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# Assisted Living in the United States: an Open Dataset

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## Abstract

The first United States case of COVID-19 was identified in early 2020, after which nursing homes became a hotspot for the spread of the coronavirus that led to a global pandemic. The ease with which COVID-19 spread throughout nursing homes led to significant disparity in the rates of COVID-19 in nursing home residents compared with older adults living in the community [12], and gave rise to significant policymaker attention on the need for further investment in home and community-based services. Such investment would allow individuals with long-term care needs to age outside of nursing homes in independent living or assisted living communities or in their private residences [18]. An assisted living facility (ALF) is a place where someone can live, have access to social supports such as transportation, and receive assistance with the activities of daily living such as toileting and dressing. Despite the important role of ALFs, they are not required to be certified with Medicare and there is no public national database of these facilities. We present the first public dataset of assisted living facilities in the United States, covering all 50 states with 43,830 facilities and over 1.2 million beds for people in need of housing and assistance. This dataset can help provide answers to existing public health questions, in particular with respect to access to care. To validate the dataset, we replicate the results of a nationwide study of ALFs that uses closed data [4], where the prevalence of ALFs is assessed with respect to county-level socioeconomic variables related to health disparity such as race, disability, and income. To further showcase the value of this dataset, we also propose a novel metric to assess access to community-based care. Using variables from the American Community Survey, we define an individual’s need for assisted living at a county level, and compute the average distance from a group of individuals with assisted living need (across a census-defined area) to an ALF. This allows for a visualization of access to community-based care at the level of an entire country. We hope this dataset provides a resource for policymakers and machine learning researchers to improve public health policy, reduce health disparity, and improve access to community-based care in the United States. The dataset and all pre-processing scripts are available at [onefact.org/assisted-living](https://onefact.org/assisted-living).

## 1 Introduction

The coronavirus pandemic has highlighted several concerns about the lack of access to alternative options for housing an aging population in the United States. Deficiencies in nursing facilities exposed

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\*These authors contributed equally to this work.

