

## Assumptions \& Postulations

- We can define functions that transform accuracy metrics into Fitness-for-use scores, e.g. FFU $=\left\{\begin{array}{l}1 \text { if Abs Perc Error }<10 \% \\ 0 \text { if Abs Perc Error } \geq 10 \%\end{array}\right.$
- Fitness-for-use is better scored at each geographic area and aggregated independent from accuracy metrics
- At the local level, fitness-for-use scores can be combined, allowing for scoring multiple accuracy metrics
- Fuzzy membership functions transform multi-valued accuracy metrics into fitness-foruse scores in interval [0, 1]
- Age is measured on an interval scale and usability is impacted differently whether biases are clustered or spread out


## Fuzzy membership

- Transforms value X into degree of membership: $\mu_{\mathrm{A}}$ : X $\rightarrow[0,1]$
- In this paper:
- Highly accurate $\rightarrow$ FFU $=1$
- Highly inaccurate $\rightarrow \mathrm{FFU}=0$

- Linear decreasing membership in between


## Aggregating Fuzzy membership

- Often used Fuzzy "and" operators

| FFU1 | $\mathbf{0 . 2}$ | $\mathbf{0 . 5}$ | $\mathbf{0 . 8}$ | $\mathbf{0 . 2}$ |
| :--- | :---: | :---: | :---: | :---: |
| FFU2 | $\mathbf{0 . 2}$ | $\mathbf{0 . 5}$ | $\mathbf{0 . 8}$ | $\mathbf{0 . 8}$ |
| Min | 0.2 | 0.5 | 0.8 | 0.2 |
| Product | 0.04 | 0.25 | 0.64 | 0.16 |
| Hamacher <br> product | 0.11 | 0.33 | 0.67 | 0.19 |

- Hamacher product: $\frac{F F U 1 * F F U 2}{F F U 1+F F U 2-F F U 1 * F F U 2}$


## Data used

- August 2022 demonstration data state summary files (New York)
- 2010 SF1 state summary files (New York)
- Different Geographic Summary levels, places split by using PLACECC
- Unincorporated places farther from "Optimized Spine"
- $3 * 24=72$ age distributions per geography
- Sex: Total, Male, Female
- Table PCT12: age by sex is repeated in iterations A through O
- Total
- A-G: 6 race alone + TOMR
- H: Hispanic
- I-O: Non Hispanic race alone + TOMR
- All Non Hispanic and Hispanic race alone + TOMR added by subtraction
- Total group size in SF1 is used to create population size bins $(>=500)$


## Example Age distribution

Example of DP (August 2022) and SF1 age distributions for the Female Black alone population in NY State Senate District 22

In grey is the difference between those two

Total SF1 population is 2,056 Total DP population is 2,068

NY State Senate District 22, Female Black Alone



## Metric 1:

## Signal Noise

Grey area makes the 'pyramid' symmetrical and is the absolute error for each age.

$$
\text { Metric }_{1}=\frac{\text { Total Absolute Error }}{\text { SF1 population }}
$$

Metric value in this example $=$

$$
824 / 2056=40 \%
$$



## Metric 1: Signal Noise



|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 0.004 | 0.209 | 0.194 | 0.050 | 0.127 | 0.071 | 0.018 | 0.048 |
| $1,000-1,999$ | 0.228 | 0.681 | 0.676 | 0.387 | 0.609 | 0.491 | 0.289 | 0.383 |
| $2,000-4,999$ | 0.765 | 0.968 | 0.965 | 0.883 | 0.941 | 0.929 | 0.790 | 0.843 |
| $5,000-10,000$ | 0.995 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.994 | 0.998 |
| $10,000+$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

## Metric 2:

## Moving Totals with big errors

Step 1: calculate 5 -year moving total
Step 2: Flag ages where:

