare providers, the local government-defined building density and zoning laws, the investment in and use of public parks, regulations on pollution, location of jobs, etc. Long-term fixes to loneliness like developing new public space, changing commute patterns, and expanding access to healthcare are typically out of scope for local community organizations that need to support their residents today.

To support local communities in **local, rapid, and affordable** interventions on loneliness, we've developed a loneliness index that can be used to identify at-risk populations and individuals and focus intervention activities to directly address loneliness.

This index is mapped at the U.S. Census block group level, including more than 218,000 block groups. This level of granularity is critical for understanding the nuanced differences between communities within a neighborhood. This paper focuses on 1) the development of a community-level approach for identifying areas to invest in anti-loneliness measures, and 2) showing how diving deeper than the typical census tract level (of which there are 72,000-plus) can allow for more nuanced investigation of crises like loneliness.

Census block group analysis can empower communities to make deliberate, impactful decisions, which optimize outreach efforts to at-risk populations. We can organize programs for those who **live alone** (e.g., the Maryland Daily Wellness Check for Seniors). We can work with **single parents** to integrate their families into community activities to provide safe spaces for children after school (e.g., Teen Nights). We can translate for people with **limited English-speaking skills** and introduce them to others in the community who speak their native languages (e.g., language events and promotion of specific language books at the public library). We can support strategic carpooling or alter bus routes for those doing **super-commutes alone** (e.g., the "slug-line" network in Washington D.C.). We can organize supplemental employment, training, and support for basic healthcare for the **poor, underemployed, or uninsured** (e.g., organizing volunteers to run sign-up drives for healthcare.gov in communities with limited digital skills or internet connectivity).

Yet these local interventions are only useful if the built environment factors that exacerbate loneliness are not insurmountable. We show via highly granular analysis, that even *within* a census tract, there can be significant variation in our loneliness index. Since census tracts are themselves granular and often used as the unit of measure for a built environment,[2] variations of loneliness within them provide evidence that built environment factors can be overcome through local, rapid, and affordable interventions at the census block group level.

[1] Wendy Sanchez 2015

[2] Jessica M Keralis 2020

Introduction

U.S. Census data not only determines political representation and $100 billion-plus in annual federal funding, but it and its inter-decennial estimates, such as the American Community Survey (ACS), are critical in how corporations, nongovernmental organizations, not-for-profits, and federal/state/local governments understand the people and communities they serve.

In our work supporting the public sector at Guidehouse, we've used U.S. Census data extensively in our artificial intelligence practice across domains including defense, public health, national security, cybersecurity, housing, economic development, and more. Inspired by this experience and publicly available mapping applications like the Centers for Disease Control and Prevention's **social vulnerability index**, we decided to develop this paper showcasing interesting patterns we find across the country.

This paper introduces the **Loneliness Index** to identify areas of the country where we expect public health resources to be urgently needed to combat loneliness at the highly granular census block group level.

Why Loneliness?

The world is facing a loneliness epidemic, with significant percentages of the population reporting persistent feelings of loneliness. In the U.S., a 2010 study reports about one-third of adults over age 45 meet the UCLA Loneliness Scale criteria for being lonely.[3] A 2016 Australian survey showed that 34% of surveyed respondents felt they didn't have anyone to talk to when they felt alone.[4] In the UK, research by the Campaign to End Loneliness revealed roughly 20% of the UK population feels lonely often or always. These feelings are particularly common among seniors, and researchers predict the number of individuals over age 50 experiencing chronic loneliness will rise 49% over the next 10 years.[5] Factors like age and living alone put individuals at greater risk for experiencing loneliness.

The World Health Organization lists loneliness as one of its determinants of health, stating stronger social support networks are linked to better health outcomes. Loneliness leads directly to negative health outcomes, including chronic diseases, depression, and an increased likelihood of suicidal ideation.[6] A 2015 meta-analysis by Holt-Lunstad and Smith estimates loneliness causes 29%-32% increases in the likelihood of premature mortality. [7] The Global Council on Brain Health reports that social isolation is associated with increased risks of depression, dementia, and cognitive decline.[8] The strength of social ties can also influence health-related physiology; greater isolation has been associated with worse blood pressure, immune functioning, inflammation, and medication tolerance.[9] To summarize, feeling loneliness has significant negative impacts on health, and individuals can feel lonely even when surrounded by millions of people.

[3] AARP Magazine 2010

[4] Lifeline Australia 2016

[5] Campaign to End Loneliness n.d.

