

# Comparative Analysis of Socioeconomic Indicators of USA's Most and Least Populated States



Submitted by  
Manjusha Madhukar Ghatke

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# Introduction

## Socioeconomic Indicators

- Measures that reflect an individual's/a community's economic and social status .
- Income, gender, literacy, unemployment, race, education, geographical area of origin, income source, occupation, age distribution, health, marital status
- Importance:
  - Assessing inequalities
  - Public health research
  - Effect of recession
  - Assessing country's overall condition

# Purpose

- Policy Making & Resource Allocation
- Economic Analysis
- Educational Planning
- Social Services Planning
- Migration and Development Studies
- Research and Academia
- Investment Decision Making
- Workforce Development

# Purpose

End-users:

- State and federal policy makers
- Economic development agencies
- Educational institutions
- Social service organizations
- Business strategists
- Urban planners
- Researchers and academics
- Investment analysts

# Data- Source

File name: RuralAtlasData24.xlsx

Organization: U.S. Department of Agriculture

Link: <https://catalog.data.gov/dataset/atlas-of-rural-and-small-town-america>

The screenshot shows a web browser displaying the 'Atlas of Rural and Small-Town America' dataset page on the Data Catalog. The page features the USDA logo and the Department of Agriculture. The dataset title is 'Atlas of Rural and Small-Town America', with metadata updated on February 24, 2021. The description states: 'View the diversity of challenges and opportunities across America's counties within different types of rural regions and communities. Get statistics on people, jobs, and agriculture.' The 'Access & Use Information' section indicates the dataset is public and uses a Creative Commons Attribution license. The 'Downloads & Resources' section lists three items: a 'Data file' (29 views) with a 'Download' button, 'GIS API Services' with a 'Download' button, and an 'Interactive map' (25 views) with a 'Visit page' button. There is also a 'Zip of CSV files' (29 views) with a 'Download' button. The left sidebar includes sections for 'Topics' (Climate), 'Publisher' (Economic Research Service, Department of Agriculture), 'Contact' (John Cromartie), and 'Share on Social Sites' (Twitter, Facebook).

# Data- Preprocessing

```
income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 3280 entries, 0 to 3279
```

```
Data columns (total 16 columns):
```

#	Column	Non-Null Count	Dtype
0	FIPS	3280 non-null	int64
1	State	3280 non-null	object
2	County	3280 non-null	object
3	Median_HH_Inc_ACS	3273 non-null	float64
4	PerCapitaInc	3274 non-null	float64
5	Poverty_Rate_0_17_ACS	3273 non-null	float64
6	Poverty_Rate_ACS	3274 non-null	float64
7	Deep_Pov_All	3274 non-null	float64
8	Deep_Pov_Children	3274 non-null	float64
9	NumAll_inPOV_ACS	3274 non-null	float64
10	PCTPOV017	3194 non-null	float64
11	POV017	3194 non-null	float64
12	MedHHInc	3194 non-null	float64
13	POVALL	3194 non-null	float64
14	PCTPOVALL	3194 non-null	float64
15	Num_inPOV_0_17_ACS	3274 non-null	float64

```
dtypes: float64(13), int64(1), object(2)
```

```
memory usage: 410.1+ KB
```