- Absolute difference $>=50$ and
- Absolute \% difference >= $10 \%$

Metric $_{2}=$ number of ages with big errors in 5 yr moving totals

NY State Senate District 22, Female Black Alone

|  | 5 yr Moving Total |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Age midp | Demo | SF1 | Abs Diff | Abs \% Diff |
| 17 | 168 | 114 | 54 | 47\% |
| 18 | 167 | 103 | 64 | 62\% |
| 19 | 164 | 106 | 58 | 55\% |
| 24 | 146 | 203 | 57 | 28\% |
| 25 | 141 | 214 | 73 | 34\% |
| 26 | 162 | 221 | 59 | 27\% |
| 27 | 161 | 226 | 65 | 29\% |
| 28 | 175 | 227 | 52 | 23\% |
| 30 | 166 | 223 | 57 | 26\% |
| 31 | 168 | 231 | 63 | 27\% |
| 32 | 182 | 235 | 53 | 23\% |
| 33 | 152 | 242 | 90 | 37\% |
| 34 | 146 | 241 | 95 | 39\% |
| 35 | 157 | 222 | 65 | 29\% |
| 36 | 131 | 204 | 73 | 36\% |
| 37 | 116 | 182 | 66 | 36\% |
| 61 | 126 | 71 | 55 | 77\% |
| 62 | 125 | 65 | 60 | 92\% |
| 63 | 120 | 51 | 69 | 135\% |
| 64 | 112 | 55 | 57 | 104\% |
| 65 | 102 | 47 | 55 | 117\% |
| 66 | 97 | 45 | 52 | 116\% |
| 67 | 98 | 40 | 58 | 145\% |
|  |  |  |  |  |
| $N=23$ |  |  |  |  |

## Metric 2: Big errors in 5yr Moving Average



|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 |
| $1,000-1,999$ | 0.996 | 1.000 | 1.000 | 0.997 | 1.000 | 1.000 | 0.991 | 0.996 |
| $2,000-4,999$ | 0.950 | 0.999 | 0.998 | 0.989 | 1.000 | 0.995 | 0.893 | 0.953 |
| $5,000-10,000$ | 0.828 | 0.992 | 0.994 | 0.973 | 0.999 | 0.987 | 0.706 | 0.863 |
| $10,000+$ | 0.985 | 0.996 | 0.993 | 0.998 | 1.000 | 0.993 | 0.921 | 0.952 |

## Metric 3: large age group with large \% error

## Steps:

1. Create cumulative populations over age and cumulative difference.
2. Find ages where cumulative difference is minimal (a1) and maximal (a2)
3. Range of cumulative difference is max - min
4. SF1 population for ages a $1<$ age $<=$ age 2 can be found in cumulative pop chart
NOTE: SF1 = DP + Range

$$
\text { Metric }_{3}=\frac{\text { Range }}{S F 1_{a 1+1, a 2}}
$$

Metric $_{3}$ is Absolute Percent Error for this age range
Metric value in this example $=$

$$
305 / 1149=27 \%
$$

Metric $_{3}$ is only calculated if age $2-$ age $1>=10$ and $S F 1_{\mathrm{a} 1+1, \mathrm{a} 2}>=10 \%$ of $\mathrm{SF}_{\text {total }}$ to eliminate results from noise and low numbers

NY State Senate District 22, Female Black Alone


NY State Senate District 22, Female Black Alone


## Metric 3: \% error of large age group with large \% error

|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 0.293 | 0.615 | 0.624 | 0.336 | 0.538 | 0.410 | 0.272 | 0.344 |
| $1,000-1,999$ | 0.533 | 0.833 | 0.834 | 0.608 | 0.815 | 0.723 | 0.518 | 0.581 |
| $2,000-4,999$ | 0.834 | 0.954 | 0.953 | 0.877 | 0.944 | 0.924 | 0.784 | 0.832 |
| $5,000-10,000$ | 0.953 | 0.992 | 0.995 | 0.989 | 0.990 | 0.987 | 0.929 | 0.960 |
| $10,000+$ | 1.000 | 0.999 | 0.999 | 0.999 | 1.000 | 0.999 | 0.994 | 0.994 |

## Metric 4: Absolute difference in median age

Steps:

1. Create cumulative age distributions
2. Determine at what age $50 \%$ is less than age x (median age)

Metric $_{4}$
$=\mid$ Median Age $_{D P}$

- Median Age $e_{S F 1}$

Metric $_{4}$ is Absolute Difference in median age
Metric value in this example $=$

$$
37.6-34.1=3.5
$$



## Metric 4: Difference in median age



|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 0.903 | 0.975 | 0.973 | 0.848 | 0.967 | 0.918 | 0.844 | 0.867 |
| $1,000-1,999$ | 0.959 | 0.997 | 0.996 | 0.954 | 0.997 | 0.987 | 0.942 | 0.960 |
| $2,000-4,999$ | 0.995 | 1.000 | 0.999 | 0.997 | 1.000 | 0.999 | 0.989 | 0.994 |
| $5,000-10,000$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 |
| $10,000+$ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