[6] A. Stravynski 2001

[7] Holt-Lunstad 2015

[8] Global Council on Brain Health 2017

[9] Holt-Lunstad 2017

Redefining “Community-Level” in Health Data

There are over 72,000 census tracts in the United States composed of over 220,000 census block groups. Using open source data from Safegraph, one of the world’s premier **geospatial data companies**, we combed over 7,600 variables to create this loneliness index at the census block group level, using their aggregation of the U.S. Census 2016 ACS, which at the time of writing, was the most recent available data at this level of granularity.

Not only is this level of granularity relatively rare in both public health and open source projects, but working with urbanists and public health practitioners, we believe the features we’ve engineered and the composite index we’ve developed can provide meaningful insights into the geographic spread of mental health issues correlated with loneliness and ultimately act as a guide for allocating resources for related health initiatives in a way that is three times more precise than the census tract level. Our emphasis on features whose interventions are local, rapid, and affordable make this a ready-to-use index for community groups and local governments looking to improve the efficacy of their loneliness interventions.

More technically, by only accepting the common practice that census tracts are an effective unit of measure for the built environment in terms of aggregating individual behavior and understanding differences in health outcomes via differences in census tracts, the intricacies of these areas are obscured. A more granular census block group analysis that shows significant variation within a census tract provides a pseudo-causal framework (similar to regression discontinuity) for understanding how local interventions can improve health outcomes.

Description

Our loneliness index is composed of the following variables taken from a cross-section of international literature on loneliness, its comorbidities, and its determinants. We emphasize here features whose interventions can be local, rapid, and affordable.

We acknowledge important factors for understanding loneliness such as the availability and use of green space, public parks, and intact infrastructure, the impact of pollution, and other correlated items more indicative of the traditional meaning behind the word “built environment” are excluded. Ultimately, those factors did not align to our local, rapid, and affordable interventions on loneliness. We can’t build a park overnight, but we can make sure to canvass a particular community for integration into public events.

Feature	Calculation	Notes
Live Alone % [10]	Population 18–64 years of age identified as living in a household and living alone divided by population 18–64.	We chose to use 18-64 years of age as census block groups are small enough to where differences in concentrations of the elderly (e.g., senior living facilities or group quarters-living alone) would overly skew the variable.
Single Parent % [11, 12, 13]	Men-headed families with children but no wife + women-headed families with children but no husband divided by the number of total families.	While most research is based on loneliness and single mothers, we have decided to align with the CDC social vulnerability index and combine both single parent groups.
English Less-Than-Well % [14, 15]	Population 18–64 non-native English speakers who self-describe as speaking English "not well" or "not at all" divided by the population 18–64.	Non-native English speakers are especially reliant on local social networks and organization abilities to provide translation and education services. We use 18–64 to remain consistent across variables.
Long Commute % [16]	Population 16+ with commutes greater than 60 minutes divided by the population 16+ who commute to work (i.e., do not work from home).	Long commutes (or "super-commutes") are associated with disproportionately less time spent with family and friends. It is correlated with depression and comorbid health issues related to stationary lifestyles.
Drive Alone % [17, 18]	Population 16+ who commute via driving alone divided by population 16+ who commute to work.	Public transportation and other commute methods have higher resistance to the negative impacts of long commutes. Research in isolated driving are typically focused on professional drivers (especially in the freight and logistics industry).
Low Income % [19, 20, 21]	Income to Poverty Ratio < 2.00 for population for whom income was determined.	We expect this to correlate with several of our variables but felt it imperative to include an economic component directly. The literature finds that low income, in addition to more traditional factors of the built environment (such as perception of neglect of neighborhood buildings, infrastructure), spurs depression that can be mediated via relieving a sense of loneliness.
No Health Insurance % [22, 23]	Population 18+ without health insurance divided by population 18+ where health insurance was determined.	Lacking health insurance exacerbates the development of chronic physical and mental health conditions, which as a whole act as a strong predictor of loneliness, even adjusted for quality of social contacts, age, gender, and socio-economic status.
Prime Underemployment % [24, 25]	Population 25–54 did not work full-time in previous 12 months divided by the 25 – 54 population.	Unemployment and underemployment significantly impact self-image, the development of social networks, and comorbidities such as depression. We use 25-54 instead of 18–64 like other variables to align to the Bureau of Labor Statistics definition of prime working age. Typically, prime working age has been used in economic studies on the labor force participation of men. We do not make a distinction on sex in our variable.