✕ ✓  $f_x$

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	FIPS	Stat	County	Median_HH_Inc_AC	PerCapitaInc	Poverty_Rate_0_17_AC	Poverty_Rate_AC	Deep_Pov_A	Deep_Pov_Childre	NumAll_inPOV_AC	PCTPOV01	POV01	MedHHInc	POVAL	PCTPOVAL	Num_inPOV_0_17_AC	
2	00000	US	United States	69021	37638	17.04670519	12.63185031	5.777394811	7.691714615	40661636	16.9	12343219	69717	41393176	12.8	12443424	
3	01000	AL	Alabama	54943	30458	22.26193645	15.78512663	7.077315689	10.39058157	769819	22.7	250327	53990	800848	16.3	245696	
4	01001	AL	Autauga	62660	30968	18.67386389	13.57847378	6.2502163	8.592895178	7847	16.1	2199	66444	6296	10.7	5560	
5	01003	AL	Baldwin	64346	35384	11.29982166	9.204904993	4.043401319	5.503711999	20598	16.4	8207	65658	25526	10.8	5449	
6	01005	AL	Barbour	36422	21325	43.74401026	26.47191011	12.82696629	26.72925848	5890	35.1	1776	38649	5089	23	2283	
7	01007	AL	Bibb	54277	24787	28.04290718	16.94285714	9.076190476	17.51313485	3558	29	1275	48544	4204	20.6	1281	
8	01009	AL	Blount	52830	27309	17.28166827	13.23663049	5.291223017	6.344745988	7720	16.7	2236	56894	6992	12	2337	
9	01011	AL	Bullock	29063	21012	49.74805314	30.9345983	10.1937828	18.27759963	3065	41.7	903	32027	2764	32.1	1086	
10	01013	AL	Butler	45236	23897	29.60556845	18.17700053	6.66136725	11.18329466	3430	34.2	1441	39442	4226	22.7	1276	
11	01015	AL	Calhoun	50977	26440	21.60229476	17.53843981	8.32965586	11.17081448	19870	25.2	6205	48166	21630	19.2	5347	
12	01017	AL	Chambers	47232	24840	25.33333333	15.0713246	5.091703057	7.958333333	5177	32.2	2258	45447	6699	19.7	1824	
13	01019	AL	Cherokee	43475	26867	18.80704734	14.97337074	5.073789487	5.625132658	3683	26.6	1235	46365	4513	18.2	886	
14	01021	AL	Chilton	56243	26426	16.16829596	15.7239819	6.004524887	3.76853249	6990	22.4	2362	55142	6973	15.5	1687	
15	01023	AL	Choctaw	39581	25163	34.93740219	21.56629374	9.402623209	18.81846635	2718	32.4	809	40601	2893	23.3	893	
16	01025	AL	Clarke	44108	25263	29.8389672	21.90612902	10.55722302	13.18012178	5036	29.2	1419	45447	4366	19.4	1519	
17	01027	AL	Clay	45163	26255	22.67247163	16.92627352	5.59902375	9.845947756	2398	27.6	792	47036	2560	18.4	678	
18	01029	AL	Cleburne	48333	27026	20.29154519	14.17920473	5.333154218	5.772594752	2111	22.1	755	49769	2236	15	696	
19	01031	AL	Coffee	59034	29688	25.01400336	15.94036697	7.327981651	12.25894215	8340	24.2	3087	55052	8516	15.9	3126	
20	01033	AL	Colbert	52017	28090	23.42852315	15.13205869	6.957759004	12.00574518	8508	23.6	2841	53341	9396	16.5	2773	
21	01035	AL	Concho	37986	22841	22.31303637	12.96864349	6.833674165	16.30568043	1522	33.9	762	35621	2528	22.4	546	
22	01037	AL	Coosa	50013	26718	20.45990566	11.14754098	4.232488823	9.84669813	1122	29.9	499	49594	1754	17.1	347	