| County Characteristic                  | No Facilities    | Assisted Living Facility Penetration |                  |                  |                   |
|--|------------------|--------------------------------------|------------------|------------------|-------------------|
|  |                  | Quartile 1                           | Quartile 2       | Quartile 3       | Quartile 4        |
| # facilities per 1000 people $\geq 65$ |                  | 0.06–12.40                           | 12.40–21.38      | 21.38–32.34      | $\geq 32.34$      |
| Number of Counties                     | 1204             | 507                                  | 506              | 506              | 507               |
| Median age                             | 42.1 $\pm$ 5.4   | 42.4 $\pm$ 5.1                       | 41.2 $\pm$ 5.2   | 40.8 $\pm$ 5.3   | 39.9 $\pm$ 5.3    |
| Percent of population, age $\geq 65$   | 19.3 $\pm$ 4.7   | 19.4 $\pm$ 4.3                       | 18.7 $\pm$ 4.5   | 18.3 $\pm$ 4.9   | 17.6 $\pm$ 4.3    |
| Percent of population, age $\geq 85$   | 2.3 $\pm$ 1.0    | 2.2 $\pm$ 0.7                        | 2.1 $\pm$ 0.7    | 2.2 $\pm$ 1.0    | 2.3 $\pm$ 1.0     |
| Less than high school                  | 14.7 $\pm$ 8.0   | 14.1 $\pm$ 6.0                       | 13.5 $\pm$ 5.2   | 12.0 $\pm$ 5.0   | 10.6 $\pm$ 4.8    |
| College education or higher            | 19.8 $\pm$ 8.2   | 19.8 $\pm$ 8.6                       | 21.1 $\pm$ 8.0   | 24.6 $\pm$ 9.5   | 27.5 $\pm$ 11.6   |
| Median household income (\$1000s)      | 48.7 $\pm$ 14.7  | 51.3 $\pm$ 13.2                      | 52.2 $\pm$ 12.6  | 56.6 $\pm$ 14.7  | 59.6 $\pm$ 16.4   |
| Unemployment rate                      | 6.4 $\pm$ 2.6    | 7.1 $\pm$ 2.1                        | 7.3 $\pm$ 2.2    | 6.9 $\pm$ 2.0    | 6.5 $\pm$ 2.1     |
| Poverty rate                           | 17.8 $\pm$ 10.8  | 15.9 $\pm$ 5.9                       | 15.6 $\pm$ 5.5   | 14.5 $\pm$ 5.5   | 13.2 $\pm$ 5.2    |
| Home ownership rate                    | 73.0 $\pm$ 8.3   | 72.6 $\pm$ 7.8                       | 71.3 $\pm$ 7.5   | 70.1 $\pm$ 7.9   | 68.8 $\pm$ 9.2    |
| Median owned home value (\$1000s)      | 127.0 $\pm$ 71.8 | 149.4 $\pm$ 94.5                     | 148.7 $\pm$ 69.4 | 172.6 $\pm$ 92.1 | 199.2 $\pm$ 135.6 |
| Percent white population               | 83.4 $\pm$ 18.5  | 82.0 $\pm$ 17.3                      | 81.0 $\pm$ 17.3  | 81.6 $\pm$ 16.2  | 83.1 $\pm$ 14.7   |
| Percent black population               | 7.7 $\pm$ 14.5   | 10.7 $\pm$ 16.0                      | 11.0 $\pm$ 15.1  | 10.2 $\pm$ 14.1  | 8.0 $\pm$ 12.8    |
| Percent hispanic population            | 15.1 $\pm$ 26.8  | 10.4 $\pm$ 15.9                      | 9.2 $\pm$ 12.8   | 9.2 $\pm$ 10.8   | 9.3 $\pm$ 10.9    |
| Ratio men to women (100s)              | 101.8 $\pm$ 13.1 | 101.4 $\pm$ 10.8                     | 100.1 $\pm$ 10.7 | 98.6 $\pm$ 7.9   | 99.8 $\pm$ 9.4    |

**Table 1: The assisted living facility (ALF) dataset presented here can be used to replicate existing work by Cornell et al. [4] on access to community-based care, by computing county traits by assisted living penetration per quartile.** County characteristics and statistics are drawn from the 2015–2019 American Community Survey data [1], besides the 2020 unemployment rate [11].

by the pandemic have motivated policy conversations around the need to support opportunities for older adults to age at home or in the community (i.e., in independent living or assisted living).

One of the largest community-based care options in the United States is the system of ALFs. For comparison, there are around 15,000 licensed nursing homes in the United States [10], while the number of ALFs is over 40,000 [4], with both systems housing over one million people each. As over half of Americans turning 65 today are projected to require some form of long-term assistance due to disability [6], the need for greater access to long-term services and supports will become even more important.

An ALF is a place where someone can live, have access to social supports such as transportation, and receive assistance with activities of daily living. For example, an individual with serious mental illness who lives in an ALF may need staff assistance with taking medications, while an elderly person living in an ALF may require help with activities of daily living, such as getting dressed or eating.

But while over one million people live and receive care in ALFs in the United States, there is no public dataset with which to quantify the number of facilities, how they are licensed, and where they are located, since they are regulated on a state-by-state basis. Further, it is estimated that there are a significant number of unlicensed facilities in some states [9]; the possibility of abuse of the elderly or people with serious mental illness at such unlicensed locations further highlights the lack of transparency and data on community-based care.

We build the first public dataset of ALFs, validate the dataset by replicating recent work that studies access to community-based care, and propose a new metric to understand community-based care and health equity at a national level. By documenting the data collection process, we highlight the difficulty of data access. This illustrates some of the structural barriers to what should be public and easily-accessible data: these barriers pose a serious problem to the public, policymakers, and researchers. We hope that this dataset will enable increased transparency and accountability of ALF licensing, and enable the development of machine learning methods to answer public health questions [13], such as how best to expand access to community-based care in the United States and other countries.