[10] Beutel 2017
[11] Chesser 1981
[12] Shenoy 2015
[13] Quanquan Wang 2020
[14] Julia B. Ward 2018
[15] Shengfeng Lu 2019
[16] Christian 2012
[17] Quanquan Wang 2020
[18] Ali Hatami 2019
[19] Beutel 2017
[20] Chesser 1981
[21] Sarah D. Kowitt 2020
[22] Tian 2012
[23] Marco Solmi 2020
[24] Hansson 1990
[25] Gregory C. Murphy 1999

Methodology

Using the 2016 ACS at the census block group level, we combed the .csv exports open-sourced by Safegraph to generate our **naïve** index (see: **Caveats**).

Through our experience working with data at the census tract level, places such as prisons, universities, reservations, parks, airports, and nonresidential areas require omission due to missing data. Any census block group without a minimum number of households to contain all available features are excluded. A total of 218,407 census block groups of the available 220,333 are included in this application.

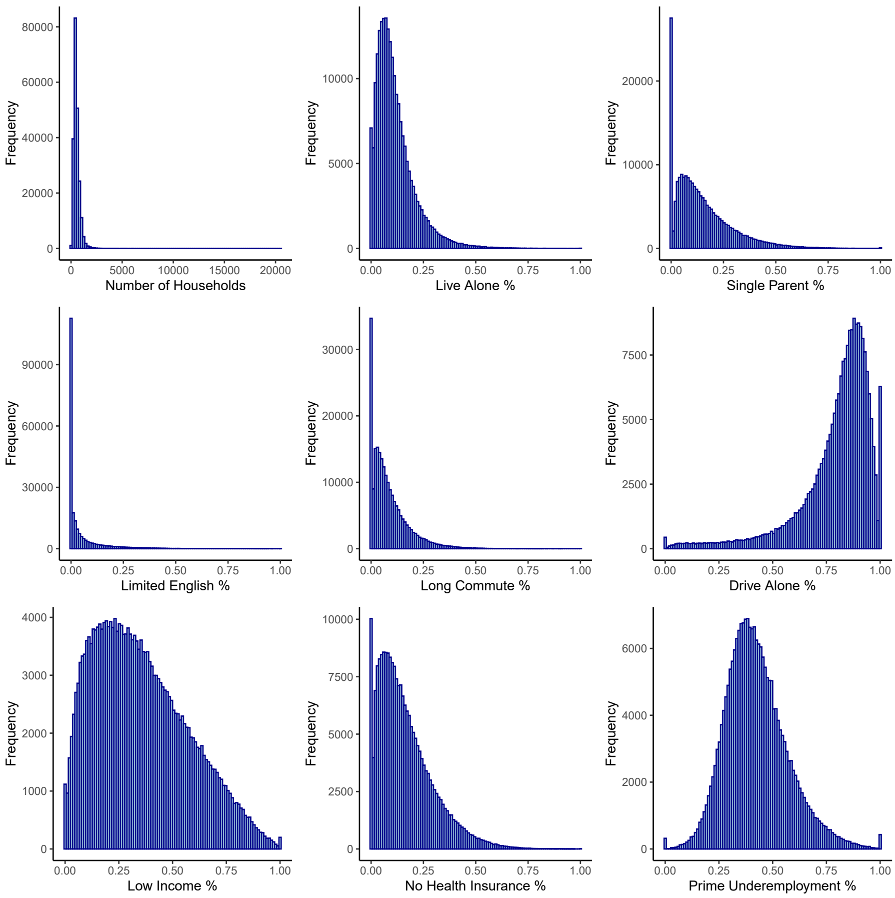

Figure 1. Density distributions of the features in our index. Note that the vast majority of workers who do not work from home commute via driving a car/van/truck alone, and the vast majority of people aged 18 to 64 in the U.S. speak English at least well.

To make these variables comparable, we scale each feature of the data to be between 0–1, combine all the features additively, and then rescale them to generate a final loneliness index for all 218,407 census block groups between 0–1.

For example, a census block group with 9% of its age 18–64 population living alone would be a little below the 50th percentile (the median of living alone % is 0.0953). Specifically, a living alone percent value of 9.00% converts to a percentile of 0.4829. This percentile would be added up with the percentiles from the other seven features, and this sum value (which could be anywhere from 0 to 8 theoretically) would get rescaled to form the final percentile between 0–1. Thus, all census block groups are assigned their loneliness index value based on their relative loneliness compared to all other census block groups.