23	01039	AL	Covington	46186	26138	25.8163894	18.03933286	8.024121258	13.2224276	6641	28.3	2304	44188	7317	19.8	2095	
24	01041	AL	Crenshaw	43103	28097	15.85488747	13.10107198	4.8486960643	7.759489419	1711	28.9	854	38037	2267	17.5	472	
25	01043	AL	Cullman	52690	26508	14.93699416	12.1860843	5.725403647	7.591435304	10519	17.5	3432	55036	11898	13.5	2916	
26	01045	AL	Dale	50052	26469	27.26867534	16.71052082	8.868980495	16.43786771	8002	22.7	2558	50086	7587	15.7	3059	
27	01047	AL	Dallas	34957	20748	38.03107682	24.30519548	8.905423623	16.26643486	9375	45.4	3924	33159	10914	29.5	3500	
28	01049	AL	DeKalb	44037	23947	31.61751876	20.57219744	7.162382268	10.5333566	14525	29.3	4981	45062	13783	19.4	5436	
29	01051	AL	Elmore	67597	31185	13.81956771	10.28199619	4.048460128	5.147749817	8470	17.3	3347	63147	10138	12	2647	
30	01053	AL	Escambia	38464	19581	33.84559535	23.48629794	12.29800135	18.92545983	7979	29.9	2445	40506	8147	23.8	2797	
31	01055	AL	Etowah	45884	26026	24.29974536	16.01345537	6.214308065	10.51746089	16376	25	5464	46308	17605	17.4	5344	
32	01057	AL	Fayette	43960	24268	32.40714672	21.33490771	9.359269157	15.37171904	3433	26.5	901	46122	3123	19.6	1113	
33	01059	AL	Franklin	43633	22500	30.09622689	18.06636147	6.734043274	8.890341859	5720	25.1	1968	45440	5995	18.9	2377	
34	01061	AL	Geneva	43681	23338	35.26744745	23.51242496	5.254958584	9.544208362	6188	29.1	1672	43206	5566	21.1	2057	
35	01063	AL	Greene	28826	16282	61.37184116	39.79578648	14.9828913	34.23586041	3079	51.8	848	30225	2520	33.2	1020	
36	01065	AL	Hale	32294	20849	38.46153846	24.9124734	7.956339672	14.2351901	3629	32.6	1128	41895	3221	22.1	1305	
37	01067	AL	Henry	55870	28304	23.8294065	14.39453008	6.585497511	12.7348643	2400	24.6	867	56389	2694	15.6	799	
38	01069	AL	Houston	50222	29388	26.03491684	17.66523132	7.77083868	12.76166672	18584	27.1	6511	48701	20210	19.1	6308	
39	01071	AL	Jackson	43795	25153	25.71844307	17.61233633	5.55865331	8.257548199	9160	27	2906	46398	9951	18.9	2828	
40	01073	AL	Jefferson	58330	34860	22.83916525	15.89747566	7.317955594	11.16414849	104579	23.6	35575	55210	110131	16.9	34737	
41	01075	AL	Lamar	43324	22678	18.79623403	16.27568119	5.464082763	8.977807666	2234	24.7	715	44265	2300	17	559	
42	01077	AL	Lauderdale	50000	29667	16.93923968	13.30227573	5.744562186	7.46777862	12164	22.8	4187	52222	14838	16.2	3128	
43	01079	AL	Lawrence	51712	26810	24.5142565	15.38414578	5.619486585	10.07686932	5040	23	1638	55555	4566	13.9	1754	
44	01081	AL	Lee	57191	30680	20.42960349	19.92484373	11.49324918	10.27684332	33086	18.4	6767	54188	30989	18	7409	
45	01083	AL	Limestone	70736	33428	15.53772358	11.48487179	5.007457045	6.903662528	11243	11.8	2743	69207	10363	9.9	3466	
46	01085	AL	Lowndes	31961	21936	32.28204898	21.48264674	9.27148067	18.17783818	2185	43	946	36993	2786	28.3	737	