## 2 Building an Open Dataset of Assisted Living Facilities

Unlike nursing homes, ALFs are not federally regulated. Each state licenses different forms of ALFs, under varying names and varying regulations. For example, states may license these facilities as ALFs, Residential Care Facilities, Housing with Services, Homes for the Aged, Residential Health Care Facilities, Shared Housing, Personal Care Homes, among other license types.

We follow the National Center for Assisted Living regulatory review of assisted living to define an ALF [2]. This review delineates the regulatory requirements for ALFs based on state-by-state license types and other criteria. We verified this definition with how the federal government defines ALFs (as residential care communities) in its National Post-Acute and Long-Term Care Study [15].

**Data Collection.** All ALFs collected for this dataset came from state licensing agencies, but with significant differences in the ease, transparency, or reproducibility of data access and collection. Of the 50 states and the District of Columbia, 20 states did not have a satisfactory dataset of ALFs online, necessitating a byzantine series of steps to acquire data.

As an illustrative anecdote of the structural barriers to data access, we describe the collection process for Arkansas. For this state, the data was not available on a state website and thus required emailing a state licensing agency. This agency was only able to provide half of the dataset of ALFs; the other half is licensed by a different agency in the state. This resulted in a referral to the second department, which had a policy not to share licensed facilities and meant we had to submit a Freedom of Information Act request. The first such request was denied and had to be resubmitted by a resident of the state on our behalf.

For states with data available online, half a dozen states only provided data directly in their webpage and half a dozen only provided data as a PDF. Data directly on webpages was parsed to extract information into a comma-separated value (CSV). For data available as a PDF, we used optical character recognition to convert the PDF into text and then extracted the textual information into a CSV. For the remaining states, the data was available as a CSV.

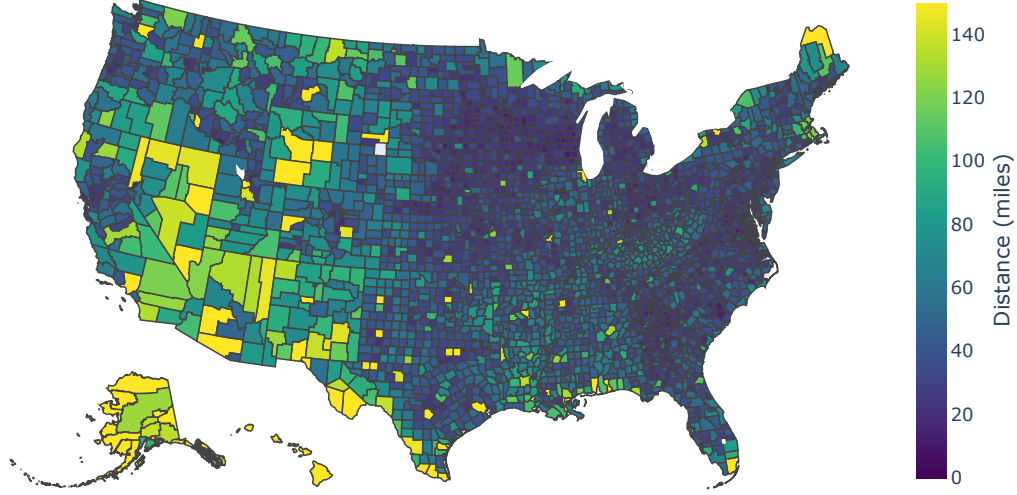
For the rest of the states, licensing agencies were contacted directly. Some states provided data as a CSV and some states only released data as a PDF. Data had to be purchased from one state for \$15 (and turned out to have the highest level of missing attributes of any state). Four states, such as Arkansas, refused to provide a directory of licensed ALFs. For these states, Freedom of Information Act (FOIA) requests were submitted. Two requests were approved, and two were denied, and we had to contact residents of the state who then successfully submitted the FOIA requests on our behalf. After the data was collected, it was cleaned and pre-processed as described in Appendix B.4.