We then output this final data as both a .csv file and a shapefile (with the geometries attached).

Results

1 Loneliness is not isolated to physically distant, rural, or isolated areas. In fact, some of those areas are noticeably not lonely. Urban Loneliness is thus a unique phenomenon: feeling alone when surrounded by millions.

Figure 2 shows census block group centroids within the top 10% of the loneliness index ("intense loneliness"). Centroids were used to visually adjust for differences in sizes of the census block groups. Census block groups are already planned to make the number of households in each relatively comparable (the interquartile range of number of households in census block groups is 343–666 households) making comparison of points and point density an appropriate way to assign loneliness index to geographic areas (in addition to the index already being adjusted for population sizes).

When we think lonely, we think physical isolation. And it's true, we see intense loneliness concentrated in rural and isolated areas, such as the Navajo Nation at the four corners of Utah, Colorado, Arizona, and New Mexico. In fact, seemingly all the major cities in the South (Atlanta, Jacksonville, Charlotte, Charleston, etc.) have block groups of intense loneliness in their far suburbs, also known as "exurbs"— the small and mid-size towns along the I-95, I-10, and Mississippi River corridors. This argument is bolstered by the commute rates for these exurb census block groups. People living in these towns may not have sufficient employment nearby and thus drive 60-90-plus minutes each way to work in their closest major city. This idea may also be transferable to the I-5 corridor from San Diego to Seattle.

Every state in the contiguous U.S. contains at least a few block groups within the top 10%, but the focus of this paper is on Urban Loneliness — the unique feeling of loneliness when you're surrounded by millions. We see in **Figure 2** there are significant concentrations of intense loneliness in the most populous cities in the country.

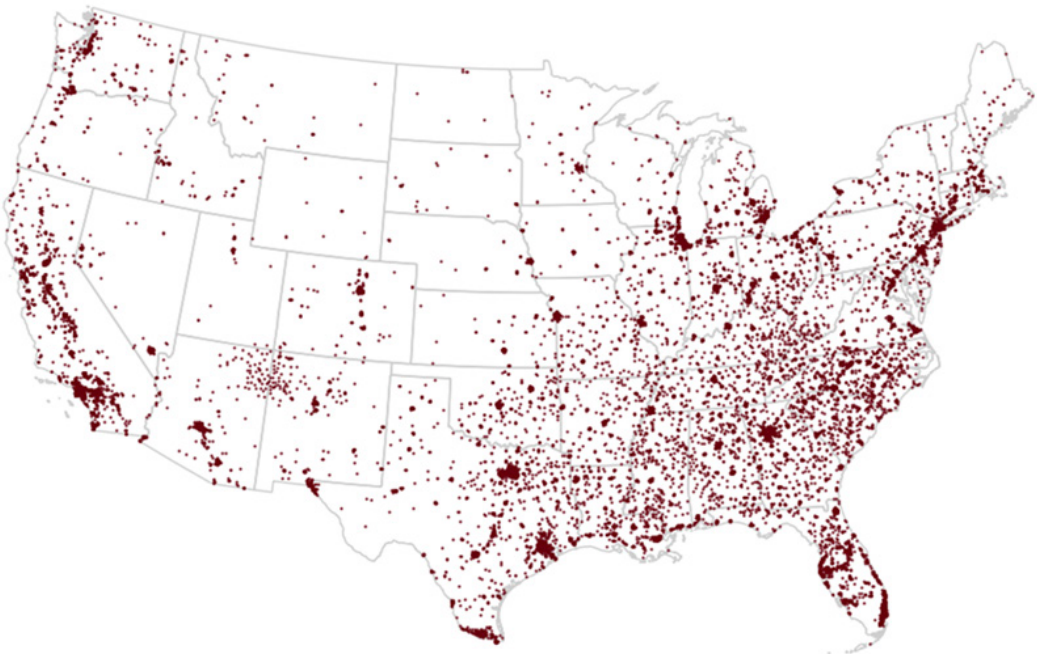

Figure 2. The top 10% loneliest census block groups in the U.S., shown as centroids to adjust for differing sizes of census block groups. All shapefiles used to generate Figures 2–4 and the maps were generated using open source software: QGIS (formerly Quantum GIS).