# Data Preprocessing

Python:

1. Dropping columns and rows
2. Checking for and dropping null values
3. Reset index
4. Export data

```
income.drop('FIPS', axis=1, inplace=True)
income.drop(0, inplace=True)
income.head()
```

```
income.isnull().sum()
```

```
#drop rows containing Null values
before=income.shape[0]
cols=['Median_HH_Inc_ACS', 'PerCapitaInc',
      'Poverty_Rate_0_17_ACS', 'Poverty_Rate_ACS', 'Deep_Pov_All',
      'Deep_Pov_Children', 'NumAll_inPOV_ACS', 'PCTPOV017', 'POV017',
      'MedHHInc', 'POVALL', 'PCTPOVALL', 'Num_inPOV_0_17_ACS']
```

```
for column in cols:
    income = income.dropna(subset=[column])

after=income.shape[0]
print('Number of rows with null values removed:', before-after)
```

Number of rows with null values removed: 87

```
income.reset_index(drop=True, inplace=True)
```

```
income.to_excel('RuralAreaafinal.xlsx', sheet_name='Income')
```

# Data- Preprocessing

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3192 entries, 0 to 3191
Data columns (total 15 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   State                                3192 non-null   object
1   County                              3192 non-null   object
2   Median_HH_Inc_ACS                   3192 non-null   float64
3   PerCapitaInc                        3192 non-null   float64
4   Poverty_Rate_0_17_ACS               3192 non-null   float64
5   Poverty_Rate_ACS                    3192 non-null   float64
6   Deep_Pov_All                        3192 non-null   float64
7   Deep_Pov_Children                   3192 non-null   float64
8   NumAll_inPOV_ACS                    3192 non-null   float64
9   PCTPOV017                           3192 non-null   float64
10  POV017                              3192 non-null   float64
11  MedHHInc                            3192 non-null   float64
12  POVALL                              3192 non-null   float64
13  PCTPOVALL                           3192 non-null   float64
14  Num_inPOV_0_17_ACS                  3192 non-null   float64
dtypes: float64(13), object(2)
memory usage: 374.2+ KB
```

# Data- Preprocessing

income										
	State	County	Median_HH_Inc_ACS	PerCapitalInc	Poverty_Rate_0_17_ACS	Poverty_Rate_ACS	Deep_Pov_All	Deep_Pov_Children	NumAll_inPOV_ACS	PCTPOV01
0	AL	Alabama	54943.0	30458.0	22.261936	15.785127	7.077316	10.390582	769819.0	22
1	AL	Autauga	62660.0	30968.0	18.673864	13.578474	6.250216	8.592895	7847.0	16
2	AL	Baldwin	64346.0	35384.0	11.299822	9.204905	4.043401	5.503712	20598.0	16
3	AL	Barbour	36422.0	21325.0	43.744012	26.471910	12.826966	26.729258	5890.0	35
4	AL	Bibb	54277.0	24787.0	28.042907	16.942857	9.076190	17.513135	3558.0	29
...	...	...	...	...	...	...	...	...	...	...
3187	WY	Sweetwater	76668.0	36233.0	13.501566	10.481391	5.646027	7.358630	4396.0	9
3188	WY	Teton	94498.0	66296.0	8.315204	7.117040	2.547332	0.652647	1654.0	5
3189	WY	Uinta	75106.0	30586.0	7.466063	7.958751	3.508166	2.071006	1613.0	11
3190	WY	Washakie	62271.0	31032.0	5.125149	6.571842	2.607665	3.694875	499.0	12
3191	WY	Weston	65566.0	31190.0	7.303807	14.085591	6.250000	2.175602	915.0	12

3192 rows × 15 columns

# Data- Preprocessing

Same preprocessing steps have been performed for other sheets in the file

```
jobs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 3186 entries, 0 to 3185
```

```
Data columns (total 78 columns):
```

#	Column	Non-Null Count	Dtype
0	State	3186 non-null	object
1	County	3186 non-null	object
2	UnempRate2021	3186 non-null	float64
3	PctEmpChange2021	3186 non-null	float64
4	UnempRate2020	3186 non-null	float64
5	PctEmpChange1920	3186 non-null	float64
6	UnempRate2019	3186 non-null	float64
7	UnempRate2018	3186 non-null	float64
8	UnempRate2017	3186 non-null	float64