**Linking assisted living facilities to American Community Survey data.** We augmented the ALF dataset with relevant societal metrics. Each ALF is connected to county information on racial demographics and socioeconomic statistics retrieved from the American Community Survey (ACS) 2015-2019 longitudinal study [1]. Additionally, we associate each ALF with the need-based metric for community care which is described in Section 4.

Details about the dataset are described in Appendix B using the dataset documentation framework from Gebru et al. [7].

### 3 Validation

To highlight the utility of an open dataset for answering public health questions with computational methods, we first undertake a conceptual replication of the analysis of Cornell et al. [4] by assessing the prevalence of ALFs with respect to socioeconomic characteristics. Specifically, we replicate Table 1 in Cornell et al. [4] in the present Table 1. While the numbers are overall quite similar, one difference in the replication is that the number of counties with no ALFs in our conceptual replication study is higher than reported in [4]. One potential reason for this is that Cornell et al. [4] focus on county-level capacity information which is easier to access compared to assessing individual facilities as we do in this dataset. This also highlights the need for transparent data collection methods (Cornell et al. [4] do not specify how data on ALFs was collected). Perhaps the method we describe in Section 2 of reaching out to state licensing agencies leads to less capacity information than other (potentially non-public) methods of data access. Despite this difference, the statistics between Cornell et al. [4] and our study are comparable, validating the overall aims of the dataset to enable assessment of access to community-based care and correlation to health equity measures.



**Figure 1: The assisted living facility (ALF) dataset can be used to design and evaluate new metrics to measure access to assisted living for people in need.** This map shows the average distance of every ALF in the United States to people in need of assisted living (where need is defined in Section 3).

#### 4 Need-based Metric for Access to Community-Based Care

Besides using the open dataset to validate socioeconomic and demographic characteristics of access to assisted living, we develop a need-based metric for directly assessing such access. Using data from the American Community Survey, we define someone’s need for assisted living using the self-care, cognitive, ambulatory, and independent living difficulty variables. We designate an individual as being in need of an ALFs if they have at least two of {independent living, cognitive, or ambulatory difficulty}, *and/or* if they have self-care difficulty. This definition of assisted living need is based on Medicaid waivers for reimbursement of the cost of assisted living: several states specify an individual must require assistance with at least two activities of daily living difficulties to qualify for an assisted living waiver [14]. The retrieval of American Community Survey data is described in Appendix B.

To select a variable to assess access to assisted living, we use the location of an ALF. According to a report on how people choose nursing homes, the “single most frequently cited factor in the selection of a facility was location” [17], and we assume that this is the case for ALFs as well. We define the need-based metric per county as the average distance that an individual in need of assisted living must travel to reach a bed in an ALF.

This metric is computed as the average distance from the centroid of each county to the set of facilities needed to satisfy the  $n$  individuals in the county with assisted living need. This is accomplished using shapefiles of each county in the United States and determining their centroids. A k-d tree of all ALFs is created, with the value of the nodes being their capacity. For the 14% of facilities without capacity information, their capacity is imputed as the mean of ALFs with known capacity. For each county, the nearest ALFs to the centroid of the county in the k-d tree are computed, with new facilities added to a running list until the sum of the capacities exceeds the assisted living need of the county. Since the coordinate system in the dataset is in latitude and longitude, the Haversine formula is used to approximate the distance between the centroid of a county and each of these facilities. The mean approximate distance to this subset of facilities is reported.

**Conclusion.** Open data and reproducible, open source methods can lead to increased transparency and accountability of community-based care services such as ALFs. Open datasets such as what we

present can also lead to better tools for people with which to decide where to live and receive care. We hope that this dataset will help researchers and policymakers use and develop machine learning methods to assess health disparity and expand access to community-based care facilities such as ALFs for the elderly and people with serious mental illness.