Now, knowing that extreme loneliness is pervasive, the natural thing to verify is that we're not just looking at a population map. We can see intense clustering around major cities such as Seattle, Portland, San Francisco, Los Angeles, San Diego, Dallas, Houston, Tampa, Atlanta, Chicago, Detroit, and the entire Boston-Washington. D.C., corridor centralized around New York City. To support that **our index is usable in local, rapid, and affordable interventions** we would need to identify that these areas of intense loneliness do not have insurmountable barriers in overcoming loneliness. To do this, we asked, how close are these intensely lonely areas to areas of **"intense belonging"** — i.e., census block groups in the bottom 10% of loneliness index.

Figure 3 shows this opposite intensity — the bottom 10% in the loneliness index ("intense belonging") are shown at the census block group centroid level. As we'd hoped, there are significant overlaps here implying that the barriers are not insurmountable. Unfortunately, these overlaps are almost exclusively within medium to majorly populated cities. The implication here is that the vast majority of the exurbs and small towns on the corridors we previously mentioned do not have comparable neighborhoods nearby that can model the kind of interventions that lead to belonging. Knowing that these urban areas have both intense loneliness and intense belonging implies interventions can play a positive impact in belonging. The key to turning this implication into **evidence** would be showing that these areas of intense belonging and intense loneliness are **especially close together**, which would indicate that the kind of nonlocal, slow, and expensive built environment factors associated with loneliness and belonging can be overcome by local, rapid, affordable intervention.

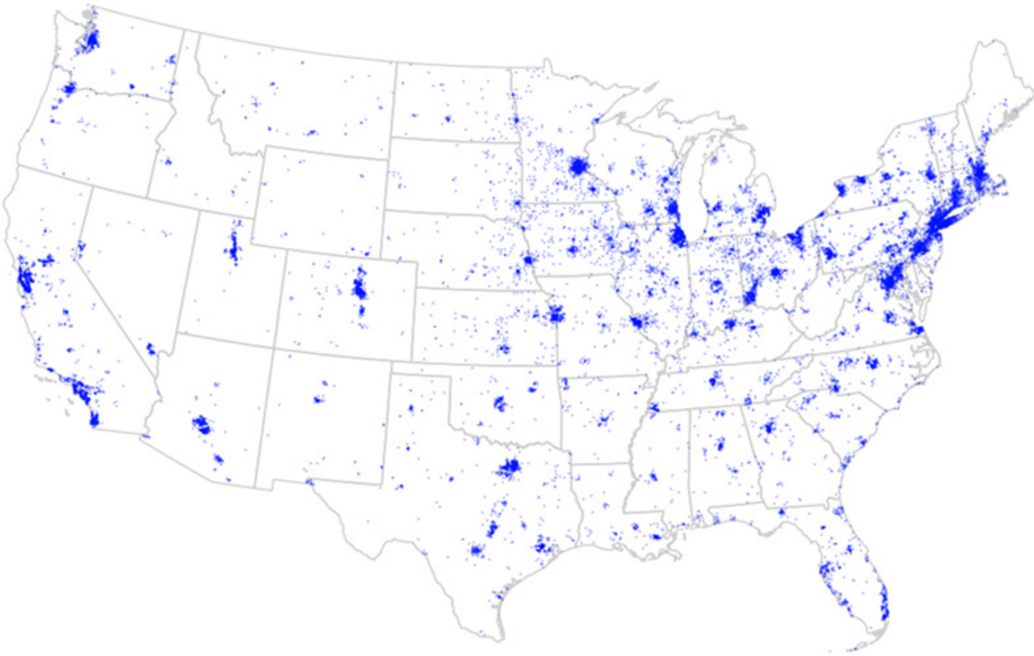

Figure 3. The bottom 10% loneliest census block groups in the U.S., shown as centroids to adjust for differing sizes of census block groups.

2 Granularity is an important determinant of how well we aggregate individual level behaviors, opinions, and feelings. Working with census block groups within census tracts shows significant variation in loneliness exists within a notable portion of census tracts. This shows that built environment characteristics (e.g., zoning laws, access to green space, intact infrastructure, public space, amenities, jobs, etc.) are not insurmountable blockers for loneliness intervention. Local, rapid, affordable interventions that are highly targeted to specific communities within small neighborhoods can close the gap without waiting for large changes in the built environment.

At approximately three times the granularity as census tract data, using census block group data can improve the targeting of interventions. Diving deeper into New York City, the most populous urban area in the U.S., significant variation exists in loneliness across the city. This is to be expected given that our features cross the spectrum from commute patterns to family size and type, to economic measures. What is especially significant is the **intra-tract variation**, where a few visually blatant examples are emphasized in **Figure 4** with black squares.