```
people.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 3138 entries, 0 to 3137
```

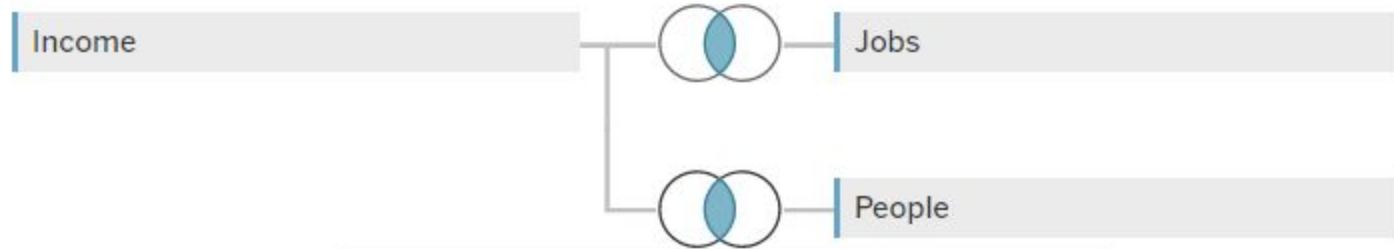
```
Data columns (total 93 columns):
```





#	Column	Non-Null Count	Dtype
0	State	3138 non-null	object
1	County	3138 non-null	object
2	Pop_change_Rate_2020_2021	3138 non-null	float64
3	POPESTIMATE2021	3138 non-null	float64
4	Net_Migration_Rate_2020_2021	3138 non-null	float64
5	Natural_Change_Rate_2020_2021	3138 non-null	float64
6	Net_InterMigrationRate_2020_2021	3138 non-null	float64
7	PopChangeRate1020	3138 non-null	float64
8	PopDensity2020	3138 non-null	float64
9	Under18Pct2020	3138 non-null	float64
10	Age65AndOlderPct2020	3138 non-null	float64
11	WhiteNonHispanicPct2020	3138 non-null	float64
12	BlackNonHispanicPct2020	3138 non-null	float64
13	AsianNonHispanicPct2020	3138 non-null	float64
14	NativeAmericanNonHispanicPct2020	3138 non-null	float64
15	HispanicPct2020	3138 non-null	float64
16	MultipleRacePct2020	3138 non-null	float64
37	Ed5CollegePlusPct	3138 non-null	float64

# Data- Preprocessing

3 different tables are joined (inner) on the 'County' (unique values) column.

Income is made of 3 tables. ⓘ



Join			
 Inner	 Left	 Right	 Full Outer
Data Source		People	
County	=	County (People)	
Add new join clause			

# Data- Preprocessing

## Calculated fields

AvgUnempRat1721

```
( [UnempRate2017] + [UnempRate2018] + [UnempRate2019] + [UnempRate2020] + [UnempRate2021] ) / 5 |
```

WorkingAgePct2020