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## References

- [1] *American Community Survey Public Use Microdata Sample 2015-2019*. EN-US. URL: <https://www.census.gov/programs-surveys/acs/microdata.html> (visited on 09/23/2021).
- [2] *Assisted Living State Regulatory Review*. Tech. rep. National Center for Assisted Living, 2019. URL: [https://www.ahcancal.org/Assisted-Living/Policy/Documents/2019\\_reg\\_review.pdf](https://www.ahcancal.org/Assisted-Living/Policy/Documents/2019_reg_review.pdf).
- [3] US Census Bureau. *Sample ACS and PRCS Forms & Instructions*. EN-US. URL: <https://www.census.gov/acs-forms-and-instructions> (visited on 09/21/2021).
- [4] Portia Y. Cornell, Wenhan Zhang, Lindsey Smith, Shekinah Fashaw, and Kali S. Thomas. “Developments in the Market for Assisted Living: Residential Care Availability in 2017”. en. *Journal of the American Medical Directors Association* (2020). (Visited on 08/26/2021).
- [5] *FACT SHEET: The American Jobs Plan*. en-US. 2021. URL: <https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/31/fact-sheet-the-american-jobs-plan/> (visited on 09/21/2021).
- [6] Melissa Favreault and Judith Dey. *Long-Term Services and Supports for Older Americans: Risks and Financing, 2020*. en. Tech. rep. U.S. Department of Health and Human Services, 2021. URL: <https://aspe.hhs.gov/reports/long-term-services-supports-older-americans-risks-financing-2020-research-brief-0> (visited on 09/02/2021).
- [7] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé III, and Kate Crawford. “Datasheets for Datasets”. *arXiv:1803.09010 [cs]* (2020). (Visited on 09/21/2021).
- [8] *Geocorr Applications - MCDC*. URL: <https://mcdc.missouri.edu/applications/geocorr.html> (visited on 09/24/2021).
- [9] Angela M. Greene, Michael Lepore, Linda Lux, Kristie Porter, and Emily Vreeland. *Understanding Unlicensed Care Homes: Final Report*. en. Tech. rep. U.S. Department of Health and Human Services, 2015.
- [10] Lauren Harris-Kojetin, Manisha Sengupta, Jessica Penn Lendon, Vincent Rome, Roberto Valverde, and Christine Caffrey. *Long-term care providers and services users in the United States, 2015-2016*. en. Tech. rep. U.S. Department of Health, Human Services, Centers for Disease Control, and Prevention, 2019.
- [11] *Local Area Unemployment Statistics*. en. URL: <https://www.bls.gov/lau/> (visited on 09/23/2021).
- [12] *Medicare COVID-19 Nursing Home Analysis*. Tech. rep. U.S. Centers for Medicare & Medicaid Services, 2021. URL: <https://www.cms.gov/files/document/medicare-covid-19-nursing-home-analysis.pdf> (visited on 09/23/2021).
- [13] Vishwali Mhasawade, Yuan Zhao, and Rumi Chunara. “Machine learning and algorithmic fairness in public and population health”. en. *Nature Machine Intelligence* (2021). (Visited on 09/02/2021).
- [14] Robert L. Mollica. *State Medicaid Reimbursement Policies and Practices in Assisted Living*. Tech. rep. National Center for Assisted Living American Health Care Association, 2009. URL: <https://www.ahcancal.org/Assisted-Living/Policy/Documents/MedicaidAssistedLivingReport.pdf> (visited on 09/23/2021).
- [15] *National Post-acute and Long-term Care Study (NPALS)*. Tech. rep. Centers for Disease Control and Prevention, 2018.