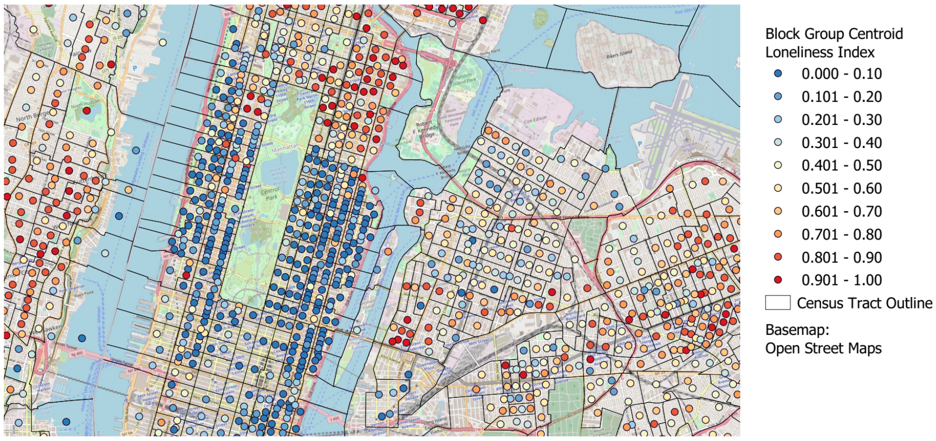

Figure 4. New York City with census block group centroids indicating loneliness index value. Census tract outlines show intra-tract differences in loneliness can be significant as numerous hues of blue, white, and red are especially visible North and West of Central Park.

The implications here are stark — census tracts are often divided based on natural barriers, such as rivers, but even within a census tract, block groups can be further divided by built environment barriers like train tracks. These built environment factors have implications for how people move and live within a city, including isolating people and exacerbating loneliness.

Shown in **Figure 5** is another prime example. These two census block groups combine to form a single census tract in Prattville, Alabama. Using a single value for this census tract obscures that one census block group contains significantly more lonely individuals living "on the wrong side of the tracks," here almost perfectly bisected by the **Autauga Northern Railroad (AUT).**

Whenever possible, researchers should seek to model individual behavior and characteristics at the closest level of granularity when working in geographic information systems- as exemplified in the article on the **modifiable areal unit problem**. All aggregations of individuals to areas will suffer this problem – and the primary mechanism for mitigating the (sometimes arbitrary) boundaries we use when doing health research is to use as granular of area as possible.

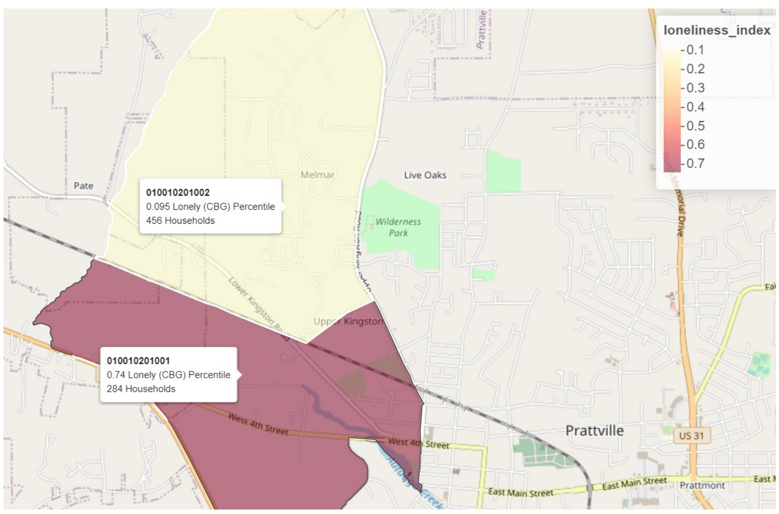

Figure 5. Composite image of loneliness index for Prattville, AL, census tract: 020100.

To summarize, census tracts are a highly granular and commonly accepted unit for aggregating individual behaviors to a geographic level. Accepting this practice, we can treat census tracts as units of the built environment.[26] Variation within a census tract (i.e., the census block group level) provides evidence (using a regression discontinuity framework) that built environment factors (i.e., access to jobs, amenities, public space, infrastructure) can be overcome by local, rapid, and affordable interventions on loneliness because everyone in the census tract gets the same built environment — so differences in these people's loneliness (aggregated at the **more granular** census block group level) would be a result of changeable nonenvironmental factors such as how they drive, the jobs they have, the people they know, the events they go to, and ultimately how they can (flexibly) belong to a community.