## Aggregated Fitness-For-Use score

## Average Fitness-For-Use score

|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 0.003 | 0.176 | 0.164 | 0.038 | 0.102 | 0.051 | 0.011 | 0.037 |
| $1,000-1,999$ | 0.166 | 0.604 | 0.601 | 0.306 | 0.534 | 0.404 | 0.197 | 0.284 |
| $2,000-4,999$ | 0.648 | 0.929 | 0.926 | 0.795 | 0.895 | 0.866 | 0.604 | 0.705 |
| $5,000-10,000$ | 0.796 | 0.985 | 0.989 | 0.963 | 0.989 | 0.975 | 0.678 | 0.842 |
| $10,000+$ | 0.985 | 0.996 | 0.993 | 0.997 | 1.000 | 0.993 | 0.919 | 0.949 |

\% of age distributions with Fitness-For-Use score $>=0.5$

|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | $0 \%$ | $10 \%$ | $9 \%$ | $1 \%$ | $3 \%$ | $1 \%$ | $0 \%$ | $2 \%$ |
| $1,000-1,999$ | $7 \%$ | $68 \%$ | $68 \%$ | $25 \%$ | $57 \%$ | $37 \%$ | $8 \%$ | $20 \%$ |
| $2,000-4,999$ | $73 \%$ | $97 \%$ | $97 \%$ | $86 \%$ | $96 \%$ | $93 \%$ | $66 \%$ | $78 \%$ |
| $5,000-10,000$ | $82 \%$ | $99 \%$ | $99 \%$ | $97 \%$ | $100 \%$ | $99 \%$ | $71 \%$ | $87 \%$ |
| $10,000+$ | $99 \%$ | $100 \%$ | $100 \%$ | $100 \%$ | $100 \%$ | $100 \%$ | $93 \%$ | $96 \%$ |

## Fitness-For-Use score (Aug 2022 vs Oct 2019)

## Average Fitness-For-Use score August 2022

|  | County | MCD | Place inc | Place <br> uninc | Tract | School <br> District | Legislativ <br> e | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $500-999$ | 0.003 | 0.176 | 0.164 | 0.038 | 0.102 | 0.051 | 0.011 | 0.037 |
| $1,000-1,999$ | 0.166 | 0.604 | 0.601 | 0.306 | 0.534 | 0.404 | 0.197 | 0.284 |
| $2,000-4,999$ | 0.648 | 0.929 | 0.926 | 0.795 | 0.895 | 0.866 | 0.604 | 0.705 |
| $5,000-10,000$ | 0.796 | 0.985 | 0.989 | 0.963 | 0.989 | 0.975 | 0.678 | 0.842 |
| $10,000+$ | 0.985 | 0.996 | 0.993 | 0.997 | 1.000 | 0.993 | 0.919 | 0.949 |

Average Fitness-For-Use score October 2019

|  | County | MCD | Place inc | Place | Tract | School | Legislativ | ZCTA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 500-999 |  | 0.000 | 0.000 | 0.002 | 0.001 | 0.000 |  | 0.000 |
| $1,000-1,999$ |  | 0.000 | 0.000 | 0.003 | 0.002 | 0.000 |  | 0.006 |
| $2,000-4,999$ | 0.000 | 0.000 | 0.000 | 0.006 | 0.001 | 0.000 |  | 0.005 |
| $5,000-10,000$ | 0.000 | 0.000 | 0.000 | 0.004 | 0.000 | 0.000 |  | 0.001 |
| $10,000+$ | 0.211 | 0.033 | 0.013 | 0.000 | 0.000 | 0.012 | 0.049 | 0.000 |

## Wrap-up

- Fuzzy membership functions are useful to score fitness-for-use
- Fitness-for-use scores allow for considering multiple accuracy metrics at the record level
- There is room to develop more accuracy metrics for variables measured on an interval or ratio scale
- Similar frameworks can be used in estimates evaluation