- [16] *Provider Information - Centers for Medicare & Medicaid Services*. 2021. URL: <https://data.cms.gov/provider-data/dataset/4pq5-n9py> (visited on 09/21/2021).
- [17] Lisa R. Shugarman and Julie A. Brown. *Nursing Home Selection: How Do Consumers Choose? Volume I: Findings from Focus Groups of Consumers and Information Intermediaries*. en. Tech. rep. U.S. Department of Health, Human Services, Office of Disability, Aging, and Long-Term Care Policy, 2006. URL: <https://aspe.hhs.gov/reports/nursing-home-selection-how-do-consumers-choose-volume-i-findings-focus-groups-consumers-information-1> (visited on 09/22/2021).
- [18] Molly O'Malley Watts, MaryBeth Musumeci, and Meghana Ammula. *State Medicaid Home & Community-Based Services (HCBS) Programs Respond to COVID-19: Early Findings from a 50-State Survey*. en-US. Tech. rep. KFF, 2021. URL: <https://www.kff.org/coronavirus-covid-19/issue-brief/state-medicaid-home-community-based-services-hcbs-programs-respond-to-covid-19-early-findings-from-a-50-state-survey/> (visited on 09/23/2021).



## A Description of Variables in Assisted Living Dataset

| Variable                                  | Description   | Percent Filled |
|---|---|----------------|
| Facility Name                             | Name of the facility  | 100%           |
| Facility ID                               | Facility identification number                                  | 65%            |
| License Number                            | Facility license number   | 48%            |
| Address                                   | Primary physical address of the facility                        | 100%           |
| City                                      | City of the facility  | 98%            |
| State                                     | State of the facility   | 100%           |
| Zip Code                                  | Zip code of the facility  | 97%            |
| County                                    | County of the facility  | 100%           |
| County FIPS                               | County identification code                                      | 100%           |
| Latitude                                  | Latitude of the facility  | 100%           |
| Longitude                                 | Longitude of the facility                                       | 100%           |
| Facility Type Primary                     | Primary licensing type of the facility                          | 100%           |
| Facility Type Secondary                   | Secondary licensing type of the facility                        | 41%            |
| Capacity                                  | Total capacity of the facility (number of beds)                 | 86%            |
| Ownership Type                            | Ownership structure of the facility                             | 27%            |
| Licensee                                  | The license holder of the facility                              | 48%            |
| Phone Number                              | Phone number associated with facility                           | 98%            |
| Email Address                             | Email address associated with facility                          | 35%            |
| Date Accessed                             | Date facility information retrieved from state licensing agency | 100%           |
| Total County AL Need                      | Computed need-based metric for county of facility               | 100%           |
| County Percent of Population 65 or Older  | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Median Age                         | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Homeownership Rate                 | Retrieved from 2015-2019 ACS data                               | 100%           |
| County College Education or Higher Rate   | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Percent Black Population           | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Median Home Value of Owned Homes   | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Percent Hispanic Population        | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Percent of Population 85 or Older  | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Median Household Income            | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Unemployment Rate                  | Retrieved from 2020 ACS data                                    | 100%           |
| County Less Than High School Diploma Rate | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Percent White Population           | Retrieved from 2015-2019 ACS data                               | 100%           |
| County Poverty Rate                       | Retrieved from 2015-2019 ACS data                               | 100%           |

**Table 2: Variables associated with every assisted living facility in this open dataset.**

The table contains one row for each variable in the dataset. A description of the variable is given. The Percent Filled column describes what percent of ALFs in the dataset contain the respective variable.

## B Datasheets for Datasets

We use the dataset documentation framework from [Gebu et al. \[7\]](#).

### B.1 Motivation

**For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.**

A key part of the Biden administration’s \$2 trillion infrastructure plan is \$400 billion allocated to home and community-based care in the United States [5]. However, basic questions about where, how, and to whom these monies and resources should be allocated remain, and there is no public dataset with which to answer these questions for policymakers, researchers, and the public. Machine learning methods to assess cost, health disparities, and quality of assisted living facilities will be key to planning and maintenance of this public health infrastructure. This dataset was created in support of these aims.

**Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?**

Anton Stengel and Jaan Altosaar created the dataset on behalf of research activities in the Elhadad Lab at Columbia University.

**Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.**

Anton Stengel was funded by Princeton University Center for Career Development.

**Any other comments?** [N/A]

## **B.2 Composition**

**What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.**

The instances represent assisted living facilities in the United States, which are licensed homes for the elderly and people with serious mental illness to receive food, shelter, care, help with activities of daily living and other necessities.

**How many instances are there in total (of each type, if appropriate)?**

There are 43,830 assisted living facilities in the dataset.

**Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).**

The dataset contains all possible instances of licensed assisted living facilities in the United States as of 3/24/21. Data was collected between 6/24/21 and 8/24/21. The conservative date is three months prior to the earliest access point because some states' licensing agencies update their public databases on a quarterly basis.

**What data does each instance consist of? "Raw" data (e.g., unprocessed text or images) or features? In either case, please provide a description.**

Each instance consists of raw data and cross-linked or pre-processed variables. The variables associated with every assisted living facility are in Table 2.

**Is there a label or target associated with each instance? If so, please provide a description.**

No.

**Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.**

Yes. States' licensing agencies provided different levels of detail about individual instances. The missing data was not filled in, besides for county information and facility type, which were manually inputted when empty.

**Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.**

Yes. Assisted living facilities within the same state are licensed by the same licensing agency.

**Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.**

No.

**Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.**

Optical character recognition, HTML parsing, and manual transcription was required for data from some states in the dataset, which may induce some errors. A small amount of noise from optical character recognition or manual error is possible for instances in these states.



Some states' directories of licensed facilities seemed to contain occasional misspellings, formatting issues, duplicate facilities, and closed facilities. This could lead to a small amount of error in the dataset.

**Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time?; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.**

The dataset is self-contained.

**Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description.**

No.

**Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.**

No.

**Does the dataset relate to people? If not, you may skip the remaining questions in this section.**

No, the dataset does not relate to individual people. It is a database of assisted living facilities, and to assess assisted living need, it includes aggregate information about people at a population and county level.

**Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.**

The dataset identifies subpopulations of the United States by some demographic characteristics at the county level. Their distributions are given in Table 1.

**Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how.**

No. Public use microdata areas defined by the Bureau of the Census contain no fewer than 100,000 people each, and we employ statistics at the microdata level [3].

**Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.**

No. The race, age, gender variables are at a de-identified microdata area level.

**Any other comments?** [N/A]

### B.3 Collection Process

**How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.**

See 2 for information on how the ALF data was collected.

Here we describe how the need-based metric data and some ALF location data was collected.

To compute the need-based metric, The Census's Microdata Access Tool (MDAT) was queried to get Public Use Microdata Samples (PUMS) of around three million individuals in the United States in 2019 [1]. Each PUMS instance consists of an anonymized individual with variables for self-care, cognitive, ambulatory, and independent living difficulty, as well as the specific Public Use Microdata Area (PUMA) within which the individual is located. PUMAs are geographic areas that partition each state into areas containing at least 100,000 people each. Whether each individual has assisted living need was computed as a function of the four variable disabilities [4]. The number of individuals with assisted living need in each PUMA was counted. Then the count per PUMA was converted to count per county using the Missouri Census Data Center's PUMA-county equivalence file, which provides the overlapping percentage of population between every physically overlapping PUMA and county in the United States [8]. We used a weighted sum of the overlapping populations to estimate the statistic per county.

Location data was then added to each ALF. Google Maps Geocoding API was queried to get latitude and longitude information and county name information for each ALF with a corresponding address. The Federal Communications Commission Area and Census Block API was then queried to get the county Federal Information Processing Standards code for each ALF, which are a five-digit code which uniquely identifies counties and county equivalents in the United States. These codes are useful for linking the assisted living data to county statistics.