Caveats

All features generated are weighted equally in the index. Our ideal analysis would have used a formal national survey with the UCLA Loneliness scale as the questionnaire to assign loneliness scores to sampled census block groups. These would become the training set for a machine learning model that is predictive of the loneliness scores. This model would generate predictions for the census block groups that weren't surveyed.

We contacted the only national survey firm who had done a survey relevant to this problem recently enough to apply to 2016 ACS data, but they did not own the data, and the owners of the data were not interested in open sourcing the data at this time.

Accepting the assumption (and common practice) that census tracts can act as a unit for the built environment is only a first step for a formal regression discontinuity analysis (which we did not complete here). A formal regression discontinuity analysis to partition how much of our intra-tract loneliness index variation is behavioral (as opposed to environmental) would benefit from bringing our built environment characteristics down to the census block group level as well.

[26] Jessica M Keralis 2020

Extras

Out of curiosity, we use least absolute shrinkage and selection operator (LASSO) to calculate the top three features for predicting our loneliness index and use **predictive power score** in comparison with a correlation matrix to show asymmetric relationships between the features. More information on predictive power score can be found at its **open source documentation.**

LASSO

Selecting three variables from our LASSO function, we find that the most significant features for explaining differences in the composite loneliness index are single-parent percentage, low-income percentage, and no health insurance percentage. This aligns directly to the results detailed in the Predictive Power Score Section.

Requested Variables: 3

Deviation Explained by N Variables: 0.5411468

Selected Variables

Single Parent Percent   Low Income Percent   No Health Insurance Percent

Coefficients Table

Variable	**Estimated Coefficient**
(Intercept)	0.27938845
Census Block Group	0.00000000
Number of Households	0.00000000
Live Alone Percent	0.00000000
Single Parent Percent	0.02035059
Limited English Percent	0.00000000
Long Commute Percent	0.00000000
Drive Alone Percent	0.00000000
Low Income Percent	0.52523848
No Health Insurance Percent	0.18794281
Prime Underemployment Percent	0.00000000

Predictive Power Score

Correlations are strictly linear comparisons of how two features move together (or don't move together or move in opposite directions). The standard Pearson correlation is useful, but in everyday use, people overinterpret the measure and its ability to help with issues like feature selection. It doesn't identify nonlinear relationships, and it assumes any relationships found are symmetric. The problem with this can be made obvious on a toy example like car efficiency. With a dataset like 1974 Motor Trend magazine's automobile performance (the famous "mtcars" dataset in the statistical programming language R), you can readily find engine size and miles per gallon are correlated. It is of course the size of the engine that affects miles per gallon, not the miles per gallon affecting engine size. Yet a standard correlation doesn't differentiate the direction between these relationships.

Figure 6 illustrates how the standard correlation metric fails to find significant relationships in data when that data is non-linear and asymmetric. All of these points have an underlying pattern, but in all 7 instances the correlation is 0. Predictive Power Score (PPS) seeks to solve this problem.

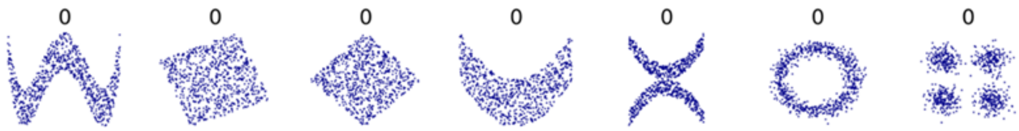

Figure 6. Data with clear (nonlinear) patterns but correlations of 0, from user DenisBoigelot on the Correlation and Dependence Wikipedia page. https://en.wikipedia.org/wiki/Correlation_and_dependence

Shown in **Figure 7** is a standard correlation matrix for the features in our index, including the index itself. These matrices can often confuse the issue, inspiring difficult questions like:

- With multicollinearity present how can we hypothetically simplify our index to make interventions even more targeted?
- What should we do with the knowledge that our most highly skewed variables (long commutes and driving alone) have low or even negative correlations with an index that is composed of these variables?
- We know for a fact that the index weights these features all equally, so what should we do when the result of combining correlated data gives us unintuitive correlations?