```
100 - [Age65AndOlderPct2020] - [Under18Pct2020] |
```

# Visualization

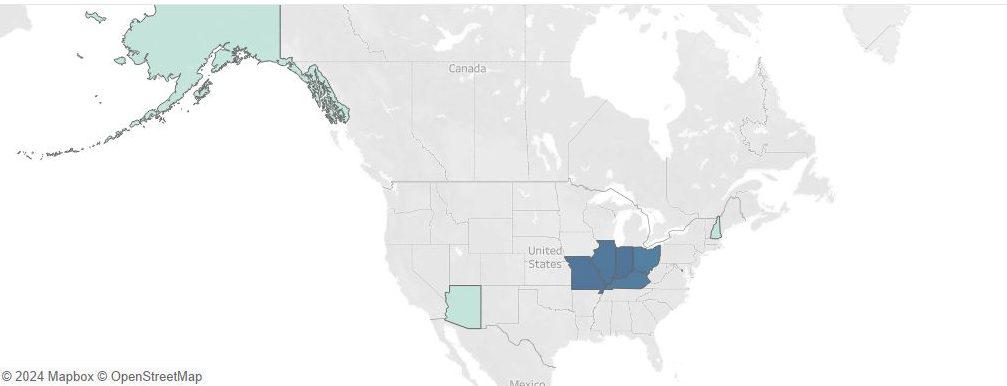
Tool used: Tableau

Visualization Title	Visualization Type
Population Overview Map	Filled Map
Top and Bottom 5 Populated States Demographics	Bar Chart
Economic Health Overview	Bar Chart
State-wise Age Distribution	Bar Chart
Education & Income Relationship	Scatter Plot

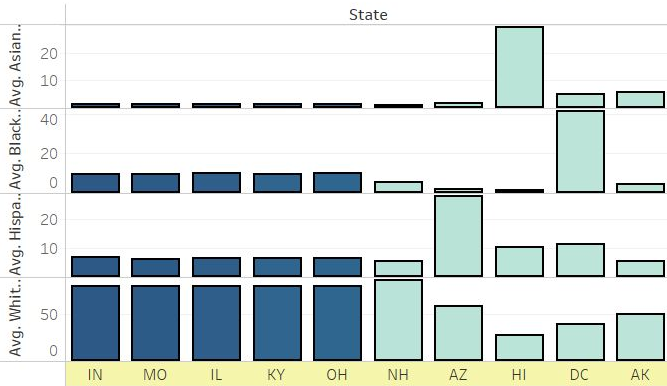


# Comparative Analysis of Socioeconomic Indicators of Population Extremes

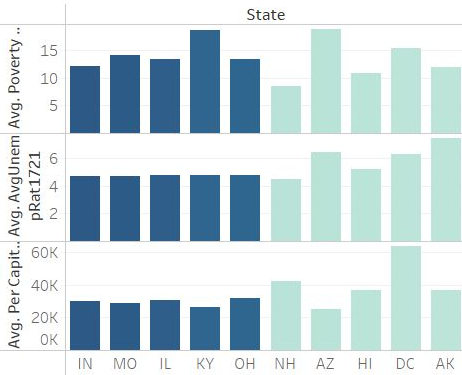
Population Overview Map



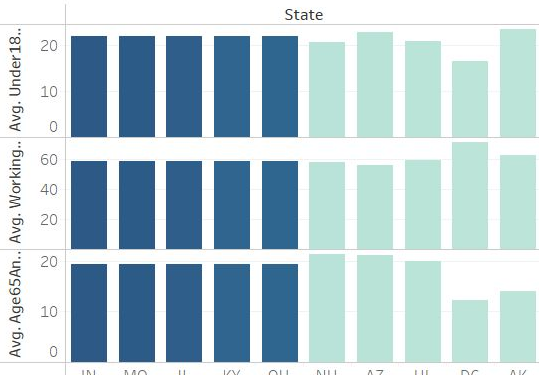
Top and Bottom 5 Populated States Demographics



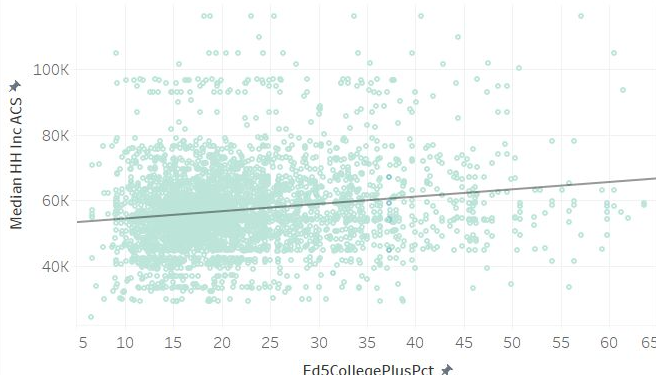
Economic Health Overview



State-wise Age Distribution



Education & Income Relationship



- State
- ☒ (All)
  - ☒ AK
  - ☒ AL
  - ☒ AR
  - ☒ AZ
  - ☒ CA
  - ☒ CO
  - ☒ CT
  - ☒ DC
  - ☒ DE
  - ☒ FL
  - ☒ GA
  - ☒ HI
  - ☒ IA
  - ☒ ID
  - ☒ IL
  - ☒ IN
  - ☒ KS
  - ☒ KY
  - ☒ LA
  - ☒ MA
  - ☒ MD
  - ☒ ME
  - ☒ MI
  - ☒ MN
  - ☒ MO
  - ☒ MS
  - ☒ MT
  - ☒ NC
  - ☒ ND
  - ☒ NE
  - ☒ NH
  - ☒ NJ
  - ☒ NM
  - ☒ NV
  - ☒ NY
  - ☒ OH

Popestimate2021





# Visualization

## Key Insights

### Population Overview Map & Top and Bottom 5 Populated States Demographics

#### 1. Demographic Composition:

- a. The Midwestern states (shown in blue) appear to have relatively consistent demographic patterns across racial/ethnic categories: >75% White, <20% other ethnic groups
- b. States like Hawaii (HI) (>30% Hisp) and DC (>40% Black) show comparatively different demographic > higher diversity
- c. Alaska (AK) shows relatively lower populations across all demographic categories

#### 2. Plausible Reasons:

- a. Historical settlement patterns: The Midwest's demographic consistency likely reflects historical immigration and settlement patterns | top populated states shown (IN, MO, IL, KY, OH)
- b. Geographic factors: Hawaii's unique demographic makeup reflects its Pacific location and Native Hawaiian population | bottom populated states (NH, AZ, HI, DC, AK) are more geographically diverse, including territories from different regions
- c. Urban concentration: DC's distinct pattern reflects its nature as an urban federal district
- d. Industrial development: The Midwest's population patterns may relate to its industrial and agricultural heritage.

#### 3. Applications:

- a. Policies: Language services and cultural program development
- b. Business: Retail location planning | Product development tailored to regional demographics
- c. Social welfare: Cultural sensitivity training for service providers

# Visualization

## Key Insights

### Economic Health Overview

1. Per capita income: :
  - a. High Income Areas:  
DC: high concentration of federal jobs and professionals  