**What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?**

Manual human curation and software programs. These mechanisms and procedures were validated by cross-referencing the datasets with states' assisted living facilities, and comparing the total number of facilities to previous work on similar data [4].

**If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?** [N/A]

**Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?**

The lead author led the data collection process and was compensated \$600/week for the duration of the summer.

**Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.**

Data was collected between 6/24/21 and 8/24/21. This broadly matches the creation timeframe of the data associated with the instances; some states update their directories as new facilities are licensed, while other states only update their directories on a quarterly basis.

**Were any ethical review processes conducted (e.g., by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.**

No.

**Does the dataset relate to people? If not, you may skip the remainder of the questions in this section.**

Yes.

**Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?**

Aggregate population- and county-level statistics were obtained from the Bureau of the Census.

**Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.** [N/A]

**Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and pro-**

vided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented. [N/A]

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate). [N/A]

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation. [N/A]

Any other comments? [N/A]

#### **B.4 Preprocessing/cleaning/labeling**

**Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.**

After collecting data for all 48 states, data cleaning was carried out. First, the facility name and address information were parsed into well-formatted columns and capitalization was standardized. Next, duplicate facilities were removed. Duplicates were identified as facilities that have identical names and license numbers or identical names and facility identifiers. For states where there was no license number or facility identifiers available, we considered facilities to be duplicates if they had identical names and addresses.

**Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.**

Yes. It is in the linked repository.

**Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.**

Yes. It is in the linked repository.

Any other comments? [N/A]

#### **B.5 Uses**

**Has the dataset been used for any tasks already? If so, please provide a description.**

No.

**Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.**

Yes. The link will be made available upon publication.

**What (other) tasks could the dataset be used for?**

Besides developing metrics to assess assisted living need and availability as in the present work, machine learning methods could be used to assess health disparity, inequality in access to assisted living, and various other tasks.

**Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?**

No.

**Are there tasks for which the dataset should not be used? If so, please provide a description.**

The dataset is de-identified, and in accordance with data privacy practices should not be used in an attempt to identify individual people living at the assisted living facility locations. A similar dataset already exists for nursing homes provided by the Centers for Medicare & Medicaid Services [16], where similar considerations apply. We acknowledge that the assisted living facility dataset elevates the addresses or prominence of some smaller facilities into the public eye, but that this information is already a matter of public record through state licensing agencies. The dataset, as-is, should not be used to assess the quality or appropriateness of a facility for an individual. There is no assessment of quality or recommendation of whether the facilities are appropriate for any individual in need of assisted living.

**Any other comments?** [N/A]

## **B.6 Distribution**

**Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.**

No.

**How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?**

On GitHub and on the website. There is no digital object identifier yet.

**When will the dataset be distributed?**

Upon publication.

**Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.**

No.

**Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.**

No.

**Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.**

Regulatory restrictions apply to individual assisted living facilities, and vary state-by-state.

**Any other comments?** [N/A]

## **B.7 Maintenance**

**Who is supporting/hosting/maintaining the dataset?**

<https://onefact.org>

**How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**

Anton Stengel and Jaan Altosaar can be contacted at [astengel@princeton.edu](mailto:astengel@princeton.edu) and [j@jaan.io](mailto:j@jaan.io).

**Is there an erratum? If so, please provide a link or other access point.**

The erratum will be kept updated on the GitHub page, <https://github.com/onefact/assisted-living>.

**Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?**

The dataset will be updated through pull requests submitted via GitHub at anytime by anyone. Any dataset updates will be reviewed and merged by team members.

**If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced. [N/A]**

**Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.**

Yes. Older versions of the dataset will continue to be hosted on GitHub.

**If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.**

Yes. This paper describes the process for how the dataset was collected, and anyone can build on this dataset by following the outlined steps. Contributions will be reviewed as pull requests to the GitHub repository.

**Any other comments? [N/A]**