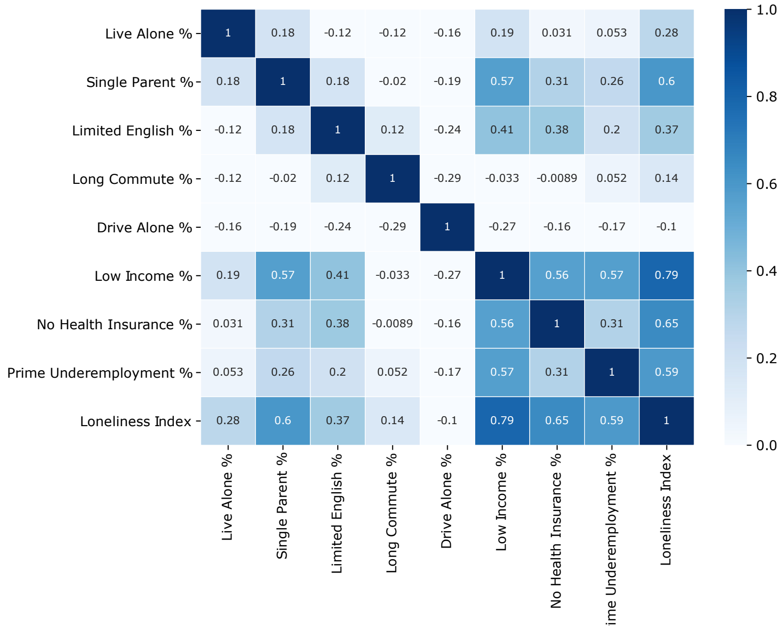

Figure 7. Traditional correlation matrix of all features.

Figure 8 details the PPS, a recently released Python package, that uses univariate decision trees to assess the ability of a variable to **predict** another variable better than a baseline (e.g., better than simply guessing the median or mean). The details of the algorithm are better described in the **open source documentation**, but it's clear the heat map produced by PPS is much easier to think about than the correlation matrix. The horizontal variables are the *features* and the vertical variables are the *dependents*. The intersection of a feature and a dependent tells us the normalized significance of that feature's ability to predict that dependent. So, similar to a correlation chart, the diagonal is 1 because any feature can predict itself. Yet unlike the correlation chart, the **relationships are not assumed to be symmetrical**.

Low income percentage is the strongest predictor of the loneliness index (which is to be expected given how many of our features are themselves highly correlated with low income), and next is lacking health insurance percentage, then single-parent percentage, and finally prime age underemployment (extremely marginal, but still predictive). Most interesting is how **none of the features are predictive of each other in isolation**. So, although they correlate heavily, the only feature that is predicted by another is that low-income percentage is predicted by the loneliness index itself. This information will inspire us to continue discussion over the effectiveness of the loneliness index and proves the items we note in our Caveat section as significant potential improvements to the loneliness index

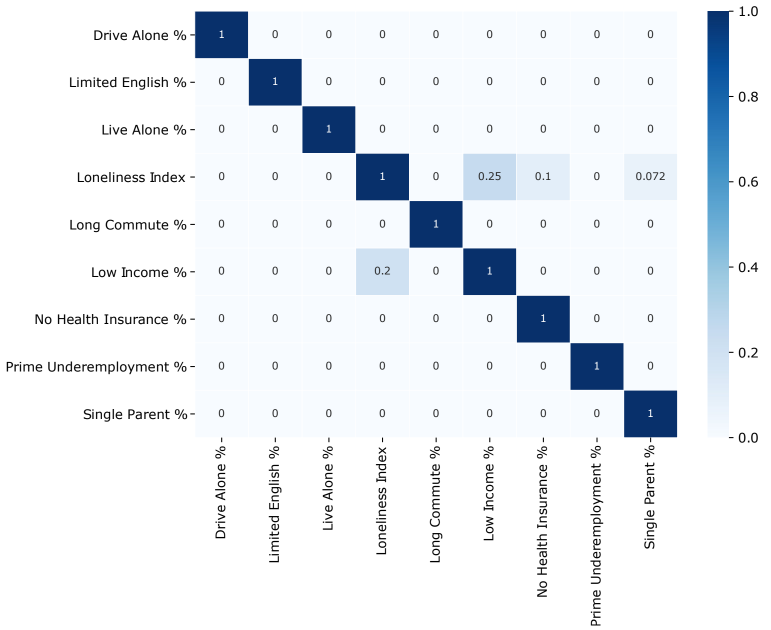

Figure 8. The Predictive Power Score Matrix for all features.

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Acknowledgments

The authors would like to acknowledge the following people for their contributions: Alex Gromadzki and Cara Klanksek

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