NH and HI's: tourism, specialized industries and high cost of living  
AK: higher income likely reflects oil industry revenues and high cost of living
  - b. More Populated States:  
The Midwest states (OH, IL, IN, MO, KY) show relatively consistent income levels | more diverse economies including manufacturing, agriculture, and services.
2. Unemployment and Poverty rates:
  - a. Midwest states' consistent unemployment rates reflect similar industrial/economic bases  
AK's high unemployment might relate to seasonal work and resource-dependent economy  
NH's low unemployment & poverty rates might reflect diverse economy and proximity to Boston metro area
3. Applications:
  - a. Policies: Education institutes | Raising minimum wage | Small business Support | Improve access to food, healthcare, housing to tackle high poverty rates  
Business: Training programs | Market expansion according to worker availability.

# Visualization

## Key Insights

### State-wise Age Distribution

1. More populated states show more stable distributions due to diverse economic bases
  - a. DC's high working-age population reflects its status as a job center
2. Less populated states show more variation based on specific economic/lifestyle factors
  - a. Arizona's higher elderly population likely due to retirement migration
  - b. Alaska's younger demographic may reflect job opportunities in resource industries
3. Applications:
  - a. Policies: Medical facilities and specialists | Senior care facilities | Developing health programs  
Infrastructure: School system capacity | Retirement community planning

# Visualization

## Key Insights

### Education (4-yr college degree or higher) & Income Relationship

1. Income spread is wider in counties with higher education levels.
2. High incomes despite moderate education levels: indicating presence of specific industries or economic conditions.
3. Applications:
  - a. Policy: Higher education funding | Workforce skill development
  - b. Business: Expansion based on workforce skill

# Conclusion

A Comparative Analysis of Population Extremes can lead to valuable insights regarding the country's economy, health status, areas of opportunities, migration, major areas of development, and factors affecting population growth/decline (regulate population).

## Limitations:

- All attributes do not belong to the same year/year group, so the most recently collected data is used for comparison.
- Missing values ~100 have been excluded from the visualization.

# References

- U.S. Department of Agriculture
- 2024 Stack Exchange Inc
- U.S. Bureau of Labor Statistics
- Resource Development Council for Alaska, Inc.
- 2024 NH Department of Business and Economic Affairs,
- Office of the Deputy Mayor for Planning and Economic Development - DMPED
- Vision Retirement

**THANK YOU**